UNIVERSITY OF TWENTE.

# Data envelopment analysis for project efficiency evaluation

by

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# Abstract

In today's complex and resource-limited project environments, organizations face increasing challenges in selecting and managing projects efficiently. To address these issues, this study proposes a Data Envelopment Analysis (DEA)-based evaluation framework designed to support early-stage project assessment and selection, allowing decision-makers to benchmark and prioritize projects before execution.

The framework design was informed by a systematic literature review, which revealed that while DEA is widely used in sectors such as healthcare and education, its application to pre-project evaluation remains unexplored. It was developed in response to the limitations of traditional project evaluation methods, which often overlook the multi-dimensional nature of project efficiency by focusing on single metrics such as cost or financial outcome. By integrating multiple inputs and outputs, the DEA approach provides a comprehensive relative efficiency score for each project among other metrics which allows an objective comparison across projects. Additionally, we propose a set of key requirements for designing a DEA-based framework to support the selection and evaluation of early-stage projects. These requirements were derived from a review of relevant literature, practical considerations in project efficiency evaluation and the methodological constraints of DEA.

To ensure practical relevance, we formulated Key Performance Indicators (KPIs) based on DEA results, incorporating inputs such as estimated costs, timelines, and resources alongside projected outputs like probabilities and financial outcomes. The study also compares Charnes, Cooper and Rhodes (CCR) and Banker, Charnes and Cooper (BCC) models for suitability in pre-execution contexts.

A real-world case study validated the framework, demonstrating its ability to improve resource allocation, strategic alignment, and project evaluation. The developed KPIs bridge technical efficiency analysis and managerial decision-making.

In conclusion, this research extends DEA use from retrospective to proactive project selection, laying the foundation for future improvements such as real-time data integration and automated decision-making to boost organizational project success and competitiveness.

**Keywords:** Data Envelopment Analysis; Project Selection; Project Management; Efficiency Measurement; Decision Support; Key Performance Indicators

# AUTHOR'S DECLARATION

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# ABBREVIATIONS

**ANP** Analytic Network Process.

**BCC** Banker, Charnes and Cooper.

**CCR** Charnes, Cooper and Rhodes.

**CRISP-DM** CRossIndustry Standard Process for Data Mining.

**CRS** Constant Return to Scale.

**DEA** Data Envelopment Analysis.

**DMU** Decision Making Unit.

**DRS** Decreasing Returns to Scale.

**EVMS** Earned Value Management System.

**IRS** Increasing Returns to Scale.

**KPI** Key Performance Indicator.

**MPCS** Multidimensional Project Control System.

**ROI** Return On Investment.

**RTS** Returns to Scale.

**SLR** Systematic Literature Review.

**VRS** Variable Returns to Scale.

# 1

# INTRODUCTION

In an increasingly competitive and resource-constrained environment, organizations must ensure that projects are executed as efficiently as possible. However, project inefficiencies remain a challenge. On average, companies lose approximately 9.4% of total project investments due to poor performance and inefficiencies [3]. As a result, evaluating project efficiency has become a critical concern in project management, influencing strategic decisions and resource allocation.

Despite its importance, accurately measuring project efficiency remains complex, especially in settings where time, cost, workforce and quality all interact [4]. Traditional performance metrics [5] and KPIs , often fall short in providing a comprehensive efficiency analysis, as they typically do not account for multiple inputs and outputs simultaneously. To address this challenge, DEA has emerged as a powerful method for evaluating efficiency in multi-input, multi-output contexts. DEA is a non-parametric linear programming approach that allows comparing Decision Making Units (DMUs), such as projects, based on their relative efficiency [1].

Originally developed by Charnes et al. [1] and extended by Banker et al. [2], DEA models such as the CCR and BCC variants assess how well DMUs transform inputs into outputs without the need for predefined weights. In project management, inputs may include cost, duration, and workforce allocation, while outputs can represent project outcomes such as deliverable quality, client satisfaction or timely completion. DEA identifies those projects (i.e., DMUs) that achieve high output levels with minimal resource consumption, offering a benchmarking tool that helps distinguish best-performing units from less efficient ones [6].

DEA has been widely applied in sectors such as healthcare [7–9], finance [10], and education [11, 12] and is gaining traction in project management research [13–15]. In this context, each project is treated as a production unit, consuming inputs and generating outputs. The technique is especially useful in project-oriented organizations where multiple proposals compete for limited resources and decision-makers must prioritize efficiently [4].

Although many studies have demonstrated the value of DEA for performance evaluation [16, 17], benchmarking [18, 19], and resource allocation [20–22], its application in pre-execution projects and related decision-making remains limited. Most existing research focuses on traditional benchmarking without fully exploring how DEA results can be translated into actionable insights. Furthermore, DEA identifies inefficiencies but does not prescribe how to correct them [18]. Addressing this gap is essential for using DEA as a tool not only for evaluation, but also for supporting practical project management decisions.

This thesis aims to build on the current understanding of DEA's application in project management by exploring how different DEA models can be used to assess project efficiency more systematically specially for pre-project evaluation. By doing so, it seeks to contribute to improved decision-making, better resource utilization, and ultimately, more successful project outcomes compared to traditional methodologies.

## 1.1. THE IRON TRIANGLE IN PROJECT EVALUATION

In project management theory, the *Iron Triangle* or *Triple Constraint Model* is a foundational concept that emphasizes the trade-offs between three key dimensions: scope (or quality), time, and cost [23]. According to the PMBOK® Guide these constraints are interdependent, meaning that if any one factor changes, at least one other is likely to be affected [24]. For instance, reducing a project's duration might increase costs or require a reduction in scope. This model serves as a useful reference when evaluating project efficiency, as it reflects the multiple and often competing goals that must be balanced in real-world project environments. In this context, performance metrics and decision-support frameworks, such as the one proposed in this study, should consider these dimensions to support more effective project selection and resource allocation. By explicitly acknowledging these interdependencies, the project evaluation framework proposed in this thesis, using DEA, aims to interpret this real-world challenge of balancing scope, schedule, and budget in early-stage project selection.

## 1.2. RESEARCH MOTIVATIONS AND OBJECTIVES

In recent years, organizations have become increasingly aware of the importance of selecting the right projects to invest in, especially in fast-paced, resource-constrained environments [25]. Although there are many tools to monitor and evaluate project performance after execution, there is a significant gap in tools and methodologies that support data-driven project selection before execution [26, 27]. Traditional project selection processes often rely on intuition, past experiences, or financial metrics alone, which may overlook the multi-dimensional nature of project efficiency [28, 29].

DEA has proven to be a valuable technique for assessing performance across various sectors by comparing multiple DMUs based on their input-output ratios [7, 9, 10]. However, DEA has predominantly been used in a retrospective context, analyzing projects or operations after completion. As such, its potential as a proactive decision-support tool for project selection remains underexplored.

Given the need for more systematic and objective project evaluation methods in the early stages, this study is motivated by the idea of re-purposing DEA from a diagnostic tool into a proactive, pre-execution project selection framework, which to the best of our knowledge has not yet been proposed in the literature. By evaluating estimated inputs (such as cost, duration and resource requirements) and projected outputs (such as expected benefits, quality deliverables or stakeholder satisfaction), organizations could identify and prioritize the most efficient projects before any resources are committed.

The main objective of this research is to develop and validate a DEA-based framework that supports early-stage project evaluation and selection. The model allows organizations to compare and rank potential projects based on relative efficiency scores, integrating KPIs into the DEA models. A practical case study is conducted using real pre-project data to assess the framework's feasibility and relevance. The study also compares different DEA models (CCR and BCC) to identify the most appropriate approach for pre-execution scenarios.

With the deployment of such a framework, organizations stand to benefit in several ways:

- Optimized resource allocation: By identifying the most efficient projects early on, organizations can allocate their limited resources more effectively across portfolios.
- Objective decision-making: DEA introduces a data-driven methodology that reduces subjectivity in the project selection process.
- Enhanced strategic alignment: Projects that better convert inputs into outputs can be prioritized, improving the alignment of investments with organizational goals.

Based on these motivations and objectives, the study aims to answer the following main research question:

> *How can DEA be used as a proactive decision-support tool to evaluate and select the most efficient projects before execution?*

To support this inquiry, sub-questions organized by focused are formulated as follows:

Model Design and Feature Selection

1. What are suitable inputs and outputs for assessing projects prior to execution, and how can these be effectively selected?
2. How can DEA be integrated into an assessment framework for pre-project evaluation, and applied in real-world case studies?

Methodology and Model Evaluation

3. How do the CCR and BCC DEA models perform in the context of pre-project assessment?

4. What are the trade-offs between these models in terms of scalability, interpretability, and sensitivity?

Practical Validation and Decision Making

5. How do DEA-based project selections compare with those made using traditional methods?

6. How can model outputs be interpreted and communicated to support decision-making?

By answering the proposed research questions, this study seeks to contribute to both the theoretical development of DEA applications and the practical demands of project-oriented organizations. On the theoretical side, it explores how DEA can move beyond its traditional role as a retrospective evaluation tool and be adapted for use in the early stages of project planning. This represents a shift in perspective: treating DEA not just as a way to assess past performance, but as a proactive method for selecting projects before they begin.

The research introduces methodological refinements to tailor DEA for use in environments with limited or uncertain data, which are common conditions during pre-project assessment. It also compares the performance of different DEA models, such as CCR and BCC, providing insight into their suitability for various decision-making contexts.

A key practical contribution of this study lies in the development of a set of KPI that are derived from the DEA results. Adapting DEA-derived KPIs for stakeholders who are not familiar with efficiency modeling, such as project managers or senior decision-makers, is critical to ensuring the practical usability and impact of the method. As highlighted by Kuchta et al. [30], one of the main challenges in applying DEA in real-world project environments, especially in IT and R&D contexts, is the communication gap between technical analysts and decision-makers. As an example, their modified, stakeholder-oriented DEA approach emphasizes that for DEA to be accepted and effectively used in project ranking, its outcomes must be translated into formats that align with the perspectives and decision logic of stakeholders. In this study, the development of intuitive KPIs based on DEA results addresses this very challenge. By transforming complex efficiency outputs into actionable indicators, the approach enables project managers who may lack technical knowledge of DEA, to understand performance trade-offs, identify areas for improvement, and make informed decisions. This not only enhances the transparency and trust in the model's recommendations but also seeks broader adoption of DEA as a practical decision-support tool within organizations.

By integrating DEA into the early phases of project management, the study offers a structured, data-driven alternative to traditional, intuition-based selection processes. This can help organizations improve resource allocation, prioritize high-impact projects and align their portfolios with strategic objectives. The proposed framework is especially relevant in fast-paced sectors such as IT, where efficient project selection can be a key competitive advantage.

In this way, the thesis not only extends the application of DEA into a new phase of the project life cycle but also provides a practical toolkit (including interpretive KPIs as well as a set of requirements for its application) that enables more effective use of DEA in real-world project environments.

The remaining sections are organized as it follows: the thesis begins in Chapter 1 with an introduction to the research problem, motivations, and objectives. Chapter 2 presents a comprehensive literature review, including a systematic review methodology and an analysis of key themes, authors, and journals in the DEA and project management domains. Chapter 3 outlines the methodological foundation, including data preparation, experimental design, and model implementation, while Chapter 4 details the derived design requirements to ensure theoretical and practical validity. Chapter 5 discusses the empirical results and provides an in-depth analysis of DEA model outcomes, comparative findings, and actionable KPIs. Finally, Section 6 summarizes the main contributions, practical implications, limitations, and directions for future research. Supplementary materials and extended results are included in the Appendices A and B to support transparency and reproducibility.

# 2

# Literature Review

This chapter presents a Systematic Literature Review (SLR) focused on the application of DEA in evaluating project efficiency. While DEA has been widely applied for performance assessment in various domains, its integration into project management, particularly for pre-execution project evaluation and decision making remains limited.

The review also proposes a framework for integrating DEA into project management practices. The chapter synthesizes existing studies on DEA's use in project evaluation, highlighting key methodologies, strengths, and limitations. Ir highlights predominant themes in the literature, including common DEA models and their application contexts, sector-specific use cases (e.g., IT, banking, construction), and the role of DEA in benchmarking project efficiency. It highlights both the strengths of DEA in multi-dimensional performance evaluation and the gaps in its current use for continuous monitoring and predictive analytics.

Finally, the chapter discusses efforts to integrate DEA into broader project management frameworks and proposes a process-oriented foundation for doing so. These insights serve to inform the framework developed in this study.

## 2.1. SLR Methodology

For this SLR, we follow a clear and structured process to ensure thorough and unbiased results. Based on the framework from S et al. [31], we adopt eight steps that guide the scope and direction of the review. We begin by defining the research problem and formulating specific research questions. Next, we develop and validate a review methodology to direct the data search and analysis. The third step involves a comprehensive review of the relevant literature to ensure a full understanding of the topic. We then apply strict criteria to select studies, ensuring their relevance and quality. In the fifth step, we assess the quality of each study. After that, we extract data by systematically gathering relevant information from the selected studies. In the seventh step, we analyze and synthesize the data to uncover meaningful insights. Finally, we present the findings in a clear and organized report. This approach ensures the rigor and reliability of the review, providing valuable insights into the topic.

Scopus[1] was selected as the primary database due to its comprehensive repository of scientific articles and easy search functionalities [32, 33]. However, a combination with snowball sampling (also known as the chain referral method) was employed to gain a preliminary understanding of the topic and identify key search terms using Google Scholar [2] as the main database. Snowball sampling is a popular method of sampling in social research, particularly in education research [34] which was employed throughout the process, particularly when encountering an interesting paper, as some of its references were reviewed and selected. The advanced search function enabled the creation of custom search queries incorporating keywords derived from the research questions such as: 'DEA', 'Project Efficiency', 'Efficiency Measurement', 'DMUs', 'Efficiency', 'Project Management' and 'Performance Evaluation'. These and other keywords, combined with logical operators 'AND' and 'OR', facilitated the construction of five search queries, given the research's focus on the application of DEA in project efficiency assessment and decision-making processes:

- ("Data Envelopment Analysis" OR "DEA") AND ("Project Efficiency" OR "Efficiency" OR "Performance Evaluation")
- ("Decision-Making Units" OR "DMUs" OR "Benchmarking" OR "Frontier Analysis") AND ("Project Performance" OR "Efficiency Measurement" OR "Data Envelopment Analysis" OR "DEA")
- ("Data Envelopment Analysis" OR "DEA") AND ("Demand" OR "Opportunity" OR "Project")
- ("Data Envelopment Analysis" OR "DEA") AND ("Project Management" OR "Decision Making")

These were applied to search for keywords, abstracts, and article titles during the initial retrieval phase. These queries were applied to Scopus, and the resulting papers were filtered based on the exclusion criteria outlined in Table 2.1. Additionally, specific queries were used as well as papers identified through the snowball sampling technique. Using a four-phase strategy, we gathered 31 publications by following the methodical approach outlined in this chapter and depicted in Figure 2.1. Furthermore, publications from reputable journals in the field that were not retrieved by the search query were manually included to offer a comprehensive and benchmark perspective on the methodologies discussed in this literature review. The total number of publications analyzed in this study is 31, and a complete list of these papers and their summary is presented in Appendix A.

[1] https://www.scopus.com/home.uri
[2] https://scholar.google.com/

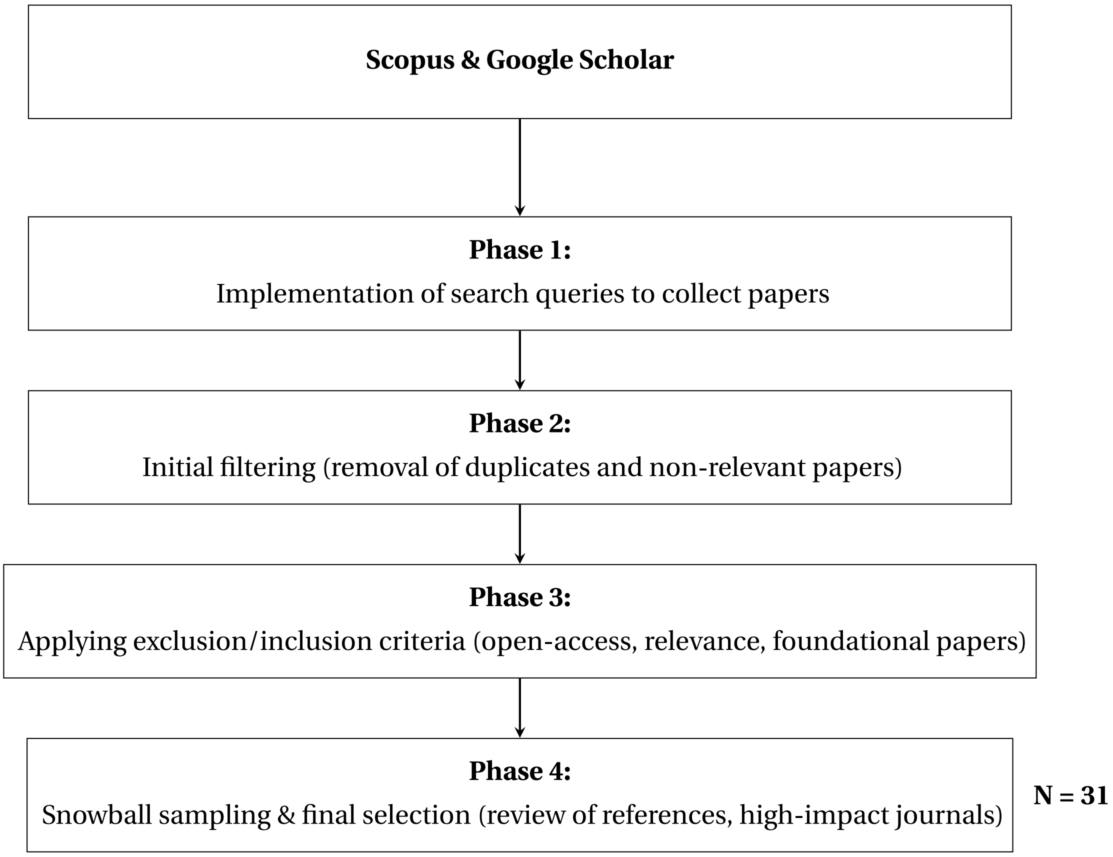



Figure 2.1: Illustration of the article selection process

Table 2.1: Summary of article selection criteria

| **Criteria** | **Decision** |
|---|---|
| Inclusion of pre-defined keywords in title, abstract, or keyword list | Inclusion |
| Article publication in a scientific journal or high-quality conference | Inclusion |
| Article written in English | Inclusion |
| Article published before a yearly threshold (e.g., 2000) but highly cited | Inclusion |
| Duplicates of an original article | Exclusion |
| Irrelevance of abstract, title, and content to research objective | Exclusion |
| Unavailability of the article online for free | Exclusion |

To ensure a comprehensive review of the DEA literature, the selection criteria were carefully designed to include both foundational and recent contributions, with an emphasis on freely accessible research. Since DEA has a well-established history dating back to [1], older, highly cited papers were included to capture its theoretical foundations and evolution. Additionally, since DEA research is often published not only in peer-reviewed journals but also in major conferences, where methodological advancements and novel applications are frequently introduced, both journal articles and high-impact conference papers were considered for inclusion.

The initial selection process focused on identifying articles based on keyword relevance, specifically looking at titles, abstracts, and keyword lists to ensure they aligned with the research objectives. For each paper, a preliminary check was made to confirm that the content was directly relevant to the application of DEA in the context of project or performance evaluation.

Next, we employed a snowball sampling method to identify further relevant studies. As we reviewed the selected papers, we carefully examined their references and citations, noting additional articles that were frequently cited or highly relevant to the scope of my review. This method allowed to discover interesting papers and ensure that key papers, particularly those that might not have appeared in the initial search, were included. For the snowball sampling, we focused on the title and abstract of the referenced papers to ensure they were directly related to DEA and its applications. If a paper seemed relevant, we conducted a quick review of the abstract and keywords to ensure its alignment with the research focus. We repeated this process iteratively, ensuring that papers with highly relevant content were progressively included in the review.

By combining keyword-based selection with snowball sampling, we were able to build a comprehensive collection of relevant studies while maintaining a balance between foundational works and newer contributions to the field. However, to maximize accessibility, paywalled articles were excluded, focusing only on studies available for free through open-access sources, institutional repositories, or preprint platforms. Duplicate studies and those with limited relevance to DEA methodology or applications were also removed. This approach ensures an inclusive and practical dataset, capturing both theoretical advancements and emerging trends in DEA research while remaining freely accessible.

## 2.2. DECONSTRUCTING THE RESEARCH LANDSCAPE

This section is organized into four parts, each offering a distinct perspective on the academic research related to DEA and its application in project management and efficiency evaluation. Section 2.2.1 delves into the temporal distribution of the related literature, offering a timeline of the scholarly contributions to these fields. This analysis will help to identify potential trends, patterns or shifts over the years, giving a historical context to the current state of research. In Section 2.2.2, we turn the attention to the sources of this literature by assessing the distribution across different journals. Understanding this distribution not only showcases the breadth of the research landscape but also highlights the most active and influential platforms fostering discourse on these topics. In Section 2.2.3, the focus is on the authors contributing to this body of literature by analyzing the distribution of publications among them. Examining the author distribution offers valuable insights into the concentration of research efforts, helping to identify key contributors and assess the diversity of academic perspectives within the field. This analysis also reveals whether the research landscape is shaped by a few prolific authors or dispersed across many occasional contributors. Finally, in Section 2.2.4, we investigate the most recurrent keywords within the examined literature. This analysis serves as a thematic compass, pointing to the core themes and concepts that anchor research in these fields, as well as hinting at emerging areas of interest.

To facilitate comprehension and offer a complete perspective, all the literature consulted for this study is indexed in Table A.1. This table provides a comprehensive overview of each paper, highlighting critical aspects such as the settings in which the respective model was employed, the main objectives of the research, the data-driven techniques applied, and the evaluation methods utilized to gauge the efficiency of the approach. This detailed catalogue not only contributes to the transparency of the research process but also allows readers to trace the intellectual journey that led to the findings of this study. Additionally, the table highlights potential gaps in the literature, serving as a valuable tool for identifying areas that may require further exploration.

### 2.2.1. TEMPORAL DISTRIBUTION OF LITERATURE

To better understand how DEA has been applied over time, we analyzed the yearly distribution of the selected articles. Figure 2.2 shows the number of publications per year is generally low and irregular. This is not entirely surprising, considering that many of the foundational DEA studies, which continue to be widely cited and applied, were published several decades ago [1, 2, 35]. However, studies applying DEA in the context of projects start to emerge around 2006. Project-related contexts refer to studies where DEA is applied to evaluate the efficiency of projects, project management processes, or organizations managing projects. These applications focus on assessing performance in terms of resource allocation, outcomes, and overall project success. Although this trend is not consistent every year, the presence of project-related DEA applications becomes more evident from 2010. Still, the overall number of articles remains limited, indicating that while DEA is a well-established methodology, its specific application to project analysis is a niche area that could benefit from further exploration.

Figure 2.2 illustrates the presence of DEA in project-related studies over recent years. Although the application of DEA in project contexts began to emerge around 2006, it has remained relatively sparse. This trend suggests that there has been limited research in this area, and the field offers significant opportunities for future studies. Despite some notable work, the overall number of studies applying DEA to projects remains small, pointing to a niche area that needs further exploration.

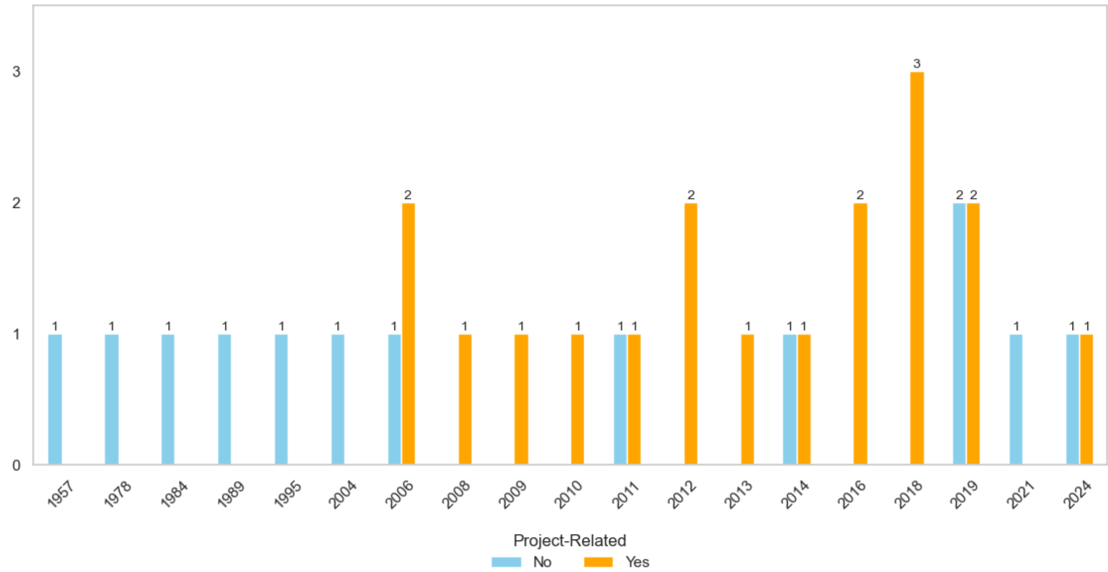



Figure 2.2: Temporal distribution of research papers on DEA, including both overall studies and those specifically related to project contexts

### 2.2.2. JOURNAL DISTRIBUTION OF LITERATURE

The following analysis reviews how project-related DEA studies are distributed across different journals and conference proceedings. This gives a clearer picture of where research on this topic is being published and how influential these studies have been within the academic community. The citation scores reported in Table 2.2 and Table 2.3 correspond to Scopus citation metrics, based on data updated in 2023. These scores offer a standardized way to assess the relative impact of each journal and conference at the time of analysis. Table 2.2 shows each study listed along with its publication outlet, citation count, and the corresponding impact factor or citation score when available. Notably, some studies such as Eilat et al. [13], which proposes an integrated DEA and Balanced Scorecard approach for R&D project evaluation, and Vitner et al. [4], which applies DEA to assess project performance in multi-project settings using Earned Value Management System (EVMS) and Multidimensional Project Control System (MPCS) - methods for monitoring and controlling project progress - have collected a high number of citations, showing their relevance and impact in the field.

An interesting observation is that these studies are scattered across a wide variety of journals and conferences, suggesting that there is no single preferred venue for publishing DEA applications in project management or project-related. Instead, the research appears in outlets ranging from well-known journals such as Omega[3] to conference proceedings like IEEM[4] or ICEIS[5], demostrate the cross-disciplinary scope of this research field. This variety also reflects the different ways researchers are approaching the topic, whether from a more theoretical or applied

[3] Omega Journal on ScienceDirect
[4] International Conference on Industrial Engineering and Engineering Management (IEEM)
[5] International Conference on Enterprise Information Systems (ICEIS)

perspective.

Table 2.2: Table reporting DEA studies

| Study | Journal/Conference | # Citations | CitationScore |
|---|---|---|---|
| Hedayat et al. [36] | – | – | – |
| Toloo and Mirbolouki [37] | Computers and Industrial Engineering | 31 | 12.7 |
| Ali Reza and Majid [38] | Conference Proceedings of the 6th International Symposium on Project Management, ISPM 2018 | – | – |
| Ku-Mahamud et al. [39] | European Journal of Scientific Research | 8 | – |
| Kuchta et al. [30] | ICEIS 2016 - Proceedings of the 18th International Conference on Enterprise Information Systems | 6 | 9.0 |
| [40] | IEEM 2009 - IEEE International Conference on Industrial Engineering and Engineering Management | 5 | – |
| Punnakitikashem et al. [41] | IEEM2010 - IEEE International Conference on Industrial Engineering and Engineering Management | – | – |
| Vitner et al. [4] | International Journal of Project Management | 81 | 12.3 |
| Lall et al. [42] | International Journal of Project Management | 50 | 12.3 |
| Frączkowski et al. [43] | Journal of Decision Systems | 4 | 6.3 |
| [44] | Journal of Industrial Engineering and Management | 40 | 4.4 |
| Gładysz et al. [15] | Journal of Information and Telecommunication | – | 7.5 |
| Stichhauerova and Pelloneova [45] | MM Science Journal | 1 | 1.3 |
| Eilat et al. [13] | Omega | 235 | 13.8 |
| Kuchta et al. [46] | Operations Research and Decisions | 4 | 1.0 |
| Dai and Li [14] | Procedia Computer Science | 4 | 4.5 |
| Li et al. [47] | Proceedings of CRIOCM 2006 International Research Symposium on Advancement of Construction Management and Real Estate | – | – |
| Bi et al. [48] | Shuili Fadian Xuebao/Journal of Hydroelectric Engineering | 3 | 2.9 |

Table 2.3 presents DEA-related studies not directly focused on projects, including their sources, citation counts, and citation scores. Foundational works like Charnes et al. [1], Farrell [35], and Banker et al. [2] stand out for their high citation numbers and are considered standard references in the DEA field. Following the same pattern, the variety of journals reflects the interdisciplinary nature of DEA research beyond project management. Following the same pattern, the variety of journals reflects the interdisciplinary nature of DEA research, extending beyond project management. Publications are also found in journals and conferences from diverse fields, highlighting the broad applicability of DEA across different domains.

Table 2.3: Table reporting DEA-related studies not directly project-related

| Study | Journal/Conference | # Citations | CitationScore |
|---|---|---|---|
| Jahangoshai Rezaee et al. [49] | Engineering Applications of Artificial Intelligence | 6 | 9.6 |
| Charnes et al. [1] | European Journal of Operational Research | 22110 | 11.9 |
| Lim et al. [18] | Expert Systems with Applications | 58 | 13.8 |
| Diaz-Balteiro et al. [50] | Forest Policy and Economics | 81 | 9.0 |
| Barros [51] | Journal of Economic Studies | 40 | 4.0 |
| Ehrgott et al. [52] | Journal of Multi-Criteria Decision Analysis | 9 | 4.7 |
| Farrell [35] | Journal of the Royal Statistical Society: Series A (General) | 32000 | – |
| Banker et al. [2] | Management Science | 11747 | 8.8 |
| Razavi Hajiagha et al. [53] | Measurement: Journal of the International Measurement Confederation | 11 | 10.2 |
| Golany and Roll [54] | Omega | 1151 | 13.8 |
| Cook et al. [6] | Omega (United Kingdom) | 635 | 13.8 |
| Charnes et al. [55] | Springer (Book) | 18000 | – |
| Rostamzadeh et al. [19] | Technological and Economic Development of Economy | 32 | – |

### 2.2.3. AUTHORS DISTRIBUTION OF LITERATURE

This analysis aims to identify which researchers have contributed most frequently to the topic, providing insight into the level of concentration or dispersion of authorship in the field.

Figure 2.3 summarizes the top eight most recurrent authors identified in the reviewed literature. In total, 72 different authors contributed to the collected studies, but only these eight appear in more than one article, highlighting a highly fragmented authorship landscape. Among them, Kuchta, D.[15, 30, 43, 46] stands out with four publications, followed by Cooper, W.W. and Charnes, A. [1, 2, 55], both with three, and recognized as key figures in the development of DEA. The presence of authors such as Despotis, D. [15, 46], Frączkowski, K. [43, 46], and Golany, B. [13, 54] reflects a mix of foundational and recent contributions to the field. This distribution suggests that while there are some recognized experts, much of the research on DEA in project-related contexts remains dispersed across a wide range of authors.

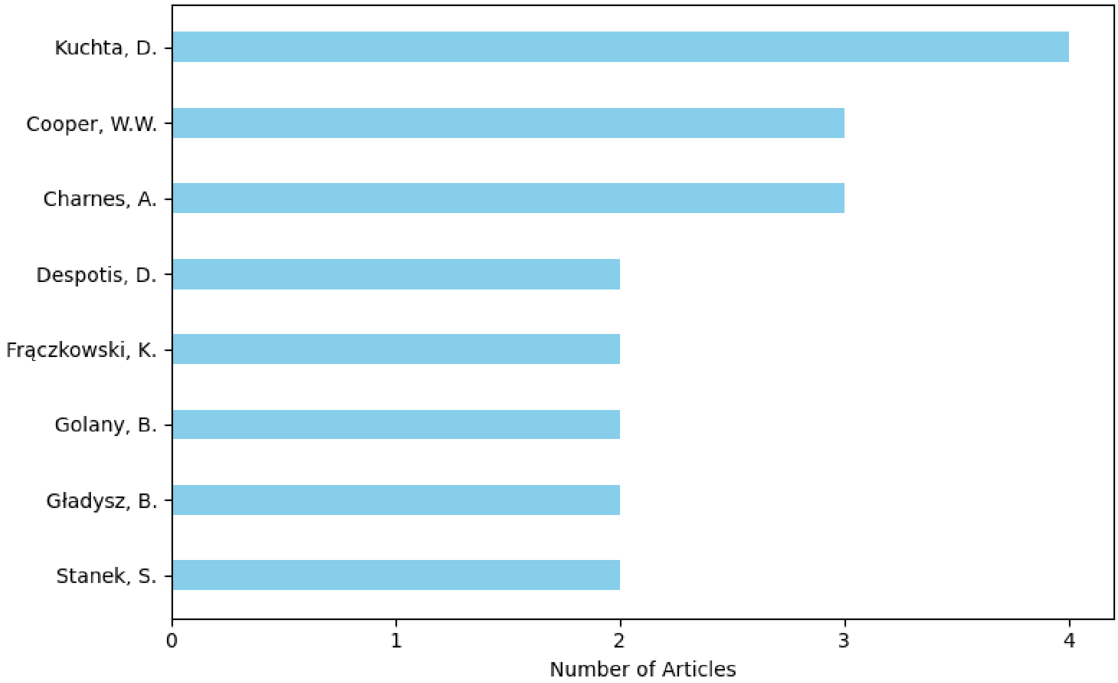



Figure 2.3: Author distribution of the literature. Top 8 authors with more than one publication

### 2.2.4. DISTRIBUTION BASED ON KEYWORDS

In this section, we present an analysis of the most frequently used keywords across the reviewed articles, with the aim of identifying the main topics and recurring themes in the literature. Keywords play a crucial role in defining the focus and scope of academic research, as they help readers and researchers quickly locate studies relevant to specific areas of interest.

During this process, we noticed that several articles did not include author-provided keywords, so those were excluded from this part of the analysis to ensure consistency. Therefore, the analysis focuses only on papers that explicitly mention keywords, offering a clearer view of the prevailing research directions.

The two visualizations represent keyword co-occurrence networks related to DEA but differ in the scope of included terms. In Figure 2.4, we created a first visualization which includes all the words used in the search queries and presents a broader view of the relationships between key terms in DEA research. Since the search terms were part of the dataset, they naturally dominate the network, creating a structure where concepts like "data envelopment analysis", "efficiency", and "decision-making" are central. This map provides insight into how the field is commonly framed and what terms researchers frequently associate with DEA applications. However, because the search terms heavily influence the visualization, the connections may reflect more of the predefined focus rather than organic relationships between concepts.

To gain a more neutral perspective, we created a second map by removing the search query words. This adjustment allows us to observe how terms relate without the direct impact of the predefined keywords. As a result, Figure 2.5 reveals a more natural clustering of concepts, such as "project input", "performance measurement", "decision support systems" and "dea models" emphasizing the key aspects of DEA applications in project evaluation. In Section 2.3, we further discuss the connections between the most frequently occurring keywords and the predominant themes identified in the literature.

By comparing both figures, it becomes evident how removing search terms helps to uncover deeper, unbiased connections within DEA-related research, while keeping them emphasizes how studies are framed around certain established concepts. The figures reveal three primary research clusters: project management and decision support, technical DEA methodologies, and information systems use. In Figure 2.5, we can identify three main keyword clusters based on their connectivity and thematic relevance. The first cluster (green) focuses on project management and decision-making, including terms like "project success", "decision support systems", and "project input/output". This cluster highlights DEA's application in evaluating project performance but can suggest that its use in real-time project decision-making remains limited. The second cluster (red) revolves around DEA models and efficiency measurement, linking concepts such as "input and outputs", "performance assessment", and "efficiency frontier". This indicates a strong focus on traditional DEA methodologies but may suggest a lack of integration with project management frameworks. The third cluster (yellow) relates to information systems and their role in efficiency evaluation, including keywords like "information use" and "information systems". However, this cluster appears weakly connected, indicating that there is limited research on how DEA is embedded into digital decision-support systems.

By analyzing the keyword distribution, it becomes clear that DEA research has primarily focused on retrospective project evaluation rather than proactive optimization. The weak links between decision-making systems and DEA methodologies suggest an opportunity for further research.

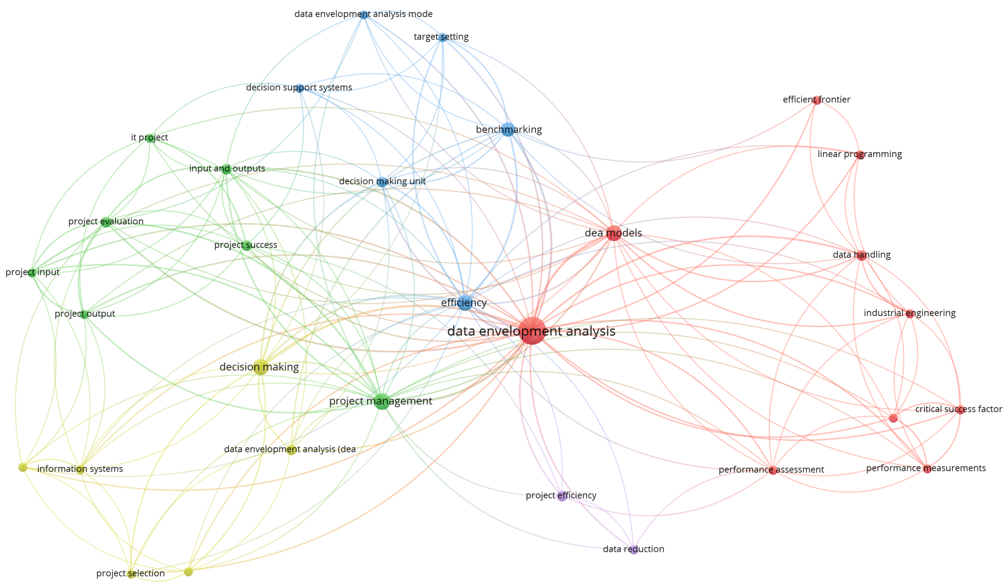



Figure 2.4: Network visualization of DEA-related articles' keywords including words used for search queries

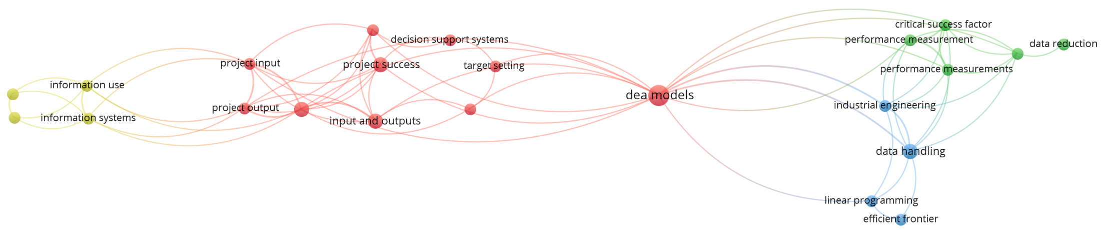



Figure 2.5: Network visualization of DEA-related articles' keywords excluding words used for search queries

## 2.3. PREDOMINANT THEMES IN LITERATURE

In exploring the application of DEA in efficiency assessment, particularly within project-based evaluations and organizational contexts, this section identifies the key themes prevalent in the literature. DEA has been widely adopted as a methodological framework for measuring efficiency, benchmarking performance, and informing decision-making processes across various industries. Given its significance in efficiency evaluation, it is essential to systematically analyze its applications, model variations, and integration within project management frameworks.

To provide a structured examination, this section is divided into three subsections, each addressing a specific theme related to DEA applications related to the research questions proposed:

- **Applications of DEA in efficiency assessment:** This subsection explores how DEA has been utilized in evaluating efficiency across different organizational contexts, particularly in project-based assessments. By examining diverse case studies and industry applications, we aim to understand the scope and impact of DEA on performance measurement.

- **Common DEA models and their application contexts:** This subsection delves into the most frequently used DEA models for efficiency assessment and the specific contexts in which they are applied. Given the variations in DEA methodologies, it is crucial to analyze the models best suited for different types of efficiency evaluations.

- **Integration of DEA into project management frameworks:** This final subsection investigates how DEA can be incorporated into project management frameworks to enhance efficiency assessment and decision-making. The integration of DEA within structured management methodologies can lead to more data-driven and objective evaluations.

### 2.3.1. APPLICATIONS OF DEA IN EFFICIENCY ASSESSMENT

In the literature, DEA has been widely employed in evaluating efficiency across various project-based contexts. Its application appears on multiple industries, offering insights into performance measurement, project selection, and optimization. This subsection explores key areas where DEA has been instrumental in assessing efficiency.

DEA has been utilized to assess project efficiency across various industries. The term "settings" refers to the context in which the studies were conducted, directly impacting the research to which they are applied.

Studies such as Frączkowski et al. [43] and Kuchta et al. [46] demonstrate how DEA aids in selecting IT projects that maximize success probability and evaluating IT project performance by analyzing efficiency and performance factors. In addition, in the context of IT projects, Gładysz et al. [15] examine how DEA can be applied to IT project evaluation, focusing on selecting appropriate inputs and outputs based on organizational needs. In the context of construction, research shows that Ali Reza and Majid [38] propose a combined Analytic Network Process (ANP)-DEA approach to improve construction project selection, while [48] apply DEA for optimizing tunnel construction projects. DEA has also been widely applied in manufacturing and lean management, with Stichhauerova and Pelloneova [45] evaluating the efficiency of lean management projects by using DEA to compare performance, while Meza and Jeong [44] assess Lean Six Sigma projects at NASA using DEA for benchmarking purposes.

Additionally, in the field of R&D and innovation, Eilat et al. [13] propose an integrated DEA and Balanced Scorecard approach to enhance the evaluation of R&D projects, offering a comprehensive framework for assessing research efficiency. Several studies apply DEA to general project settings, proving its versatility across various industries. For instance, Lall et al. [42] use DEA to prioritize projects based on efficiency and resource utilization, providing a framework for optimal project selection. Similarly, Ku-Mahamud et al. [39] analyze project efficiency by focusing on resource utilization and performance measurement across diverse project types. Additionally, Hedayat et al. [36] introduce a two-level DEA approach to assess the efficiency of project-based organizations, highlighting the adaptability of DEA in broader project evaluation contexts. These studies emphasize that DEA is not limited to specific industries but can serve as a robust methodology for assessing efficiency in general project environments.

In the literature, DEA is commonly applied to rank and select projects based on efficiency metrics such as cost efficiency, time efficiency, resource utilization efficiency, quality of output, Return On Investment (ROI), success probability, and overall efficiency scores. Lall et al. [42] and Toloo and Mirbolouki [37] present DEA-based methods for project selection, prioritizing projects that yield optimal efficiency with given resources. Additionally, Kuchta et al. [30] propose a modified version of the DEA model for evaluating and ranking IT and R&D projects. This modification addresses an important gap in the original DEA method, which fails to account for the differing perspectives of various project stakeholders. Their approach incorporates stakeholder views into the DEA framework, allowing each project to be assessed from multiple perspectives. By considering inputs and outputs that are important to different stakeholders (such as customer satisfaction, project cost, or risk), this modified model provides a more comprehensive and accurate ranking of projects, especially in cases where the outputs are qualitative in nature.

In addition, the analysis underscored that DEA has also been adapted to assess project risks and optimize performance. Dai and Li [14] introduce a DEA-based risk indicator, quantifying the negative effects of project risks. While specific examples of project risks are not provided, project risks generally encompass factors such as cost overruns, schedule delays, resource shortages, and quality issues. The DEA-based risk indicator proposed in the paper can be applied to assess the negative impact of these types of risks and help prioritize them for management. Similarly, Meza and Jeong [44] assess the efficiency of Lean Six Sigma projects at NASA using DEA, showcasing its role in continuous improvement initiatives.

Moreover, in a significant part of the literature it was found that DEA is often compared to other efficiency measurement techniques that might be already used in the organization. For example, Vitner et al. [4] integrate DEA with EVMS and MPCS to enhance project performance evaluation. On the other hand, Ali Reza and Majid [38] combine DEA with ANP - a method for decision-making that considers interdependencies among criteria Kheybari et al. [56]- for construction project selection, while Eilat et al. [13] integrate DEA with the Balanced Scorecard.

### 2.3.2. COMMON DEA MODELS AND THEIR APPLICATION CONTEXTS

As Table A.1 illustrates, the reviewed literature highlights the diverse set of applications of DEA models, each adapted to specific efficiency assessment needs. Across various studies, researchers have applied different approaches depending on the context and objectives of the evaluation. Given this diversity, it is crucial to examine which DEA models are most frequently utilized and how they are applied in different project assessment scenarios.

DEA models are broadly categorized by Charnes et al. [1] into input-oriented and output-oriented models, depending on whether the goal is to minimize inputs while maintaining output levels or maximize outputs given a set of inputs.

Charnes et al. [1] introduced the CCR model, which assumes Constant Return to Scale (CRS) and is primarily input-oriented. This model has been widely used in efficiency assessments, including project evaluation, where resource optimization is key [39, 45, 50, 51]. Banker et al. [2] later introduced the BCC model, which allows for Variable Returns to Scale (VRS), making it more suitable for projects operating under different production conditions. While these two models dominate the literature, many studies do not explicitly specify which DEA model they employ [4, 14, 18, 37, 52]. In the literature, in the context of projects, Yang and Paradi [40] employed the BCC model to assess software project efficiency, demonstrating the need for VRS in industries where project scales differ significantly.

Furthermore, Ku-Mahamud et al. [39] uses a CCR model to explored DEA's effectiveness in evaluating projects. Similarly, the model is used by Stichhauerova and Pelloneova [45], evaluating the efficiency of lean management projects using DEA to compare performance. Two studies stand out because of the use of both models in the same use case. One of them being Diaz-Balteiro et al. [50], who investigates how innovation affects efficiency in the wood-based sector, where due to the lack of information concerning the form of the production frontier, the BCC model was also used. In addition Barros [51] analyzes the efficiency of defense firms in a small

NATO country [57] and present the results with both methods for comparative purposes. The choice of DEA model significantly influences the accuracy and interpretability of efficiency results. The selection between CCR and BCC models, for instance, determines whether efficiency scores account for scale inefficiencies. Studies such as Frączkowski et al. [43] have emphasized that model selection must align with project characteristics to ensure meaningful results in IT project evaluations.

In multi-project environments, choosing the appropriate orientation for the DEA model, which refers to whether the focus is on minimizing inputs or maximizing outputs, is particularly important. Vitner et al. [4] applied DEA to compare project efficiency in a multi-project setting, demonstrating how input and output-oriented models can yield different insights depending on the context. In addition, addresses the challenge of having too many inputs/outputs by suggesting a method for their reduction.

Several studies in this review employ Network DEA or related multi-stage DEA approaches to enhance efficiency assessment in project-based environments. Network DEA is an extension of traditional DEA that is used to assess the efficiency of complex systems or processes that are made up of interconnected components or stages [58]. For instance, Eilat et al. [13] integrates DEA with the Balanced Scorecard, suggesting a multi-stage evaluation framework that aligns with Network DEA principles. Similarly, Hedayat et al. [36] proposes a two-level DEA model for project-based organizations, emphasizing a hierarchical efficiency structure. Kuchta et al. [30] incorporates stakeholder perspectives in IT and R&D project ranking, which implies an interconnected evaluation process. Additionally, Razavi Hajiagha et al. [53] introduces a bi-level DEA model for efficiency measurement and target setting, a characteristic feature of Network DEA. Furthermore, Jahangoshai Rezaee et al. [49] explores a data-driven decision support framework for DEA target setting, which often involves multi-stage efficiency considerations. Punnakitikashem et al. [41] applies DEA to assess technology transfer projects, where efficiency must be measured across multiple stages of implementation. These studies highlight the relevance of Network DEA in evaluating complex, multi-stage decision-making environments, providing a more granular analysis of efficiency within interconnected project processes.

### 2.3.3. Integration of DEA into project management frameworks

Project management methodologies such as Lean and Six Sigma focus on efficiency, waste reduction and process improvement [59]. In our SLR, DEA has been successfully applied to these frameworks to measure project effectiveness. For instance, Stichhauerova and Pelloneova [45] utilized DEA to evaluate lean management projects, highlighting its role in identifying best-performing initiatives. Additionally, Meza and Jeong [44] applied DEA to assess lean six sigma project implementation at NASA, demonstrating its capability to compare projects based on efficiency metrics rather than subjective assessments.

Furthermore, studies demonstrate how DEA can be incorporated into project management decision-making. Ali Reza and Majid [38] combines DEA with ANP to integrate subjective and quantitative project selection criteria, ensuring a more comprehensive evaluation. Vitner et al. [4] demonstrates how DEA could be used to evaluate multiple projects within an organization, which can allow managers to prioritize projects based on efficiency. The authors use EVMS and MPCS to reduce inputs/outputs, showing that DEA can complement existing risk assessment and control mechanisms in project management. Lall et al. [42] further highlightes how DEA enhances decision-making by ranking projects according to their resource utilization and output efficiency.

As project environments and their management become increasingly complex, the role of DEA in project management has the potential to expand in the future.

## 2.4. A PROCESS FRAMEWORK FOR APPLYING DEA IN PROJECT EFFICIENCY ASSESSMENT

Based on insights from the literature, this section proposes a systematic framework for integrating DEA into project evaluation. The framework outlines key steps to guide project managers in selecting the appropriate DEA model, implementing the methodology, and utilizing findings to optimize project performance.

Figure 2.6 presents the proposed framework structure, including a description of the steps to be followed. These steps account for:

- **Step 1: Define the project scope and objectives:**

  This involved identifying the main purpose of the evaluation, such as assessing resource utilization, benchmarking performance, or determining cost-effectiveness. By doing so, and establishing key research questions related to project efficiency ensures that the DEA analysis is focused with the overall goals of the project.

- **Step 2: Identify DMUs within the project:**

  Once the scope is defined, it is necessary to identify the DMUs which represent the project components or phases to be analyzed. DMUs in the context of projects, may include departments, work packages, subcontractors, or project milestones. However, this framework proposes them to be projects. To maintain meaningful comparisons, these units should be as homogeneous as possible regarding function and objectives. Additionally, selecting an appropriate number of DMUs in relation to the input and output variables is necessary for ensuring the reliability of DEA results.

- **Step 3: Select input and output variables relevant to projects:**

  Choose inputs such as budget, labor hours, and resources allocated as well as outputs such as project deliverables, milestones achieved, or quality metrics. The chosen variables should be relevant to the project's performance indicators and reflect its efficiency.

- **Step 4: Select the appropriate DEA model:**

Depends on the nature of the project and its efficiency assessment requirements. The CCR model is suitable for projects that assume constant returns to scale, whereas the BCC model is more appropriate for those with variable returns to scale.

- **Step 5: Data collection and pre-processing:**

  It is necessary to collect accurate and reliable data. This data can be obtained from project management software, reports, and financial records. The collected data must be cleaned and normalized.

- **Step 6: Conduct DEA analysis:**

  Once the data is prepared, the DEA model is applied using specialized software such as *DEA Solver, R*, or *Python*. The efficiency scores of different project phases or components are computed, providing a comparative assessment of their performance. Additionally, a sensitivity analysis can be performed to validate the robustness of the results and ensure that the efficiency rankings remain stable under different conditions. An example of this would be slightly altering input/output values to check if efficiency scores remain consistent, or using alternative DEA models, to compare results using different DEA models to verify consistency.

- **Step 7: Interpret results and benchmark project efficiency:**

  This is a critical step in the assessment process. Efficiency scores should be analyzed to identify high- and low-performance components. By understanding the factors contributing to inefficiencies, project managers can pinpoint areas for improvement and make data-driven decisions.

- **Step 8: Integrate DEA findings into project management decisions:**

  The final step involves incorporating the insights gained from the DEA analysis into project management strategies. The results can inform decisions on resource allocation, workflow optimization, and strategic planning. By using DEA findings to refine project execution strategies, organizations can enhance efficiency and improve overall project outcomes. In addition, integrating DEA-based assessments into future project planning can contribute to more consistent and objective performance evaluations.

One option is to integrate KPIs or use predictive analytics to improve decision-making. KPIs help track performance by comparing actual results to set goals, ensuring the project stays on track [60]. Predictive analytics, using methods such as DEA, can identify potential inefficiencies early and suggest better ways to allocate resources. However, these approaches are not widely discussed in the literature, especially for real-time project adjustments. By shifting to prescriptive analytics, project managers can not only predict future issues but also receive actionable recommendations for improvement. Incorporating prescriptive analytics can help project managers make smarter, data-driven decisions and improve overall efficiency [61, 62].

To illustrate the process framework, Figure 2.6 summarizes the steps and its key activities:


Figure 2.6: Visual representation of the process. Steps and its key activities

# 3

# Materials and Methodology

This chapter presents the methodology, tools and data employed to conduct the DEA-based analysis. It begins by outlining the application of the CRossIndustry Standard Process for Data Mining (CRISP-DM) process model [63], which provides a structured approach to managing the overall data analysis workflow and serves as a backbone structure for the proposed framework. Next, the experimental framework section details the step-by-step implementation of the proposed decision-making framework, including how the DEA model was used to evaluate project efficiency. It also introduces the interpretation of DEA-generated metrics such as efficiency scores [1], slacks [64], lambdas [1], reference sets [65], and returns to scale, and discusses their potential use as decision-oriented KPIs. Finally, the DEA model Comparison section contrasts the CCR [1] and BCC [2] models, justifying the modeling choices made in this study.

## 3.1. Cross-Industry Standard Process for Data Mining

In addition to applying the proposed framework developed in this study (see Section 3.3), the CRISP-DM process model was also followed to guide the data-related aspects of the project. Originally introduced in 1996, CRISP-DM provides a structured approach for handling data mining tasks, offering clear phases such as business understanding, data understanding, data preparation, modeling, evaluation, and deployment [63]. A "data mining" process refers to the automated procedure of discovering patterns in large datasets and using these patterns to extract valuable business insights and predictive knowledge [66]. This methodology supports the systematic transformation of raw data into actionable insights by identifying patterns and trends, which aligns with the analytical goals of the proposed framework (proposed framework for assessing project efficiency prior to execution presented in Section 3.3).

An overview of the whole process model of the CRISP-DM methodology is presented in Figure 3.1

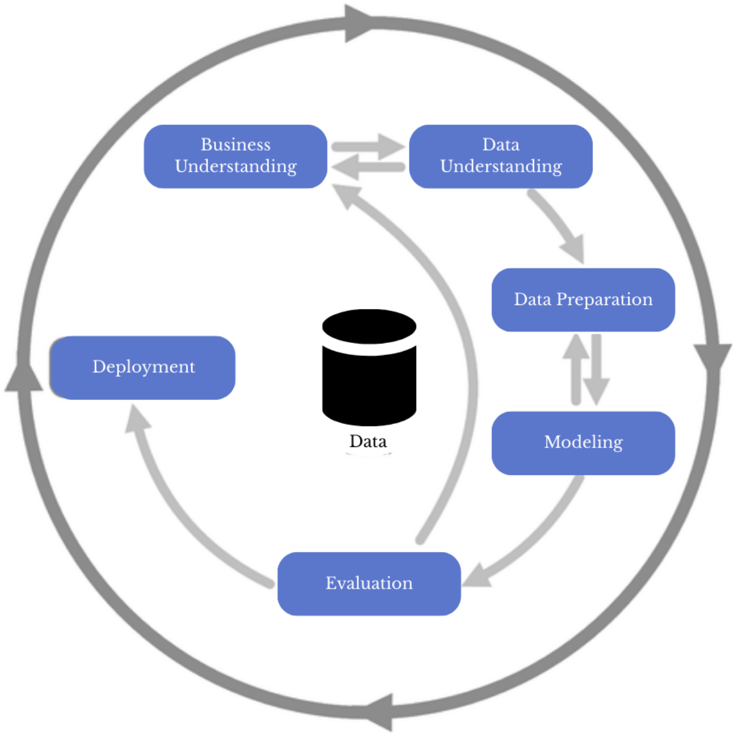



Figure 3.1: Phases of the CRISP-DM Process Model for Data Mining [63]

The model is divided into a number of phases that represent the life cycle of each data mining project. Although the steps are presented in chronological order, with arrows indicating dependencies between the different phases, the sequence should not be considered rigid or strictly mandatory in real-world applications. In practice, it is often necessary to work between the different steps [67].

The description of each phase is as it follows [63, 67]:

1. **Business Understanding**: In the initial phase, all relevant stakeholders in the project, including business analysts and data scientists, collaborate to define the project objectives and requirements from a business perspective. This understanding is then translated into a formal definition of the business problem and a preliminary project plan.

2. **Data Understanding**: The next step involves collecting and exploring the data to identify potential quality issues and to assess the completeness and relevance of the dataset.

3. **Data Preparation**: This phase encompasses all tasks required to construct the final dataset from raw data. Activities typically include data cleaning, transformation, and feature engineering, which are essential prior to implementing modeling techniques.

4. **Modeling**: Once the data preparation phase is complete and the final dataset is ready,

various analytical models are developed and fine-tuned to optimize performance.

5. **Evaluation**: In this phase, the models created are evaluated to ensure that the outcomes align with the original business objectives established in the *Business Understanding* phase. A decision is then made regarding which model to deploy as the final data mining solution.

6. **Deployment**: The final phase involves implementing the selected model in the target production environment. It is important to note that the nature of this step depends on prior business requirements and can range from generating simple business reports to establishing complex repeatable data-driven systems that require ongoing monitoring.

While the framework mostly follows the CRISP-DM structure, the Modeling phase has been omitted. This is because the study does not involve the development or training of predictive models in the traditional sense. Instead, we apply established DEA models using dedicated software, where the task is limited to selecting and configuring the appropriate model type (e.g., CCR or BCC). As DEA relies on predefined mathematical formulations rather than algorithmic modeling, this phase was not considered necessary in the workflow. The omission reflects the focus of the study: applying and interpreting DEA within a decision-making context, rather than developing new analytical models. Figure 3.2, represents the steps that have been taken into account for the project.

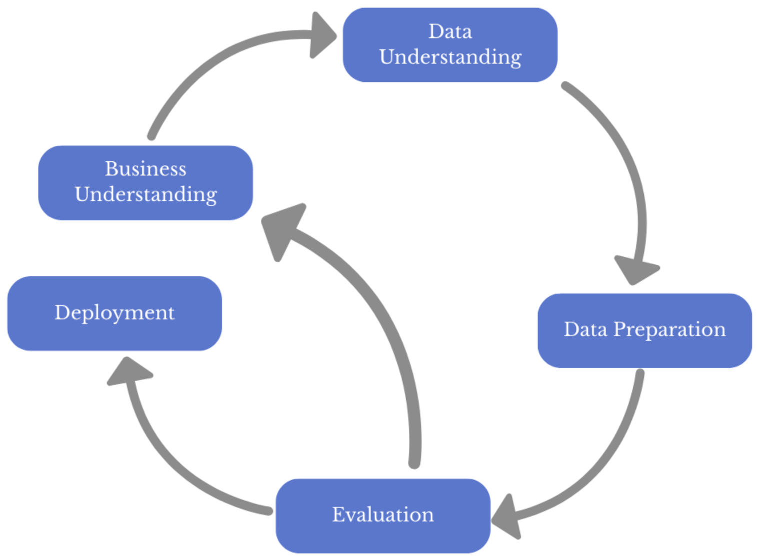



Figure 3.2: Adaptation of the CRISP-DM Process Model for Data Mining for the project

## 3.2. DATA COLLECTION AND PREPARATION

The dataset used in this study comes from a defense company's internal demand planning system, which tracks and evaluates project opportunities under consideration for future execution. These opportunities served as the DMUs for the DEA analysis.

We selected 42 project opportunities as DMUs, each representing a distinct project listed in the organization's demand plan. To ensure meaningful and reliable comparisons, all DMUs share a similar strategic purpose and expected outcomes. The selection process was based on several criteria. First, only projects with complete data for all required input and output variables were considered. Additionally, we included only those projects that had a fully developed estimation pack, ensuring consistency in data quality and comparability. Projects that were split into subcomponents or stages were excluded to avoid redundancy and inconsistency. We also excluded projects that were ambiguous in scope or significantly different from the rest in terms of objectives or context. Ultimately, the selected projects were considered to be the most representative of the broader project portfolio, based both on the availability of data and the expert judgment of relevant stakeholders.

Table 3.1 presents the selected input and output variables, along with their descriptions, types, and units. In the context of this study, the variable "Type" refers to whether each metric is treated as an input or output within the DEA model. Inputs are defined as resources consumed or constraints faced during project execution, factors that, from an efficiency standpoint, are preferable to minimize. In this case, Estimated Duration, Estimated Workload, and Estimated Cost were classified as inputs, as they represent time, effort, and financial investment required to complete a project. Outputs are the desirable results or gains associated with each project, which should be maximized in the DEA evaluation [55]. Here, Probability, reflecting the likelihood of successfully securing the project, and Stake Amount are treated as outputs. This classification aligns with the goal of identifying projects that can deliver the highest expected value while consuming the least amount of organizational resources[15].

Table 3.1: Selected DEA Input and Output Variables for Project Efficiency Assessment

| **Variable** | **Description** | **Type** | **Unit** |
|---|---|---|---|
| Estimated Duration | Total time estimated to complete the project | Input | Weeks |
| Estimated Workload | Total effort required, based on assigned hours (FTE-adjusted) | Input | FTE-hours |
| Estimated Cost | Projected financial investment required to complete the project | Input | Euros (€) |
| Probability | Combined likelihood of market opportunity and organizational win rate | Output | Probability (0–1) |
| Stake Amount | Financial value the organization expects to gain if the project is won | Output | Euros (€) |

We selected these variables based on their relevance to project performance and the availability of reliable data [15]. While most variables are tracked through the demand planning system, we obtained additional information from pre-execution estimation packs, allowing us to complete a representative dataset.

To protect confidentiality, we anonymized all project records and replaced identifiable names or codes. We excluded any projects with incomplete or inconsistent data to ensure high-quality input for the analysis.

The selected sample of 42 DMU meets the commonly accepted DEA rule of thumb, which requires a sample size of at least $\max\{m \times s,\ 3(m+s)\}$, where $m$ is the number of inputs and $s$ is the number of outputs [65]. With 3 inputs and 2 outputs, the required minimum is $\max\{6,\ 15\} = 15$, confirming that 42 projects offer sufficient size for stable and reliable results.

We did not apply normalization, as DEA allows inputs and outputs to be expressed in different units without affecting the analysis, due to its reliance on ratios and relative efficiency comparisons [1, 65]. However, we anonymized the data by transforming the original values, ensuring they still reflect real operational conditions while maintaining confidentiality. This process helped preserve the interpretability of the analysis, as the transformed values remain proportional to the original data.

This dataset offers a foundation for evaluating project efficiency and helps advance to the objective of making more informed and data-driven resource allocation decisions.

## 3.3. EXPERIMENTAL FRAMEWORK

This section outlines how the methodological framework proposed in Chapter 2 has been applied in this research, following the CRISP-DM as a methodology structure, to assess project efficiency prior to execution. Following the structure and guidelines presented earlier, a systematic approach was implemented in order to use DEA as a proactive decision-support tool.

The primary objective is to demonstrate how this approach can support resource allocation and improve strategic planning by facilitating the pre-selection of more efficient projects.

In this study, these steps account for:

- **Step 1: Define the project scope and objectives:**

  The first step involves defining the scope of the DEA application within the context of project selection. In this study, the goal is to evaluate the efficiency of potential projects before execution, helping decision-makers allocate resources more effectively. The focus is on using DEA as a proactive decision-making tool, rather than a retrospective one. For this reason, the key questions (aligned with the main research objectives) that are guiding this evaluation include:

  - How can DEA be applied to assess project efficiency before execution?
  - Which DEA model (CCR or BCC) is most suitable for pre-project evaluation?
  - What is the practical impact of using DEA for project assessment in a real-world case study?

By clarifying these objectives from the beginning, the framework ensures that DEA is used with a clear purpose aligned with organizational and business decision-making needs.

- **Step 2: Identify DMUs within the project:**

  Once the scope is defined, the next step is to identify the DMUs to be analyzed. The selection of DMUs is crucial in measuring their relative efficiency [39]. In this research, each DMU corresponds to a specific project or opportunity listed in the organization's demand plan. These are the entities whose efficiency is assessed using the DEA framework.

  To ensure meaningful and fair comparisons, DMUs should be as homogeneous as possible in terms of their function, objectives and organizational context. Although projects may differ in size or complexity, they should ideally pursue similar strategic goals and produce comparable types of outcomes. This helps ensure that efficiency comparisons are valid and based on equivalent criteria [65].

  In DEA, it is also important to maintain an appropriate ratio between the number of DMUs and the number of input and output variables. A commonly cited guideline recommends that the number of DMUs should be at least three times the total number of inputs and outputs to ensure sufficient discriminatory power and robustness of the results [68].

  As mentioned, in this study, 42 projects were selected as DMUs based on a structured set of inclusion criteria. First, only projects that had complete data for all selected input and output variables were considered. This ensured consistency and avoided introducing bias due to missing or estimated values. Second, we included only projects with a fully developed estimation pack, which confirmed that project assumptions were well-documented and based on standardized internal processes. Projects that were split into subcomponents or phases were excluded to maintain a consistent unit of analysis. Furthermore, projects that were highly ambiguous or significantly distinct in nature (e.g., exploratory or one-off initiatives) were filtered out for more representative, comparable cases. This ensured that the chosen DMUs not only met technical criteria but also reflected a realistic and meaningful selection of the organization's active opportunities.

- **Step 3: Select input and output variables relevant to projects:**

  We choose inputs such as costs, labor hours and duration as well as outputs such as stake amount and probability of success. The chosen variables should be relevant to the project's performance indicators and reflect its efficiency.

  For this study, the selected inputs and outputs aim to be easily accessible and measurable by the company, ensuring the practicality and replicability of the framework. These variables are commonly used in the company's demand planning process and provide a clear picture of project efficiency before execution. Additionally, the selection process was informed through discussions with key stakeholders to ensure that the variables align with organizational priorities and decision-making practices. This collaborative approach helped validate the relevance of each variable and ensured that the resulting model would be interpretable and actionable for end users.

**Inputs:**

- **Duration:** Estimated project duration is a key input since it directly impacts resource allocation and scheduling.
- **Workload:** Expected effort in terms of labor hours or resources, helping to represent how demanding a project will be and how much capacity from the ccompany will use.
- **Costs:** Estimated costs are crucial to evaluate the financial feasibility of a project.

**Outputs:**

- **Probability of project success:** This measure evaluates the likelihood of the project being successful, consisting of two components:
  - ◇ *Chance of winning the opportunity:* Likelihood that the company will secure the project.
  - ◇ *Market opportunity likelihood:* Whether the opportunity is viable and available in the market.
- **Stake amount:** The financial value or investment at stake, which can be a measure of the expected return or impact of the project.

• **Step 4: Select the appropriate DEA model:**

This study applies both CCR and BCC models to assess whether project efficiency varies under CRS or VRS, analyzing which is more suitable [1, 2]. A detailed explanation of these models follows in Section 3.4.

• **Step 5: Data collection and pre-processing:**

It is necessary to collect accurate and reliable data to ensure the validity of the DEA analysis [65]. In this study, data were sourced from two internal company tools: Software 1, which contains detailed estimation packs for each project, and Software 2, which manages the organization's demand plan. These two datasets were combined using a Python script that matched each project opportunity to its corresponding estimation pack. Due to confidentiality agreements, the specific structure and content of each dataset are not disclosed. However, this integration allowed for the extraction of all necessary input and output variables required for the DEA model.

Notably, some parameters (such as workload and others were not directly available in a usable format and required transformation to derive quantifiable, standardized values.

Projects with incomplete data or missing estimation packs were excluded from the analysis. Additionally, once the full dataset was compiled, a filtering process was carried out to remove outlier projects that, based on expert judgment and stakeholder consultation, were deemed unrepresentative due to their extreme values or fundamentally different nature. This helped to maintain homogeneity and ensure comparability among the selected DMUs.

To protect sensitive information, all project identifiers were anonymized. Furthermore, the data were scaled using mathematical transformations (e.g., division, multiplication, or normalization) to ensure that while the values remained representative of actual project characteristics, they could not be traced back to specific real-world figures or projects. A more detailed description of the data and how it was prepared is provided in Section 3.4.3.

- **Step 6: Conduct DEA analysis:**

  After preparing the data, the DEA models are applied using the *deaR Shiny App* [1] developed by a group of students from the Universitat de València, which offers a user-friendly interface to run various DEA models without coding. This framework uses two DEA models: the CCR model and the BCC model (see Section 3.4.1 for details on how these models function). Both models are analyzed to compare their effectiveness in evaluating project efficiency and to determine which is a better fit the context of project evaluation within the organization.

  The analysis is input-oriented (for a detailed explanation of how these orientations work, refer to Section 3.4.2), meaning the focus is on minimizing inputs (such as cost, workload, and duration) while achieving the desired project outcomes (such as stake amount and probability of success) [1]. Since project planners typically have more control over resource allocation than over the probability of success or stake size, input orientation aligns more realistically with decision-making in this context. Therefore, output orientation was not considered essential for this analysis.

  The efficiency scores computed by both models provide a comparative assessment of the projects performance. In this case, the sensitivity analysis is not applied directly by changing the input/output orientations, as the focus is on comparing models. However, any variations in data inputs (e.g., estimates of workload or duration) can be reviewed to assess the reliability of the results. The results from both models are then compared to determine which is more suitable for project selection and efficiency evaluation in the organization's specific context.

- **Step 7: Interpret results and benchmark project efficiency:**

  In this step, we analyze the results from the DEA analysis to evaluate project efficiency. This step plays a central role in extracting insights from the DEA analysis. By reviewing

[1] https://rbensua.shinyapps.io/deaR/

the efficiency scores, it is possible to interpret which projects performed well and which ones show inefficiencies. It is also essential to examine the following DEA outputs to better understand each project's performance. In addition, to be able to create the KPIs, explain the results and adapt it to current practices:

- **Targets**: These represent the ideal input or output levels each project should achieve to become efficient. Projects with inefficiencies can use their targets as performance benchmarks [65].
- **Slacks**: These indicate input excesses or output shortfalls that remain even after proportional improvements. They help pinpoint specific variables where projects are underperforming [64].
- **Lambdas**: These are the weights assigned to peer projects (reference set) that the model uses to construct the efficient frontier. A project's lambdas show which efficient DMUs serve as its benchmarks [1].
- **Returns to Scale (RTS)**: This informs whether a project operates under increasing, constant, or decreasing returns to scale, offering guidance on how changes in size may affect efficiency [2].
- **References**: These are the efficient DMUs that act as peers or comparators for inefficient ones. Understanding which efficient projects serve as references can support targeted improvements [65].

Using these performance indicators, we not only ranked the projects based on their efficiency but also gained deeper insights into where and how inefficient projects could improve. This interpretation guided benchmarking and supports data-driven decision-making for future project planning and resource allocation.

By examining these metrics, it is possible to identify high- and low-performance projects. This analysis reveals areas of inefficiency, such as resource allocation or project execution issues. It is essential to understand these inefficiencies in order to make informed decisions and implement targeted improvements. Additionally, benchmarking the results against industry standards or previous project outcomes provides a clearer picture of each project's relative efficiency.

- **Step 8: Integrate DEA findings into project management decisions:** The final step in this framework focuses on translating the results of the DEA analysis into actionable performance indicators that support proactive project management and strategic planning. In this research, this integration was accomplished by developing customized KPIs derived directly from the DEA outputs, specifically, efficiency scores, slacks, targets and reference sets.

  These KPIs provide project managers and decision-makers with interpretable metrics that highlight where inefficiencies exist and how specific projects can be improved before execution. For example, KPIs related to input slack can indicate excessive resource allocation, while efficiency scores and target values help benchmark projects against best-performing peers. These indicators were designed to align with existing internal project evaluation processes, ensuring their relevance and usability within the organization's planning framework.

To ensure adoption, the KPIs were structured to be both technically robust and practically meaningful. They serve not only as a retrospective evaluation of project efficiency but also as a forward-looking decision-support mechanism. For instance, a project with high estimated costs and low efficiency relative to peers can be choose for re-evaluation or scope adjustment. Similarly, projects operating under increasing returns to scale may be prioritized for additional investment or expansion.

By integrating these KPIs into project review meetings, demand planning workflows, and portfolio prioritization discussions, the organization is equipped with a data-driven approach to select and optimize projects. This creates a culture of efficiency-focused planning, allowing for more informed trade-offs and better alignment with strategic objectives.

In summary, the creation and use of DEA-based KPIs operationalize the findings of the efficiency analysis, bridging the gap between analytical outputs and practical decision-making. This step ensures that the DEA model is not just a technical exercise but a valuable tool embedded in the organization's project management methodology.

## 3.4. DEA Model Comparison and Implementation

This study employs two DEA models: the CCR and the BCC. Each of these models provides a different perspective on project efficiency, and comparing them allows for a more comprehensive evaluation of project performance.

### 3.4.1. CCR and BCC Models

The CCR model assumes that there is a CRS, meaning that increasing the input by a certain factor will lead to a proportional increase in the output. This model is appropriate when the project's efficiency is assumed to remain consistent, regardless of the scale of operations. In other words, whether the project is small or large, the efficiency should be the same, provided the inputs and outputs are scaled equally [1]. In our context, the CCR model is useful when assuming that larger projects should not automatically lead to inefficiencies; thus, it helps assess whether projects with similar input-output ratios perform optimally, regardless of their size or complexity.

In contrast, the BCC model uses VRS, which assumes that efficiency changes with the scale of the project. Larger projects may experience diminishing returns, while smaller projects may have increasing returns to scale. This model is particularly useful when projects vary significantly in size, scope, or complexity, and it provides a more nuanced evaluation of efficiency that accounts for these differences [2]. The BCC model is more suitable for projects where the scale influences performance, allowing for a more realistic evaluation of project efficiency in organizations dealing with a range of project sizes and resource allocations.

Table 3.2: Summary of DEA Model Comparison (CCR [1] vs. BCC [2])

| **Aspect** | **CCR Model** | **BCC Model** |
|---|---|---|
| Assumption | Constant returns to scale (efficiency remains constant regardless of project size) | Variable returns to scale (efficiency changes with project size) |
| Applicability | Suitable for evaluating projects where scale does not significantly affect efficiency | Suitable for projects with varying sizes or complexities |
| Efficiency Interpretation | Evaluates efficiency under the assumption that larger projects are not less efficient by default | Evaluates efficiency considering that larger projects might experience diminishing returns |
| Use Case in Study | Useful for projects with similar scales or where size does not vary much | Useful for projects of varying scale, scope, or complexity |

For this study, we used both models to assess the efficiency of the selected projects and compare their results. By applying both the CCR and BCC models, this study aims to assess which model provides the most meaningful insights into the project selection process. This comparison can provide insights into the relative advantages of each model for evaluating the efficiency of project selection in our case.

### 3.4.2. Input and Output Orientation

In addition to the CCR and BCC models, another critical factor in DEA is the orientation of the analysis. It can be either input-oriented or output-oriented, which affects how efficiency is evaluated. The orientation choice determines whether the analysis aims to minimize inputs for a given level of outputs (input-oriented) or maximize outputs for a given level of inputs (output-oriented) [1]. Input orientation is useful when the objective is to reduce resource consumption while maintaining the same output level. For example, if a project is overusing resources such as time, labor, or budget, an input-oriented DEA will identify ways to reduce these inputs without changing the project's expected outcomes.

On the other hand, an output-oriented model focuses on maximizing the outputs generated by a given set of inputs. This is suitable when the goal is to improve the project's effectiveness or productivity, with the goal of achieving higher outputs with the same resources. As an example, if the objective is to increase the monetary gain or the impact of the project, an output-oriented approach is typically more appropriate.

In this study, input-oriented DEA was used, as it is more appropriate for the project selection context since in this paper we assume that inputs are easier to control than outputs [45]. Since the focus is on improving resource allocation and optimizing project resources (such as time, labor and financial investment), the goal is to minimize the use of resources for each project while maintaining the expected outcomes. This aligns with the company's objective of increasing efficiency by reducing unnecessary resource usage.

Table 3.3 summarizes the comparison of both orientations. Input-orientation focuses on minimizing inputs but creating the same output or results, and is frequently used when the objective is reducing time, costs, effort or in resource conservation in general. An output-oriented model seeks to maximizing outputs, but mantain the same input level (resources). Is used when the objective is to increase the output or impact (e.g., maximizing results with the same budget) [1, 55].

Table 3.3: DEA Model Comparison with Input-Output Orientation [1]

| **Aspect** | **Input-Oriented** | **Output-Oriented** |
|---|---|---|
| Focus | Minimize inputs (resources used) for the same output level | Maximize outputs for the same input level |
| Use Case | Used when resource conservation is the priority (e.g., reducing time, costs, effort) | Used when increasing the output or impact is the priority (e.g., maximizing results with the same budget) |
| Project Type | Suitable for projects where resource optimization is key | Suitable for projects aiming to maximize productivity or returns |
| Chosen Orientation for Study | Input-oriented DEA is used to minimize project resource consumption and increase operational efficiency | Not applicable for this study |

The DEA model with the input orientation was selected for both CCR and BCC models. This ensures that the analysis focuses on identifying inefficiencies in resource usage across projects and recommending reductions in inputs for achieving more efficient project execution.

### 3.4.3. Models Implementation

After defining the dataset and model parameters, the DEA analysis was implemented using the *deaR* package in *R*. The application process involved importing the pre-processed dataset and specifying the roles of each variable. Following the typical DEA convention, all three input variables, Cost, Workload and Duration, were marked as discretionary inputs, meaning they are assumed to be controllable by the decision-makers. The two outputs, Stake Amount and Probability of Winning, were treated as desirable outputs, indicating that higher values are preferable. Table 3.4 represents the classification of variables used.

Table 3.4: Classification of Variables used in DEA

| **Variable** | **Type** | **Discretionary/Desirable** |
|---|---|---|
| Cost | Input | Discretionary / Controlable |
| Workload | Input | Discretionary / Controlable |
| Duration | Input | Discretionary / Controlable |
| Stake Amount | Output | Desirable |
| Probability to Win | Output | Desirable |

The model was run in an input-oriented configuration, with the goal to minimize inputs while maintaining the same level of outputs. In addition, similar to Stichhauerova and Pelloneova [45], in this context, we assume that inputs are more controlable than outputs. This approach is particularly relevant when organizations are constrained by limited resources and aim to optimize efficiency by reducing costs or effort [65].

Once the DEA model was executed, the software automatically identified the efficient DMUs — those that form the efficiency frontier with a score of 1 — and used them as reference points to evaluate the remaining, less efficient projects. For each inefficient DMU, the software calculated the optimal input levels (targets) needed to reach the frontier, along with slacks, lambdas (reference weights), and returns to scale. These values provide deeper insights into how performance could be improved and which efficient projects serve as peers or benchmarks.

This automated process simplifies the interpretation of efficiency scores and supports the development of targeted improvement actions. The output tables were exported and analyzed using Excel and Python to generate visualizations and identify common patterns, setting the stage for the results and KPI analysis discussed in the following chapter.

Figure 3.3 provides a high-level overview of the design of the research, illustrating the key steps involved from data preparation to insight generation. The process begins with data collection from organizational sources such as estimation packs and the demand planning system. Once gathered, the data undergoes a cleaning and anonymization phase to ensure consistency and confidentiality-this step was executed using Python and Excel. The refined dataset is then imported into the *deaR* software environment, where variables are classified as inputs or outputs depending on whether they represent resources to be minimized or outcomes to be maximized and the model and orientation are selected. This structured flow ensures that the DEA model is both methodologically sound and aligned with the practical needs of the organization.

To ensure reproducibility, the process is designed in a structured and adaptable way. Data preparation tasks that involves handling missing values and selecting relevant projects are performed using standard tools such as Python and Excel. The DEA analysis itself is conducted using the *deaR* package, which is publicly available and documented. Given that the analysis uses established CCR and BCC models, which are widely recognized and consistently implemented across different DEA tools, similar results should be achievable even with other software if the same model configuration and input-output structure are followed and provided. In addition, any replication must also respect organizational privacy and confidentiality guidelines, especially when handling sensitive internal data. This might affect the program or software selection.

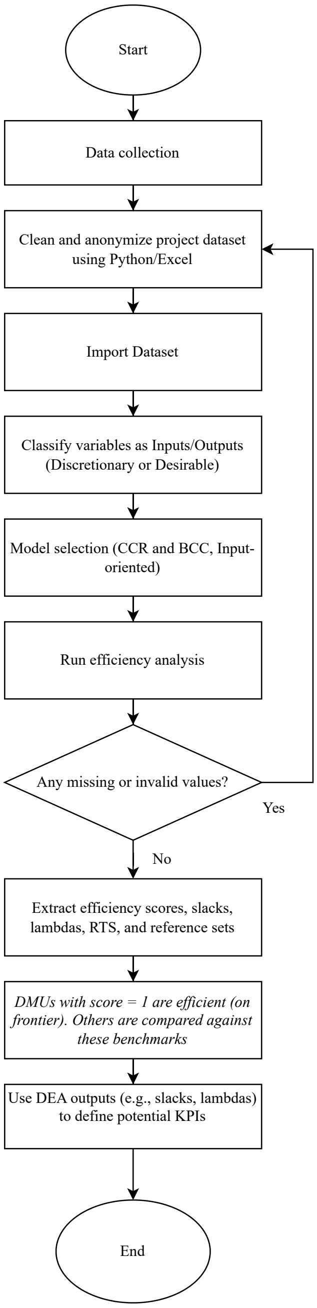



Figure 3.3: Overview of DEA implementation process

# 4

# Requirements for the DEA-Based Evaluation Framework

This chapter outlines the key requirements for designing a DEA-based framework to support project selection and evaluation. The requirements are derived from a thorough literature review, practical considerations from project efficiency evaluation, and the methodological constraints of DEA.

While the primary case study focuses on projects evaluated before execution within a defense industry company, the framework is designed to be applicable across different sectors where DEA has already been used—including IT [30], healthcare[7–9], finance [10], construction [38], and education [11, 12] —where project selection is crucial. Although this study focuses on pre-execution evaluation, since it is based on literature and current methodology, we expect the framework could also be adapted for post-execution assessments, which remains an avenue for future research.

By clearly defining these requirements, the framework ensures theoretical bases, practical usability, and reproducibility, allowing consistent application and interpretation across different organizations and project portfolios.

## 4.1. Modeling Requirements

To capture the complex and multidimensional nature of projects—particularly in sectors like defense, IT, or healthcare—the DEA model must handle multiple inputs and outputs simultaneously. For example, in our defense industry case, inputs such as project cost, duration, and workload were used alongside outputs as stake amount and probability of success. This multidimensional capability allows the framework to reflect realistic project characteristics beyond simple financial metrics.

Since traditional financial indicators (e.g., ROI or profit) are often unavailable or unreliable during early project stages, the model should support the inclusion of qualitative and proxy indicators. These can include leadership style [69], trust in the project team [70], or measures of effort [15, 71–73]. This flexibility enhances applicability across diverse project types and sectors.

The framework must accommodate heterogeneous scales of measurement—quantitative and qualitative variables alike—without distorting efficiency results. However, the selection of input and output variables must be context-aware. As the literature suggests, what constitutes an "input" or "output" may differ significantly depending on organizational goals and project nature [15]. Therefore, the framework should remain flexible to allow project managers and decision makers to define relevant variables based on their strategic priorities.

Flexibility in the orientation of the model is important, but in many practical settings (such as public associations or government projects), an input-oriented approach is often preferred. This is because outputs such as stake amount or probability of success can be influenced by external factors beyond the organization's direct control, such as available resources or stakeholder engagement. Therefore, focusing on minimizing inputs (such as cost, time, or workload) for a given level of output aligns better with how decision makers can influence project efficiency in these contexts [45]. However, the framework should remain adaptable, allowing users to select output orientation when maximizing outcomes is the priority.

Finally, the selection of inputs and outputs should align with the organization's strategic priorities and reflect the nature of the projects that are being evaluated [39, 68]. For example, in our case, some projects that appeared less efficient quantitatively were still considered strategically vital. For this reason, the model should enable customization of variables in order to maintain relevance and capture project diversity, while maintaining rigor and reproducibility.

## 4.2. DATA REQUIREMENTS

Having well-structured, consistent and high quality data is crucial for an effective application of a DEA-based project evaluation framework. Since DEA compares multiple projects (or DMUs) based on their relative efficiency, the validity of the results heavily depend on the quality and comparability of the input and output variables [68, 74].

In the practical application of this framework, data was gathered by integrating information from estimation packs and the internal demand management system. Automated scripts were developed to merge and standardize these data sources, ensuring consistency between all variables. A similar level of data integration and precision would be required in other organizational settings to ensure that the method can be reliably repeated over time and embedded into standard portfolio review cycles [75, 76].

Typically, input variables may include cost, duration and workload, while outputs could involve performance expectations such as stake amount or probability of success. However, in many early-stage projects, complete financial or quantitative data may be unavailable or uncertain.

For this reason, the framework accommodates estimated values and proxy indicators, allowing organizations to evaluate project efficiency even with limited data [15, 69, 70]. For example, even-though this where not used during this study, when the outcomes are not yet realized, stakeholder trust or leadership style can serve as qualitative proxies rated through structured expert judgments or internal assessments [71, 72].

Nevertheless, all variables used in the DEA model must be non-negative, clearly defined, and applicable to all projects under evaluation. This ensures consistency and fairness, particularly when comparing projects that may differ in scope or size [15]. Although normalization of variables can help mitigate distortions due to scale differences, care must be taken not to alter the underlying relationships within the data [74].

In line with established DEA guidelines, the number of projects analyzed should be at least three times the total number of input and output variables to maintain sufficient discriminatory power and avoid overfitting [1, 55]. In our case study, although this condition was largely respected, the portfolio included projects of different types (with different products, clients, durations), raising comparability challenges. This reinforces the importance of either selecting cross-cutting variables that are meaningful across projects or limiting comparisons to groups of similar nature [68].

Data privacy and security are also important considerations, especially in contexts where projects involve sensitive or classified information. While some DEA tools, such as the open-source *deaR Shiny App*, are easy to use, they may not be suitable for organizations with strict confidentiality requirements. In these cases, implementing the model internally through secure R or Python environments helps to maintain data integrity and protects against distortions that might arise from anonymization or external hosting [77, 78].

To ensure reproducibility and future scalability of the framework, it is critical that organizations document their data definitions, collection procedures, and processing assumptions. This makes it possible to replicate or adapt the methodology across different portfolios or sectors, and supports transparency and validation in performance evaluations [75**?** ].

## 4.3. INTERPRETATION REQUIREMENTS

For the DEA-based evaluation framework to be actionable, it must produce transparent and understandable outputs that can be effectively used by decision makers who may not have technical knowledge about DEA [30]. This means the framework should not only present efficiency scores but also provide access to reference sets (i.e., peer comparators) and target values that suggest potential areas for improvement. These elements help users understand why certain projects are deemed efficient or inefficient, facilitating clearer prioritization and resource allocation decisions [64].

Designing KPIs that are relevant and meaningful to stakeholders is crucial. The KPIs must reflect the strategic goals and unique context of the organization or sector. For instance, while slack indicators and returns-to-scale classifications may be essential KPIs in defense projects, other industries may require different or additional metrics. Tailoring KPIs to stakeholder interests ensures that the framework's outputs are both accurate and actionable.

Beyond numerical outputs, visualization plays a vital role in making DEA results accessible. Dashboards, charts, and efficiency frontiers can transform complex data into intuitive graphics that support faster comprehension and more effective communication between diverse stakeholder groups. Such visual tools reduce the reliance on specialized DEA knowledge and improve collaborative decision-making.

Regarding implementation, the generation of these KPIs and visualizations can be realized through various platforms. In this study, *Python* was used to create the visualizations. However, organizations might also use business intelligence tools like *Power BI* or *Tableau* to develop interactive dashboards that integrate them with existing data sources and automate updates.

Finally, it is important to recognize that quantitative KPIs alone cannot capture the full strategic and qualitative context of projects. Therefore, DEA results should be interpreted alongside stakeholder insights and organizational knowledge to avoid undervaluing strategically important but quantitatively inefficient projects. Combining data-driven analysis with expert judgment aligns with best practices in performance measurement and supports informed decision-making [75, 76].

## 4.4. TOOL REQUIREMENTS

When implemented as a computational tool, the DEA-based framework must offer a user-friendly interface that facilitates straightforward data entry, configuration, and management. This interface should support automatic calculation of DEA efficiency scores and generate outputs in standard, widely used formats (such as CSV or Excel) to ensure easy integration with other systems and reporting tools. To enhance user comprehension and stakeholder communication, the tool should also provide visual representations of results, including efficiency frontiers, peer comparisons, and KPIs dashboards [30].

In our implementation, *Python* was used primarily for creating visualizations to support better understanding and communication of the results. However, other platforms such as *Power BI* or *Tableau* could also be employed to develop interactive dashboards, depending on organizational preferences and available infrastructure. This flexibility enables integration with existing analytics workflows and facilitates ongoing monitoring and decision-making.

Configurability is a critical feature of the tool. Users must be able to define and modify input and output variables flexibly, allowing the framework to be adapted to different project types, organizational priorities, and industry contexts. This flexibility supports applicability across a range of scenarios.

Security and data privacy are paramount, especially for organizations handling sensitive or confidential project information. The tool should be designed to operate as a self-contained system within the organization's secure IT environment, minimizing the need to transmit data externally. This approach reduces the risk of data breaches and aligns with best practices for data protection and compliance [77, 78]. Simply anonymizing or scaling data may not be sufficient, as it can distort DEA outcomes; thus, secure internal handling of raw data is preferred.

This requirement became especially evident during our application of the framework. Due to confidentiality restrictions within the company, we were not able to run the analysis entirely in the organization's internal environment. As a result, we had to anonymize and preprocess the data before using external tools. While this ensured compliance with data protection policies, it raised concerns about whether anonymization or rescaling could have unintentionally affected the accuracy or interpretability of the DEA results. This challenge is also highlighted in the literature, which warns that anonymization processes can alter data structure and potentially compromise analysis validity [77]. This underscores the practical importance of enabling the tool to operate within secure internal environments, particularly in sectors such as defense, where data sensitivity is a major concern.

# 5

# Results and Discussion

This chapter presents and interprets the results obtained from applying the proposed DEA-based evaluation framework to a real-world dataset of pre-execution projects in the defense industry. The goal is to assess the practical utility and the insights of the framework, while also exploring its methodological implications.

The chapter starts with a descriptive overview of the dataset used for the analysis, providing context for the input and output variables. It then outlines the results from both the CCR and BCC models, followed by a comparative analysis that highlights the differences in efficiency measurement under constant and variable returns to scale.

The following sections delve into a detailed discussion of the model outputs, including slacks, target projections, returns to scale, and reference sets. These technical results are then synthesized into a set of KPIs designed to support project portfolio decision-making. These KPIs include indicators for resource optimization, scale effects, benchmarking potential, and actionable improvement targets.

Finally, the chapter links the results back to the requirements established in Chapter 4, reflecting on the implications for real-world implementation and offering insights into the practical and strategic value of the framework.

## 5.1. Descriptive Statistics of the Dataset

Table 5.1 and Table 5.2 provide an overview of the main input and output variables used in the DEA model. The variables show a considerable degree of variability, reflecting the diversity of project opportunities analyzed. For instance, the Estimated Cost ranges from €30.53 to €11,912.36, with a high standard deviation of €2,050.58, indicating the presence of both small-scale and capital-intensive projects. The interquartile range between €334.69 (Q1) and €1,432.04 (Q3) highlights this spread. Similarly, the Stake Amount, an output variable, goes from €41.20 to over €26,000, with a Q1 of €816.34 and Q3 of €7,854.17, emphasizing the varying potential financial impact across projects.

The Estimated Workload and Duration also show wide ranges and standard deviations, suggesting a mix of short projects and long-term initiatives. For example, the workload's Q1 and Q3 values (5.33 and 23.02 hours respectively) show significant spread around the median (8.57 hours). The Probability scores vary from 6 to 81 on a 0–100 scale, with the median at 63 and Q1 at 42, indicating some projects are high-risk while others have a higher likelihood of success.

Nothing analyzed appears overly abnormal given the nature of project portfolios, which typically include a wide variety of project sizes and risk profiles. The presence of projects with very low and very high estimated costs and stake amounts is expected in diverse portfolios. The skewness toward higher values in stake amount and costs is typical for portfolios mixing small and large projects. However, it is worth noting that the range of estimated duration is quite broad (2 to 69 months), which could introduce challenges in comparing projects that are very short-term with long-term ones; this reinforces the need for careful interpretation of efficiency results.

The spread of values and skewed distributions (as the mean often exceeds the median) justify the use of a non-parametric method such as DEA, which does not assume specific distributions of inputs and outputs and remains robust across heterogeneous DMUs.

Table 5.1: Descriptive Statistics of DEA Variables

| **Variable** | **Mean** | **Median** | **Std. Dev.** | **Min.** | **Max.** |
|---|---|---|---|---|---|
| Estimated Cost (€) | 1311.57 | 490.55 | 2050.58 | 30.53 | 11912.36 |
| Estimated Workload (Hours) | 18.19 | 8.57 | 19.80 | 0.80 | 82.17 |
| Estimated Duration (Months) | 19.71 | 13.00 | 16.47 | 2.00 | 69.00 |
| Stake Amount (€) | 5470.83 | 2068.66 | 6562.79 | 41.20 | 26666.67 |
| Probability (0-100) | 51.71 | 63.00 | 20.57 | 6.00 | 81.00 |

Table 5.2: Quartiles (Q1 and Q3) of DEA Variables

| **Variable** | **Q1** | **Q3** |
|---|---|---|
| Estimated Cost (€) | 334.69 | 1432.04 |
| Estimated Workload (Hours) | 5.33 | 23.02 |
| Estimated Duration (Months) | 9.00 | 27.75 |
| Stake Amount (€) | 816.34 | 7854.17 |
| Probability (0-100) | 42.00 | 63.00 |

## 5.2. DEA Model Results

### 5.2.1. Results of CCR Model

The CCR model evaluates project efficiency under the assumption of CRS. This means that efficiency is judged relative to a common frontier, assuming all projects operate at an optimal scale [1].

Out of the total 42 projects analyzed, 6 achieved an efficiency score of 1, positioning them on the efficiency frontier. These projects are considered fully efficient and serve as benchmarks for the rest of the portfolio. The remaining projects were identified as inefficient, with efficiency scores below 1, indicating potential for improvement in input use or output delivery.

Each inefficient project was associated with:

- Slack variables indicating resource excesses or output shortfalls.
- A reference set formed by efficient projects, quantified by lambda ( $\lambda$) values, which serves as a composite benchmark.
- Target values, thus the input and output levels that each project should aim for to become efficient under CCR assumptions.

Table 5.3 shows the efficiency scores for the 42 projects analyzed under the CCR model. In this case, 6 were identified as fully efficient, with scores of 1.

Table 5.3: CCR Model Efficiency Scores

| DMU | Efficiency Score | DMU | Efficiency Score |
|---|---|---|---|
| Project 1 | 0.0939 | Project 22 | 0.3762 |
| Project 2 | 0.0529 | Project 23 | 0.4903 |
| Project 3 | 0.1194 | Project 24 | **1.0000** |
| Project 4 | **1.0000** | Project 25 | 0.2446 |
| Project 5 | 0.3500 | Project 26 | 0.3457 |
| Project 6 | 0.5921 | Project 27 | 0.6459 |
| Project 7 | 0.0571 | Project 28 | 0.2721 |
| Project 8 | 0.3765 | Project 29 | 0.1463 |
| Project 9 | 0.1635 | Project 30 | 0.1436 |
| Project 10 | 0.3239 | Project 31 | 0.3385 |
| Project 11 | 0.2303 | Project 32 | 0.2206 |
| Project 12 | 0.3910 | Project 33 | 0.1794 |
| Project 13 | **1.0000** | Project 34 | 0.0503 |
| Project 14 | 0.1508 | Project 35 | 0.1324 |
| Project 15 | **1.0000** | Project 36 | 0.0736 |
| Project 16 | 0.0456 | Project 37 | 0.3612 |
| Project 17 | 0.1220 | Project 38 | 0.4364 |
| Project 18 | 0.2009 | Project 39 | **1.0000** |
| Project 19 | 0.1954 | Project 40 | 0.1802 |
| Project 20 | 0.1618 | Project 41 | 0.3851 |
| Project 21 | **1.0000** | Project 42 | 0.3161 |

### 5.2.2. RESULTS OF BCC MODEL

The BCC model introduces the assumption of VRS, allowing for a more flexible evaluation that accounts for differences in project scale. This is particularly relevant when the size or complexity of projects varies significantly, as is the case in the analyzed portfolio [2].

Under the BCC model, **8** projects were found to be fully efficient. This total includes all CCR efficient units, along with additional projects that benefit from scale-adjusted efficiency. Projects that were inefficient under CCR but efficient under BCC may suffer from scale-related disadvantages rather than operational inefficiencies [2].

In addition to efficiency scores, the model provided:

- Updated $\lambda$ values for new reference sets.
- Revised slack values and targets.
- A returns to scale classification for each project (Increasing, decreasing or constant).

Table 5.4 displays the efficiency scores under the BCC model. Here, 8 projects are classified as efficient, including all projects that were efficient under the CCR model. Notably, additional projects also become efficient under the BCC model, which allows for VRS, providing a more flexible evaluation of efficiency. Some projects that were inefficient under the CCR model are now efficient (e.g., Projects 5 and 8), indicating that scale-related factors (such as being too large or too small) rather than operational inefficiencies may have been the reason for their underperformance under the CCR model.

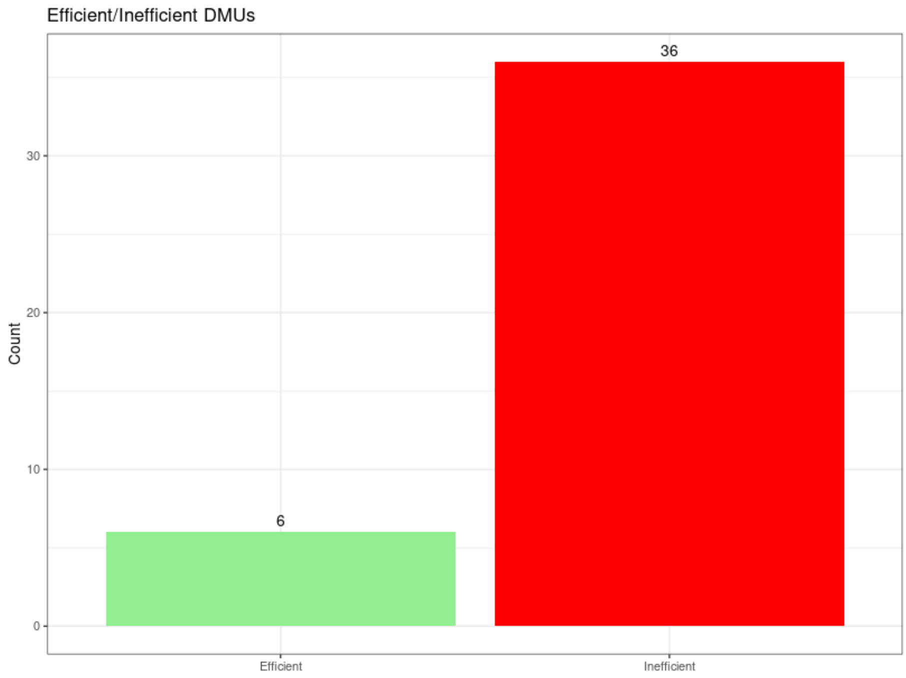
Table 5.4: BCC Model Efficiency Scores

| DMU | Efficiency Score | DMU | Efficiency Score |
|---|---|---|---|
| Project 1 | 0.1695 | Project 22 | 0.3762 |
| Project 2 | 0.1038 | Project 23 | 0.5779 |
| Project 3 | 0.1217 | Project 24 | **1.0000** |
| Project 4 | **1.0000** | Project 25 | 0.4717 |
| Project 5 | **1.0000** | Project 26 | 0.4444 |
| Project 6 | 0.6000 | Project 27 | 0.8794 |
| Project 7 | 0.1244 | Project 28 | 0.3185 |
| Project 8 | **1.0000** | Project 29 | 0.1856 |
| Project 9 | 0.1935 | Project 30 | 0.1667 |
| Project 10 | 0.3644 | Project 31 | 0.3386 |
| Project 11 | 0.2783 | Project 32 | 0.2206 |
| Project 12 | 0.4274 | Project 33 | 0.3120 |
| Project 13 | **1.0000** | Project 34 | 0.0571 |
| Project 14 | 0.1508 | Project 35 | 0.4115 |
| Project 15 | **1.0000** | Project 36 | 0.1388 |
| Project 16 | 0.1469 | Project 37 | 0.6920 |
| Project 17 | 0.1366 | Project 38 | 0.4664 |
| Project 18 | 0.2397 | Project 39 | **1.0000** |
| Project 19 | 0.1954 | Project 40 | 0.1929 |
| Project 20 | 0.1872 | Project 41 | 0.4322 |
| Project 21 | **1.0000** | Project 42 | 0.3732 |

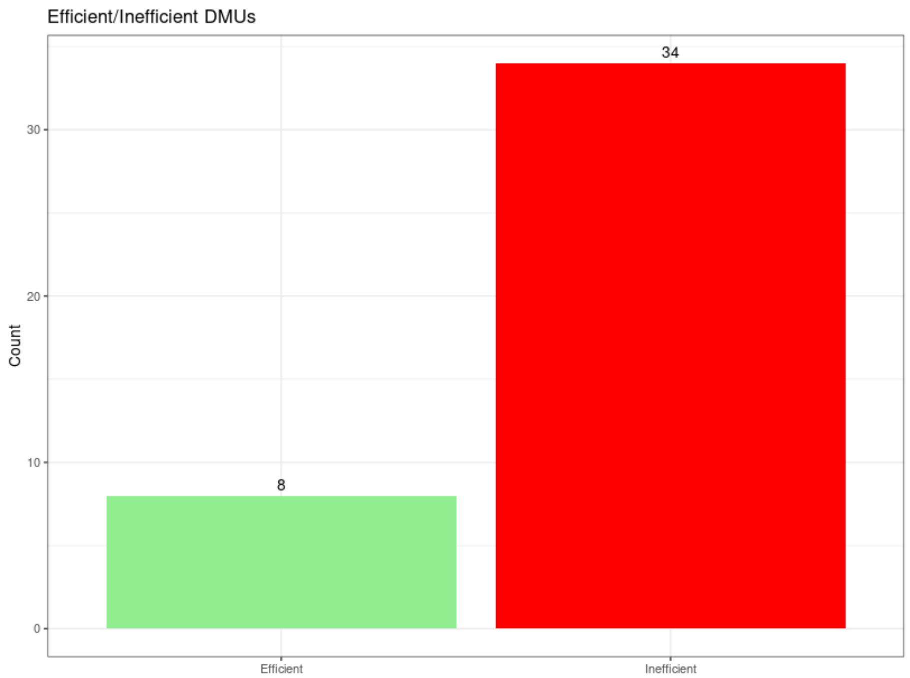
### 5.2.3. COMPARATIVE ANALYSIS

To complement the numerical analysis, several visualizations were generated to better understand the distribution and structure of efficiency accross the DMUs.

For both the CCR and BCC models, bar plots were generated to distinguish between efficient and ineficient DMUs. Figures 5.1a and 5.1b illustrate the efficiency results under the CCR and BCC models, respectively. Figure 5.1a shows that only 6 projects are efficient under the CCR model, which assumes CRS and thus creates a stricter efficiency frontier [1].




(a) CCR Model




(b) BCC Model

Figure 5.1: Efficient and Inefficient DMUs under CCR and BCC Models

Figure 5.1b shows the BCC model results, where 8 projects are identified as efficient due to the model's flexibility in accounting for VRS [2]. Importantly, all 6 projects marked as efficient under the CCR model remain efficient under the BCC model, with 2 additional projects - Project 5 and Project 8 - reaching efficiency when scale effects are considered.

By examining the projects, it is interesting to see what distinguishes those classified as efficient under the CCR and BCC models from the others. The six projects identified as efficient in the CCR model (Projects 4, 13, 15, 21, 24 and 39) tend to share some common characteristics: they generally have balanced resource use with relatively focused scopes and deliver outputs that are well matched to the inputs they consume. In simple terms, these projects achieve good "value for effort" ratios, meaning they make efficient use of their resources without unnecessary complexity or waste [2, 79].

In contrast, some larger or more resource-intensive projects that were not classified as efficient, such as Projects 3, 31 and 32 show a different pattern. These projects involve higher resource use (e.g., larger stake amounts, longer durations, or higher workload), but their outputs or outcomes do not increase proportionally. This suggests potential inefficiencies such as too much time spent on coordination, uncontrolled expansion of project scope, or suboptimal use of the available resources [80, 81].

Table 5.5 offers a simple comparison between efficient and inefficient projects to illustrate these differences.

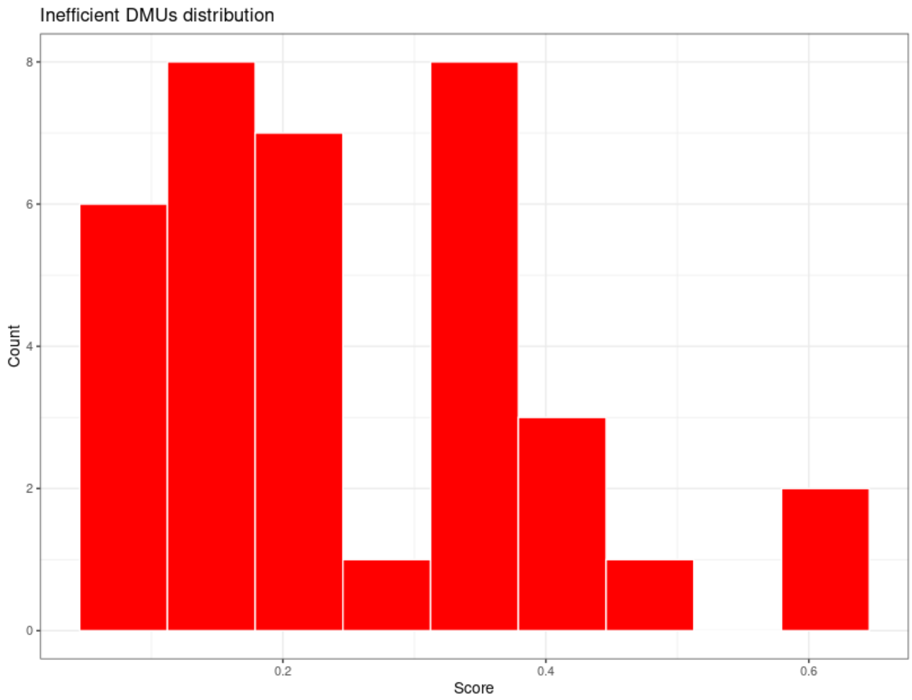
Table 5.5: Comparison Between Efficient and Inefficient Projects

| Project | CCR Efficiency | Stake Amount | Probability | Duration | Costs | Workload |
|---|---|---|---|---|---|---|
| Project 4 | 1.00 | 15538.89 | 81 | 34 | 262.59 | 3.76 |
| Project 13 | 1.00 | 333.33 | 63 | 2 | 282.95 | 4.33 |
| Project 15 | 1.00 | 12500.00 | 63 | 6 | 412.35 | 6.17 |
| Project 21 | 1.00 | 16666.67 | 81 | 10 | 356.56 | 5.43 |
| Project 24 | 1.00 | 1000.00 | 63 | 2 | 1172.71 | 18.34 |
| Project 39 | 1.00 | 422.83 | 81 | 3 | 30.53 | 0.80 |
| Project 3 | 0.12 | 12997.22 | 63 | 58 | 3033.34 | 57.03 |
| Project 31 | 0.34 | 16475.71 | 18 | 37 | 1019.24 | 16.26 |
| Project 32 | 0.22 | 6666.67 | 63 | 18 | 5332.47 | 82.17 |

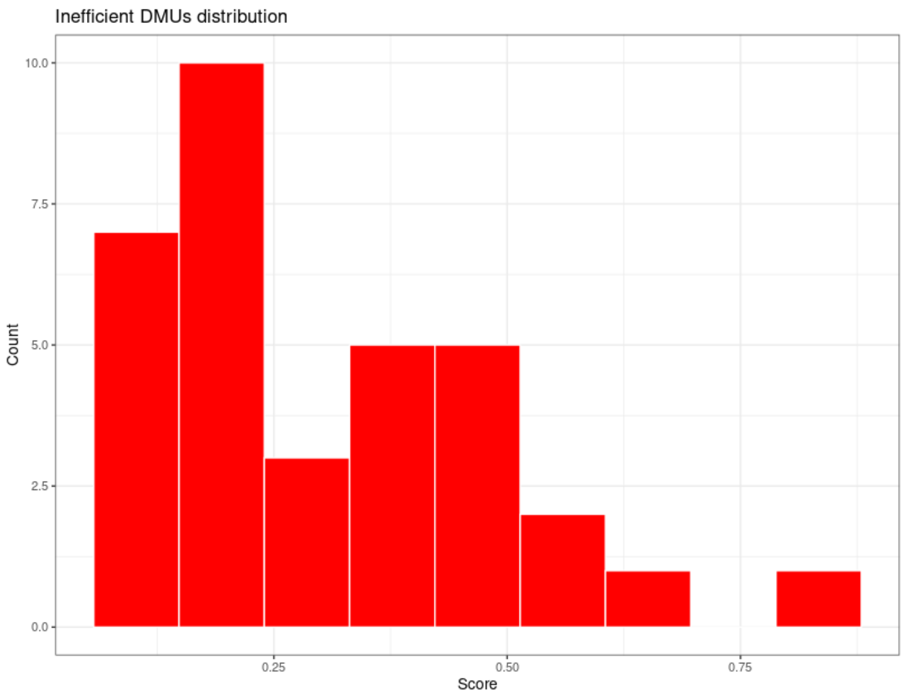
As mentioned, when using the BCC model [2] (Figure 5.1b), two additional projects (Project 5 and Project 8) are classified as efficient. These are larger projects that perform well when scale effects are considered. In practical terms, this means these projects are not truly inefficient; rather, they operate effectively given their size, even if they are not at the "optimal" scale assumed by the CCR model.

Project managers, can treat these efficient projects (e.g., Projects 4, 13, 15, 21, 24, 39) as useful benchmarks. This is further discussed and analysed in this section, when talking about which projects are used as reference for others. Managers can study their practices to understand what drives efficiency, such as focused scope and effective resource use [79]. For the inefficient, resource-heavy projects (e.g., Projects 3, 31, 32) it may benefit from reviewing and simplifying scope, reducing complexity, or improving resource coordination [80, 81]. Finally, efficient projects under BCC (such as Projects 5 and 8) which are performing well for their size should be monitored to ensure continued efficiency as they develop [2]. These insights could help managers prioritize where to focus improvement efforts, whether by learning from highly efficient projects, streamlining complex ones, or supporting projects that operate well at their current scale.

Figure 5.2 illustrates the distribution of efficiency scores among only the inefficient projects for each model. This plot helps in assessing the overall dispersion and severity of inefficiencies. Under the CCR model (Figure 5.2a), the distribution is heavily skewed toward lower efficiency values. Many projects fall below 0.4, and several are even below 0.2, indicating significant gaps from the efficiency frontier. This suggests that under constant returns, most projects in the portfolio have considerable room for improvement. The BCC model histogram (represented in Figure 5.2b) shifts the distribution slightly upward , but not dramatically. Although some additional projects reach full efficiency, most remain inefficient. A large number of projects continue to fall below 0.5, indicating that even after accounting for scale, operational inefficiencies persist for much of the portfolio.




(a) Inefficient DMUs under CCR Model




(b) Inefficient DMUs under BCC Model

Figure 5.2: Distribution of Inefficient DMUs under CCR and BCC Models

These histograms show that inefficiency is widespread and not limited to a few outliers. Scores do not cluster in a mid-to-high range, but instead spread over a broad spectrum, especially in the CCR case. This highlights the importance of identifying specific sources of inefficiency, such as excess inputs or insufficient outputs, as reflected in the slack variables and target values.

To provide clearer insight into the distribution of efficiency scores, Table 5.6 presents the number of projects within each efficiency score range, as illustrated in the accompanying histogram.

Table 5.6: Distribution of Projects by Efficiency Score Range

| **Efficiency Range** | **CCR Model** | **BCC Model** |
|---|---|---|
| [0.00, 0.20) | 13 projects | 5 projects |
| [0.20, 0.40) | 17 projects | 17 projects |
| [0.40, 0.60) | 4 projects | 6 projects |
| [0.60, 0.80) | 2 projects | 4 projects |
| [0.80, 1.00) | 0 projects | 2 projects |
| = 1.00 | 6 projects | 8 projects |

Table 5.7 groups the projects according to their efficiency scores under the BCC model. A significant portion of projects fall in the lowest efficiency bracket [0.00, 0.20), indicating notable inefficiencies for many initiatives. Meanwhile, only a few projects achieve full efficiency (=1.00), serving as benchmarks for peers. This distribution highlights the variability in project performance and suggests opportunities to target improvements, especially for projects with very low efficiency scores.

Table 5.7: ]

BCC Model: Distribution of Projects by Efficiency Range with Project IDs

| **Efficiency Range** | **Projects** |
|---|---|
| [0.00, 0.20) | Project 1, 2, 3, 7, 9, 14, 16, 17, 29, 30, 34, 36, 40 |
| [0.20, 0.40) | Project 10, 11, 22, 28, 31, 32, 33, 35, 38, 42 |
| [0.40, 0.60) | Project 12, 15, 26 |
| [0.60, 0.80) | Project 6, 37 |
| [0.80, 1.00) | Project 27 |
| = 1.00 | Project 4, 5, 8, 13, 15, 21, 39 |

Table 5.8 presents the distribution of projects across efficiency score ranges under the CCR model. Aside from having fewer projects achieve full efficiency, reflecting the stricter assumption of CRS in the CCR model, the concentration of projects in the lower efficiency brackets indicates several projects have substantial room for improvement when scale effects are not considered. This insight is useful for understanding efficiency in contexts where proportional scaling of inputs and outputs is assumed [1].

Table 5.8: CCR Model: Distribution of Projects by Efficiency Range with Project IDs

| **Efficiency Range** | **Projects** |
|---|---|
| [0.00, 0.20) | Project 1, 2, 7, 14, 16, 34, 36 |
| [0.20, 0.40) | Project 10, 11, 22, 25, 26, 28, 31, 38, 41, 42 |
| [0.40, 0.60) | Project 5, 12, 33 |
| [0.60, 0.80) | Project 6, 27, 37 |
| [0.80, 1.00) | Project 8 |
| = 1.00 | Project 4, 13, 15, 21, 24, 39 |

A comparative look at CCR and BCC results highlights several key observations:

- All projects that are efficient under the CCR model remain efficient under the BCC model, which aligns with what we expected based on the literature [2]. Specifically, the 6 projects efficient under CCR (Projects 4, 13, 15, 21, 24, 39) also appear efficient under BCC, with the latter model adding 2 more projects (Projects 5 and 8) to the efficient frontier.
- Two more projects are classified as efficient under the BCC model (Project 5 and 8). This suggests that the BCC model is better at handling differences in project scale, allowing smaller or larger projects to appear efficient if they are operating within their scale limitations, explaining why more projects are classified as efficient under BCC.
- Efficiency scores tend to be higher under BCC, especially for projects with very large or very small scales. This is because the BCC model separates scale effects from technical efficiency, meaning projects are no longer penalized just for being too big or too small. Instead, they are evaluated based on how well they perform within their own size category [2].
- The improved classification of Project 5 and Project 8 under BCC highlights how scale flexibility matters. Both projects have high stake amounts (23,333 and 26,666 respectively) and relatively high workloads (41.12 and 45.76), suggesting they perform efficiently at a larger scale. However, under the constant returns assumption in CCR, their size may have led to penalties despite strong performance.
- The $\lambda$ values and reference sets change between the models, showing how different projects are compared to one another. In the BCC model, some inefficient projects are paired with different efficient projects than they were in the CCR model. This happens because the efficiency frontier shifts when the assumption of constant scale is removed.
- The RTS classifications provide useful strategic insights. Projects that show Increasing Returns to Scale (IRS) may benefit from expanding, while those with Decreasing Returns to Scale (DRS) could be more efficient by scaling down. This information can help guide decisions about project adjustments, such as whether scaling up or down would improve efficiency.

This comparison underscores the value of using both models. While CCR offers a stricter benchmark, BCC reveals which inefficiencies come from managerial factors versus scale issues. In contexts like this where projects differ significantly in scope and resources, the BCC model may provide a more realistic view of true performance.

The finding that most projects in the analyzed portfolio fall below full efficiency is consistent with certain results reported in the DEA literature. For instance,Ku-Mahamud et al. [39] observed that only 3 out of 39 evaluated projects were efficient, with the remainder exhibiting efficiency scores as low as 0.037. These inefficiencies were attributed to imbalances between inputs such as labor cost and project duration, and the corresponding outputs. However, it is important to note that not all studies report similar trends. In contrast, Stichhauerova and Pelloneova [45] identified a comparatively larger group of efficient projects under the CCR model, suggesting that the proportion of efficient projects can vary significantly depending on the dataset, sector, and selection of inputs and outputs. This indicates that while inefficiency among projects is commonly observed, it is not a universal outcome and may reflect sector-specific dynamics or methodological choices.

The **Reference Ranking** plot illustrates how often each efficient project is mathematically selected as part of the reference set for inefficient projects by the DEA model. In DEA, when a project (or DMU) is found to be inefficient, it is compared against a weighted combination of efficient projects. These efficient projects form its reference set. This set is generated by the DEA optimization process, which identifies the efficient projects that can serve as benchmarks or peers [**?** ]. The frequency with which a particular efficient project appears in the reference sets of other (inefficient) projects indicates how broadly it serves as a model of good performance within the dataset.

In other words, an efficient project that is frequently referenced is one that the DEA method considers a common benchmark: its input-output ratio closely resembles what many inefficient projects should strive to emulate. This frequency is determined purely by the mathematical solution of the DEA model, not by human judgment or real-world practice, although it can be informative for decision makers in identifying high-performing projects that represent best practices. As noted in the literature, reference sets and peer counts provide insight into the efficiency structure within the portfolio and can help prioritize which projects to analyze more closely for learning and replication purposes [68**?** **?** ]. In the CCR model (Figure 5.3), the most frequently referenced projects serve as ideal performance benchmarks for a wide range of DMUs. These projects consistently show best practices for converting inputs into outputs with constant scale returns.

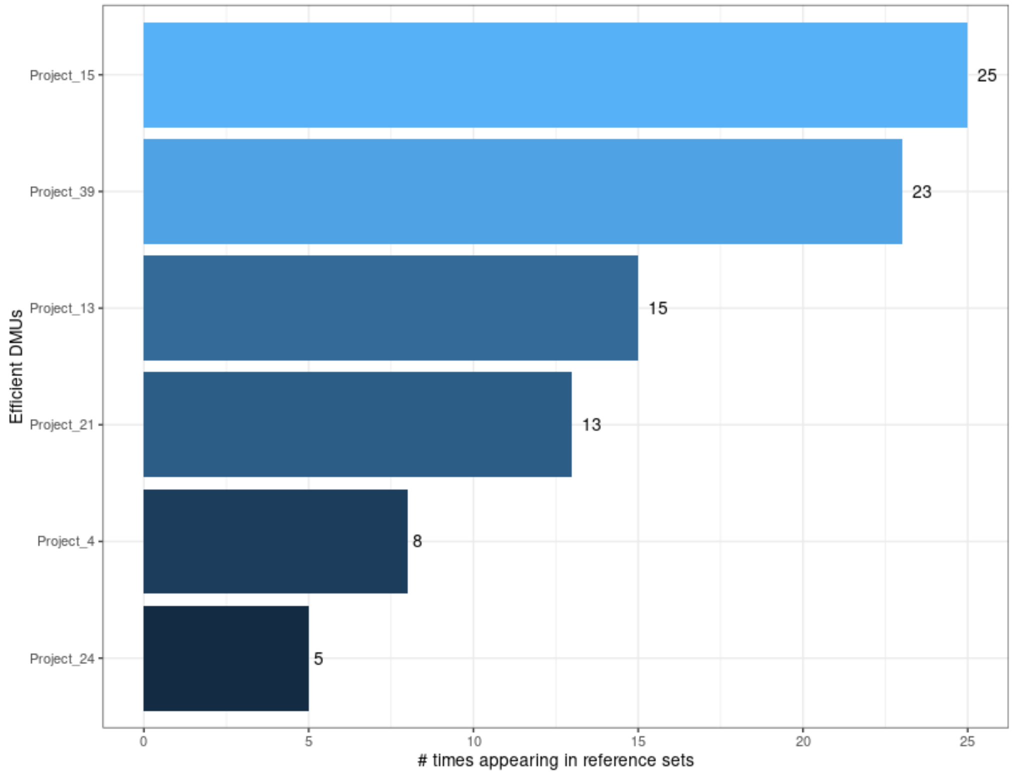



Figure 5.3: Reference Ranking for CCR model

In Figure 5.3, Project 15 and Project 39 are the two most referenced peers due to their input-to-output performance. Project 15 is located at the top of the graph and is used as reference for other projects 25 times, while Project 39 baseline referenced 23 times. In the BCC model (Figure 5.4), the reference frequency shifts slightly, as different scale assumptions affect which efficient units are considered the most relevant peers. Some units get more references, while others loose influence, suggesting that scale effects influence their relative positioning. However, we do not see any big change when comparing the results. Project 15 and Project 39 are still the most referenced projects. However, this time Project 39 is shown as the more referenced projects with a total number of 28 times, while Project 15 is referenced 25 times. Interestingly, Projects 5 and 8 are classified as efficient only under the BCC model but are not referenced by any inefficient DMUs, as indicated by their reference ranking of zero. This means that although they lie on the VRS efficiency frontier, they are not used as benchmarks for other projects. This can occur again because these projects might be operating efficiently within their scale category but do not represent typical or optimal patterns for other DMUs to copy under the BCC framework.

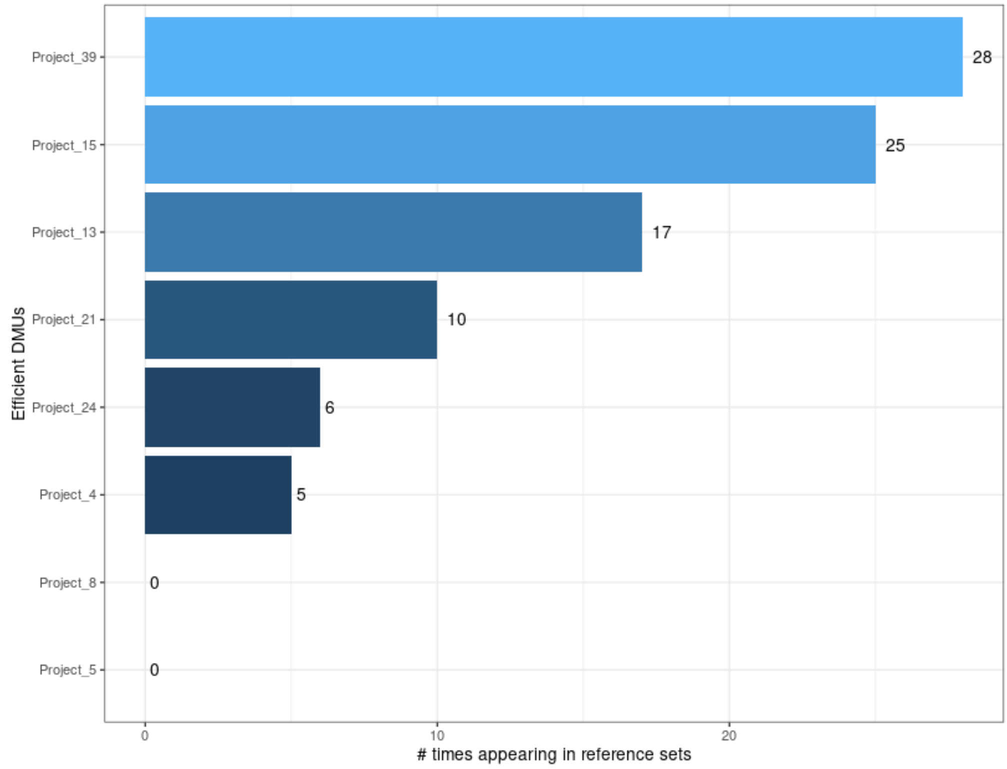



Figure 5.4: Reference Ranking for BCC model

In addition, analyzing which projects act as peers is particularly useful for practitioners: projects that appear frequently in reference sets are not only efficient but also broadly applicable models of best practice. These units may warrant closer examination to identify transferable processes or strategies.

The **Reference Graph** visualizes the network of relationships between inefficient DMUs and their efficient peers, so how inefficient DMUs are connected to the efficient ones they are compared against[1, 82]. In the figures, each green node represents a project, and the red nodes at the center correspond to the efficient units that serve as references. Edges (lines) indicate which efficient DMUs are used in the convex combination that defines the target for each inefficient project. In both the CCR (Figure 5.5) and BCC (Figure 5.6) models, we observe a similar structural pattern: a small number of efficient projects frequently appear as references for many others. Notably, Project 39 and 15 stand out in both models as the most referenced units, connected to other projects in each case. This highlights its strong benchmarking role across the portfolio as it could also be seen previously in Figure 5.3 and 5.4.

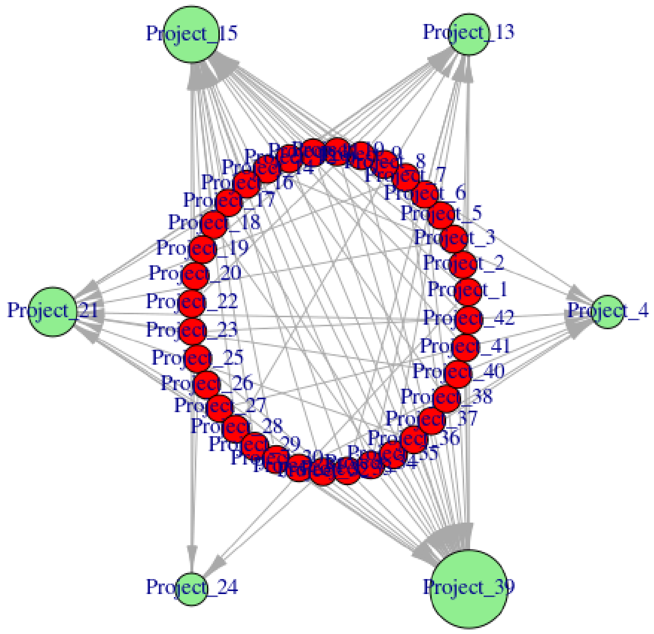



Figure 5.5: Reference Graph for CCR model

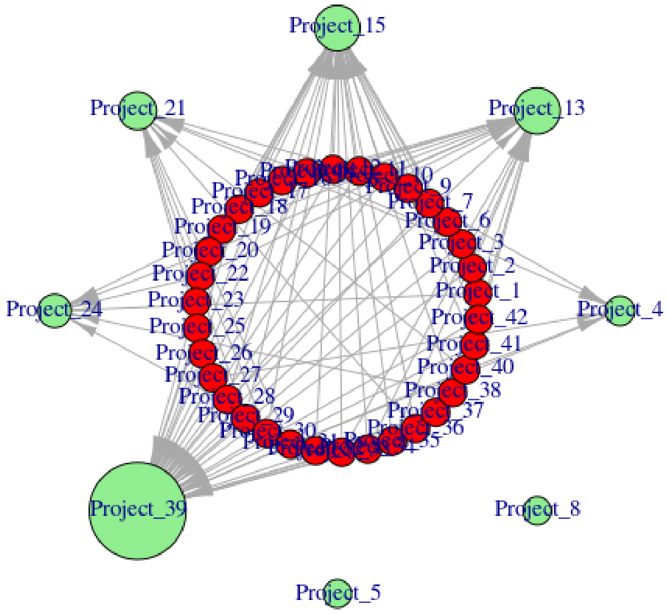



Figure 5.6: Reference Graph for BCC model

However, there are subtle differences in how influence is distributed. Under the BCC model, the structure appears more centralized, with a few highly efficient projects (notably Project 39 and Project 15) that concentrate the majority of connections. This aligns with the flexibility of the model, which allows more projects to be classified as efficient and, consequently, more likely to serve as peers.

In contrast, the CCR model results in a slightly more dispersed pattern of reference links. Although Project 39 is still a dominant reference, additional projects such as Project 24 gets more reference, suggesting that under constant returns to scale, the benchmarking relationships are more evenly distributed.

These visualizations not only validate the efficiency scores but also reveal how each project contributes to shaping the efficiency frontier. Projects that are frequently referenced, such as Project 39 and 15, play a key role in guiding performance improvements for others. Understanding these peer networks can support more informed decisions about where to focus learning, replication, or even resource reallocation. A more detailed discussion of the results can be found in Section 5.3.4.

In both the CCR and BCC models, other values were obtained that offer a deeper insight. The slack values show where there is room for improvement, whether a project uses more resources than needed or does not produce enough output [64]. The target values suggest what each project would need to achieve to be considered efficient [65]. The lambda values (or weights) help identify which efficient projects are used as benchmarks for the inefficient ones [1]. Additionally, the frequency with which a project appears in these reference sets reflects its influence as a role model within the portfolio [65]. Finally, the classification of RTS, whether increasing, decreasing, or constant, gives useful clues as to whether a project might benefit from scaling up or down [2]. All of these elements are explored in more detail later in the following section and will be key to developing practical performance indicators.

## 5.3. DISCUSSION OF KEY FINDINGS

### 5.3.1. INPUT AND OUTPUT SLACKS

One of the main features of DEA analysis is the identification of slack values. These reflect excess input usage or shortfalls in output production for inefficient DMUs, in other words, it shows where whether a project uses more resources than needed or does not produce enough output[64]. These slacks offer valuable insight into which specific variables are most associated with inefficiency in the portfolio, making it an useful tool to identify where there is room for improvement.

For both models, non-zero slacks were observed in a variety of input and output variables. For clarity, the full set of slack values is provided in Appendix B.1. In this section, the key observations and trends are summarized.

**Input Slacks**

- **Workload** appeared as the most frequently observed slack variable. Projects such as *Project_8*, *Project_20*, and *Project_32* in the CCR model, and *Project_2*, *Project_10*, *Project_31*, and *Project_35* in the BCC model show notable excess workload.
- **Costs** also show significant slack values, especially for *Project_1* (CCR: 807.7; BCC: 1457.0), *Project_32*, and *Project_38*, suggesting excessive financial resource usage.
- In the BCC model, **Duration** displays slack primarily in *Project_25*, *Project_26*, and *Project_37*, indicating room for reduction in execution time under variable RTS.

**Output Slacks**

- The most prominent output slack was found in **Stake Amount**, particularly for *Project_25* and *Project_26*, where large increases (135–381 units) are required to reach the efficient frontier.
- Slack in **Probability of Success** is also common, notably in *Project_5*, *Project_8*, and *Project_29*, suggesting under performance in expected project outcomes.

These findings imply that many inefficient projects could not become efficient through proportional input reductions alone, pointing to structural inefficiencies tied to particular variables. As mentioned, a complete overview of slacks by project is provided in Appendix B.1.

Figure 5.7 and Figure 5.8 visualize the number of projects with non-zero slack values across various variables (Duration, Costs, Workload, Stake Amount, and Probability of Success).

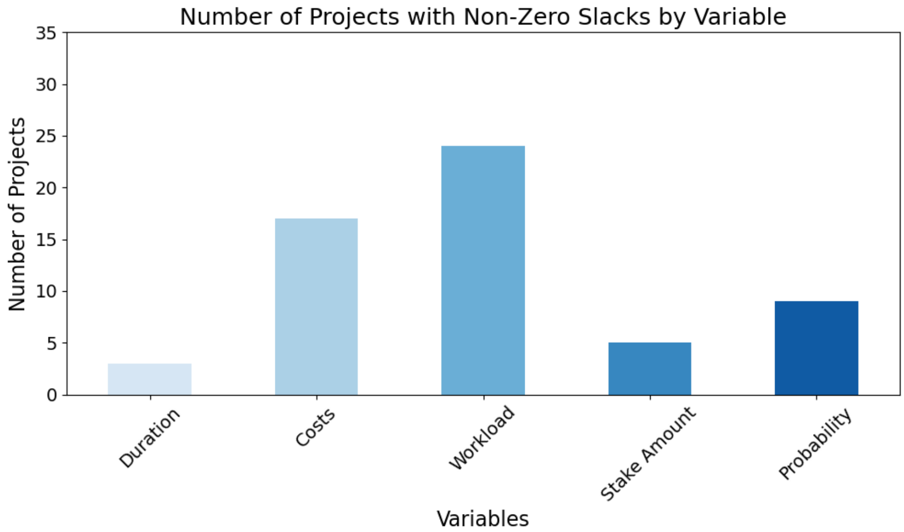



Figure 5.7: Number of projects with non-zero slacks by variable for the CCR model

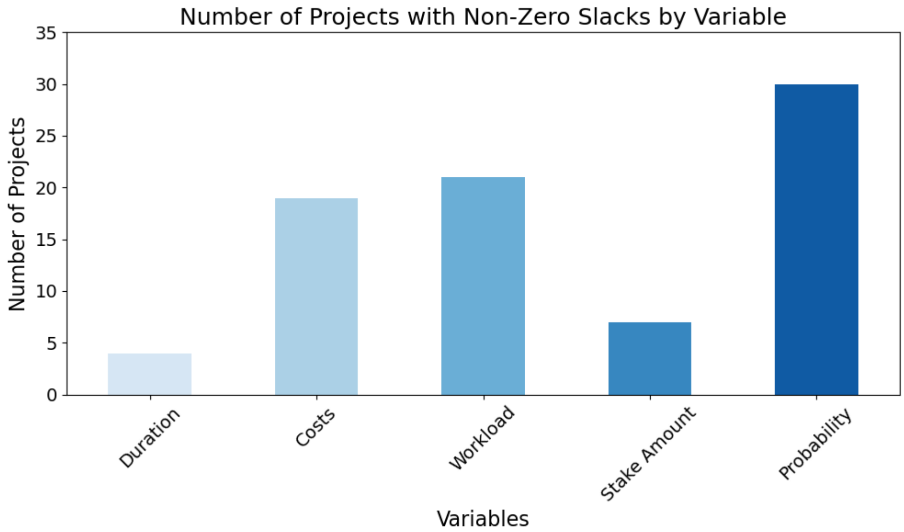



Figure 5.8: Number of projects with non-zero slacks by variable for the BCC model

### 5.3.2. TARGET PROJECTIONS

The target values from the CCR and BCC models show what each project would need to achieve in order to be considered efficient. These targets are not simply percentages to reduce or increase; they represent the performance levels each project would need to reach, based on comparisons with the best-performing projects in the dataset [1, 65].

Figure 5.9 presents a visual comparison between the actual input values and the efficiency targets suggested by the CCR model for three key input variables: Duration, Costs, and Workload. Each subplot focuses on one input and displays actual versus target values for all projects. Figure 5.9a shows that several projects have much higher actual durations than their CCR targets. This indicates that time is a potential inefficiency source. Figure 5.9b reveals that Costs are consistently over the CCR targets as well, especially for projects such as Project 1 and Project 8, highlighting that they might be over budget when compared to their benchmarks. Additionally Figure 5.9c, which covers Workload, shows significant gaps between actual and target values, with projects such as Project 8 needing to reduce Workload drastically (from actual values down to 13.2 units).

This model suggests that inefficiencies mostly arise from input overuse rather than from poor output performance. For instance, Project 1, with an efficiency score of 0.0939, is projected to reduce Workload to 4.83 units and Costs to approximately 311 units to become efficient. Similarly, Project 2 must reduce both Duration and Workload while maintaining output.

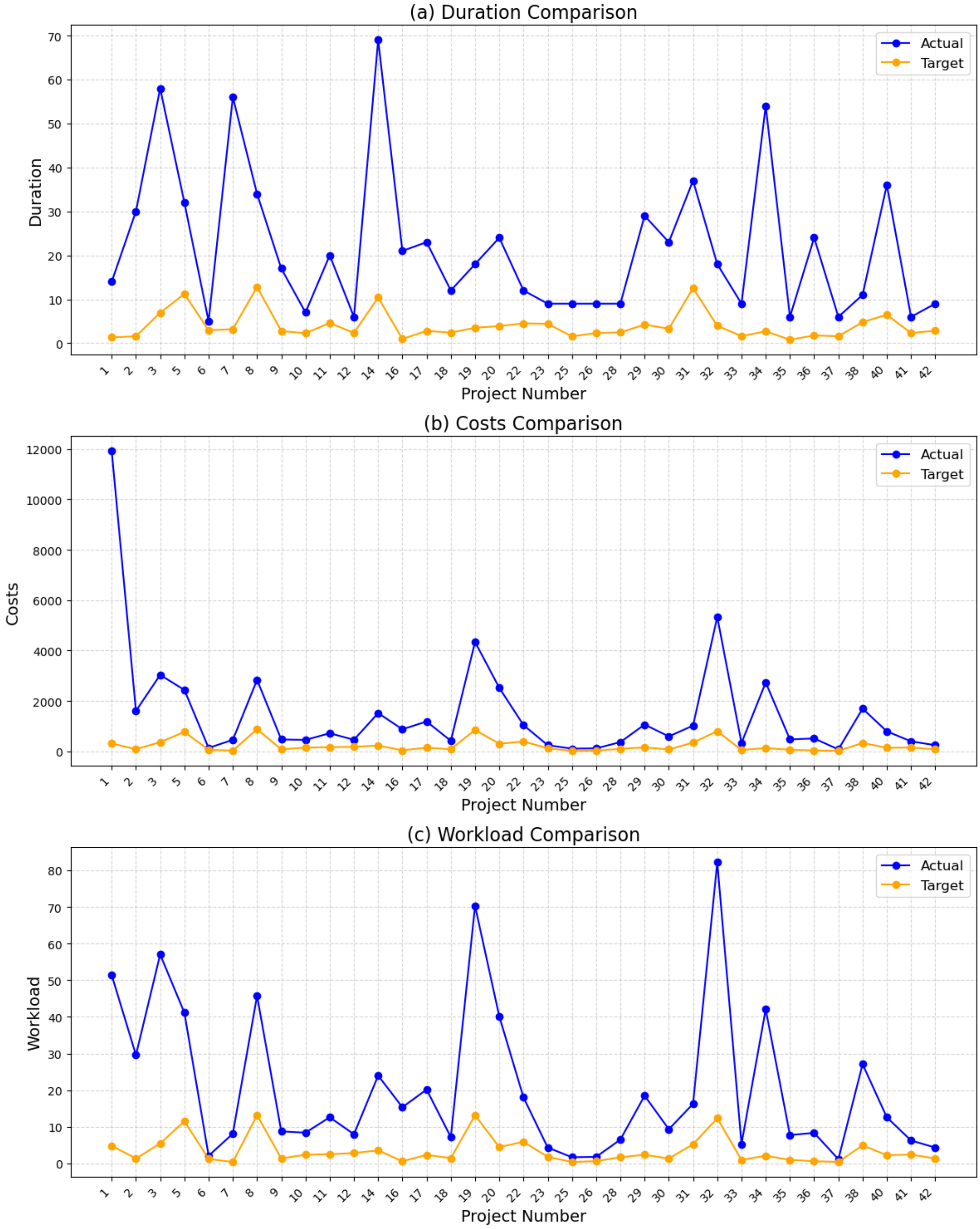



Figure 5.9: Comparison between the actual values and CCR-projected targets for the input variables. Each subplot displays a different input: (a) Duration, (b) Costs, and (c) Workload

In contrast, Figure 5.10 presents the same analysis under the BCC model. While the structure of the figure is similar, each subplot focusing on Duration, Costs, and Workload, the values tell a different story. Because the BCC model accounts for variable returns to scale, it often produces less stringent target values. In several cases, the BCC targets are higher than the CCR counterparts. For example, for Project 1, the target Workload increases from 4.83 units under the CCR model to 8.71 units under BCC. This indicates that Project 1's inefficiency may be partly due to scale effects, meaning it might not be operating at a suitable size rather than simply using too many resources. Already effective projects are not represented in the Figures. This is the case for Project 4 which in addition is efficient under both CCR and BCC frameworks, with an efficiency score of 1. Consequently, no adjustments are required in any of the input variables (Duration, Costs, or Workload). Although is not one of the top referenced projects, its actual resource usage represents a benchmark for other, less efficient projects. From a DEA perspective, as is further developed in Sections 5.2.3 and 5.3.4, efficient units such as Project 4 serve as peers or references for inefficient projects, guiding this target calculations and efficiency improvement pathways. The fact that Project 4 remains efficient under both constant and variable returns to scale also implies that it is operating not only efficiently in terms of resource utilization but also at an appropriate scale.

In addition, the BCC model also reveals subtle changes in output variables, although these are generally minor. For most projects, Stake Amount and Probability show little to no variation between actual and target values. This reinforces the earlier observation that inefficiencies are concentrated on the input side. However, exceptions do exist. Project 2, for example, is projected to increase its Probability output from 63 to 72.7 under the BCC model, indicating that even outputs may offer room for improvement when projects are evaluated in a more flexible, scale-sensitive context. When examining output variables such as Stake Amount and Probability, target projections often show minimal or no change. This indicates that most projects perform reasonably well in these areas, and that inefficiency predominantly comes from an overuse of inputs. However, in certain cases, such as Project 2, the BCC model suggests a slight increase in Probability, projecting it to rise from 63 to 72.7. This indicates that, while the inputs are a larger concern, even output performance can be improved under more flexible assumptions of returns to scale.

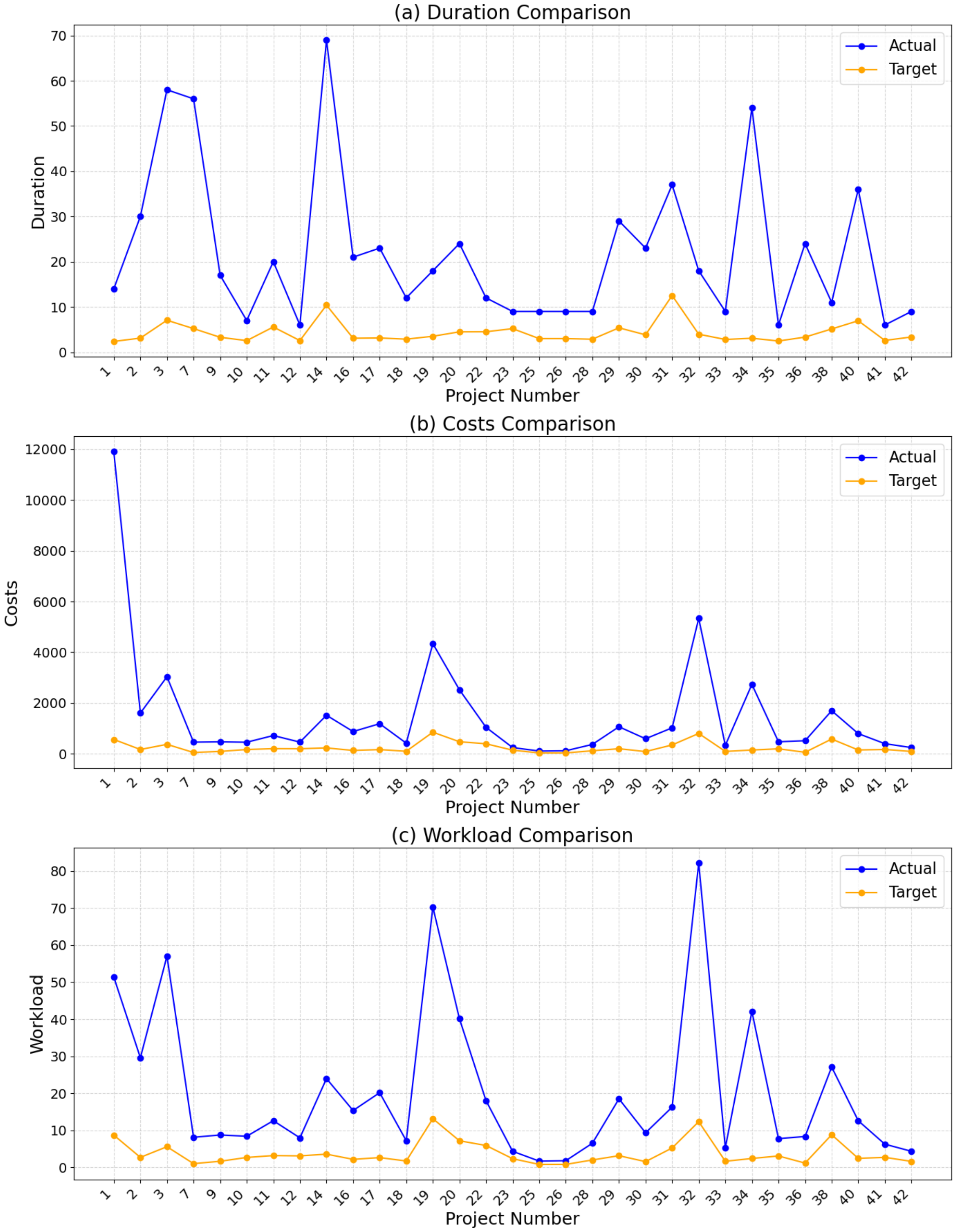



Figure 5.10: Comparison between the actual values and BCC-projected targets for the input variables. Each subplot represents a different input: (a) Duration, (b) Costs, and (c) Workload

A more direct comparison between the two models is provided in Figure 5.11, which presents side-by-side bar charts of CCR and BCC targets for the three input variables as well, Duration, Costs, and Workload for four randomly selected projects, which they are all . However, the full results can be found in Appendix B.2. Each subplot corresponds to a single project, showing blue bars for CCR targets and dark blue bars for BCC targets. This figure illustrates the relative strictness of the CCR model. For most inputs and projects, CCR targets are lower, suggesting that projects must reduce resource usage more drastically to be considered efficient. In contrast, BCC targets are generally higher, meaning that the input reductions required are less extreme. For example, Project 2 must reduce its Duration to 1.59 units under CCR, whereas the BCC target is more lenient at 3.11 units. These differences underscore the more flexible and arguably more realistic nature of the BCC model, which adjusts for scale inefficiencies and provides a fairer comparison between projects of different sizes. Project 4 again stands out with identical targets under both models, confirming that it operates at a technically and scale-efficient level. In Figure 5.11, the target values for some inputs are actually higher in the BCC model than in the CCR model. Since under the CCR model, efficiency targets tend to be lower, the projects must reduce their input usage more drastically to become efficient. This stricter requirement means that although the target values are smaller, the magnitude of change needed to reach these targets is actually greater. However, the BCC model allows projects to be evaluated relative to peers of similar scale. As a result, the input reduction targets under BCC are often higher, indicating that projects need to adjust their inputs less drastically to achieve efficiency. This reflects the more flexible and realistic assessment of efficiency provided by the BCC model, which separates scale effects from technical efficiency [2, 65].

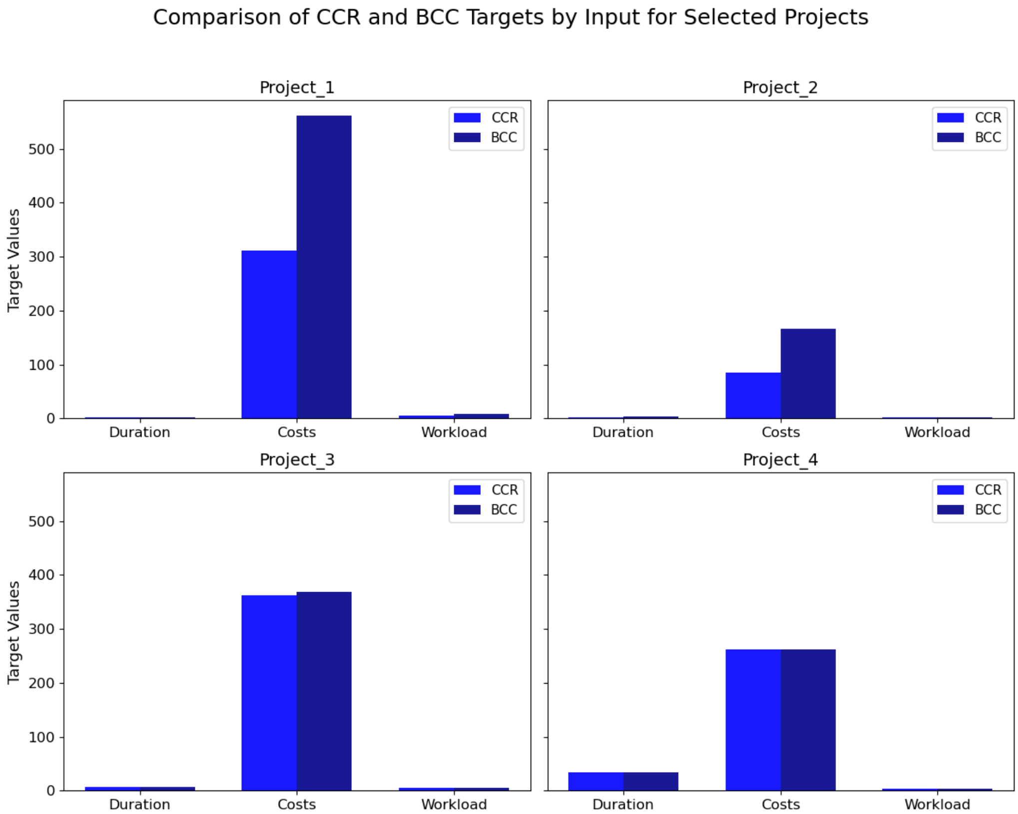



Figure 5.11: Reference Graph for CCR model

In conclusion, the targets provide a way for improving project performance. Most projects can achieve the same level of output with fewer resources, particularly by focusing on Workload and Costs. By using both CCR and BCC models we get both a strict and a more flexible interpretation of efficiency. In practice, understanding whether a project's inefficiency stems from poor resource use (technical inefficiency) or from operating at the wrong scale (scale inefficiency) can have direct implications for how improvement strategies could be designed. By addressing input inefficiencies and optimizing scale, these targets offer actionable insights to improve project execution across the portfolio. To translate these insights into action, project managers should prioritize resource optimization, especially focusing on Workload and financial expenditures, while also reassessing whether current project sizes align with operational best practices. In cases where BCC suggests that input levels should increase, this implies that certain projects may be too small to operate efficiently and may benefit from scaling up their scope.

### 5.3.3. RETURNS TO SCALE

RTS is a key concept in efficiency analysis, that indicates how changes in the scale of operations affect output. In DEA, RTS helps understand whether increasing or decreasing the size of a DMU can improve its performance. The three primary RTS categories are [2, 65]:

- **IRS**: The DMU can improve efficiency by increasing its scale of operations. Outputs increase more than proportionally to inputs. Thus, in business terms, we could say that the project could benefit from growing bigger because it becomes more efficient as it scales up.
- **CRS**: The is operating at an optimal scale. Output changes proportionally with inputs.
- **DRS**: The DMU is too large relative to its efficient size and may improve by downsizing. Outputs increase less than proportionally with inputs. For projects, this could suggest they might be too big and could work better if they were smaller or more focused.

The results obtained are summarized in Table 5.9. The main insight from this table is that under the CCR model, the majority of projects (29 out of 42) exhibit IRS, suggesting they could potentially improve efficiency by scaling up their operations. Ten projects operate at CRS, indicating they are already functioning at an optimal scale. Notably, three projects fall under DRS, which implies that these projects may be too large relative to their efficient size and could benefit from scaling down. In contrast, the BCC model, which assumes VRS by design, classifies all projects within that broader category, encompassing IRS, CRS, and DRS. This distinction highlights the flexibility of the BCC model in accounting for scale differences, while the CCR model provides specific guidance on whether scaling operations up or down might enhance efficiency. These results are useful for strategic decision-making on whether to expand, maintain, or reduce a project's scale. The full classification of returns to scale for each DMU under both models is available in Appendix B.3.

Table 5.9: Summary of Returns to Scale Classification

| **RTS Type** | **CCR Model** | **BCC Model** |
|---|---|---|
| Increasing Returns to Scale (IRS) | 29 | – |
| Constant Returns to Scale (CRS) | 10 | – |
| Decreasing Returns to Scale (DRS) | 3 | – |
| Variable Returns to Scale (VRS) | – | 42 |

The CCR model assumes CRS across all units [1]. In DEA, when we evaluate an inefficient DMU, it is expressed as a weighted combination of efficient DMUs in the reference set. These weights are called lambdas ( $\lambda$ ), and they represent how much each efficient peer contributes to the benchmark for that inefficient DMU [2, 65]. The sum of the lambdas tells us about the scale at which the DMU operates:

- If the sum of lambdas equals 1, the DMU operates at CRS.
- If the sum is less than 1, the DMU shows IRS, meaning, as previously mentioned that it could improve efficiency by scaling up.
- If the sum is greater than 1, the DMU shows DRS, indicating it might be too large and could perform better if downsized.

Figure 5.12 presents a bar chart summarizing the RTS classifications under the CCR model. As previously discussed, most projects (29 out of 42) operate under IRS, indicating that they are functioning below their optimal scale and could improve efficiency by scaling up operations, thus, increasing their size or resource usage, since doing so would likely lead to greater efficiency. This suggests that these projects are currently operating below their optimal scale and have room to grow while improving performance. Ten projects fall under CRS, suggesting they are already operating at an efficient scale. Importantly, three projects are classified under DRS, meaning they may be too large for optimal performance and could enhance efficiency by downsizing. These classifications, derived from the CCR model's assumption of CRS, offer strategic insights into how adjusting the scale of operations (either by expanding or contracting) can influence performance. Projects classified under IRS (see Table 5.10) show the best potential for improvement through growth, while those under DRS may need to streamline their operations to become more efficient.

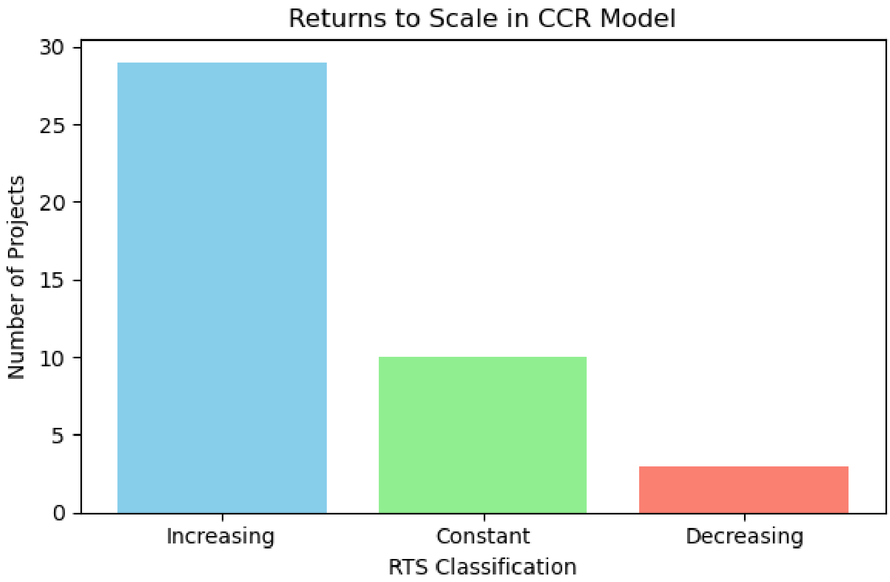



Figure 5.12: Returns to Scale classification for CCR model

Table 5.10 provides a project-level breakdown of RTS under the CCR model, what could offer guidance for targeted managerial actions. For the 29 projects operating under IRS such as Project 1, 2, 3 and 7, managers could consider strategies aimed at scaling up operations, such as increasing budget, expanding team capacity, or investing in the infrastructure to take advantage of efficiency gains associated with growth. These projects are currently underutilizing resources relative to their potential, and modest increases in scale could lead to disproportionate improvements in output. For projects such as Project 4, 13 and 14, and all the 10 projects classified under CRS, managers are advised to maintain current resource levels and processes, as these projects are already operating at or near optimal efficiency. Any changes in scale may not yield performance benefits and could even have a bad effect on the current balance. The three projects identified under DRS have the complete opposite strategy, managers should explore downsizing efforts, such as reducing scope, activities, or reallocating excess resources to other projects. These actions can help mitigate inefficiencies related to excessive scale [2, 65].

Table 5.10: CCR Model: Returns to Scale Classification per Project

| RTS Type | Projects |
|---|---|
| **Increasing (IRS)** | 1, 2, 3, 7, 9, 10, 11, 12, 16, 17, 18, 20, 23, 25, 26, 27, 28, 29, 30, 31, 33, 34, 35, 36, 37, 38, 40, 41, 42 |
| **Constant (CRS)** | 4, 13, 14, 15, 19, 21, 22, 24, 32, 39 |
| **Decreasing (DRS)** | 5, 6, 8 |

On the other hand, the BCC model incorporates the concept of VRS, which means it does not assume that all DMUs operate at an optimal or constant scale [2]. This key flexibility allows the BCC model to distinguish between inefficiencies caused by scale size and those due to pure technical inefficiency. Unlike the CCR model, which imposes a constant returns to scale assumption, the BCC model can more accurately reflect real-world conditions where some projects may benefit from scaling up, scaling down, or maintaining their current size. In our analysis, every DMU was classified under VRS, demonstrating the model's ability to accommodate a diverse range of operational scales across projects. This means the BCC model effectively captures whether inefficiencies stem from a project being too small, too large, or just not operating efficiently regardless of scale. By allowing any of the three RTS types - increasing, constant, or decreasing - to manifest, the BCC model provides a more adaptive assessment of each project's performance relative to its scale conditions [83]. This adaptability makes the BCC model particularly valuable for organizations managing heterogeneous projects (conditions where projects are quite different from each other in their size, scope, resources, or operational conditions) or units, where scale effects vary widely and require tailored efficiency improvement strategies.

### 5.3.4. Lambdas and Reference Sets

Lambda ($\lambda$) values in DEA indicate how much each efficient project contributes to forming a "virtual" efficient unit, an ideal benchmark constructed as a combination of real high-performing projects. These lambda values reveal which efficient projects serve as role models or peers when assessing the performance of less efficient projects [1, 65]. The group of efficient units with $\lambda > 0$ for a given project is known as its reference set or peer group. Essentially, these are the top-performing projects that inefficient units are compared against and from which they can draw lessons to improve.

In the CCR model, certain projects stand out as particularly influential. Projects 15, 39, 13, and 24 are referenced most frequently across multiple inefficient projects, highlighting their strong benchmarking power and suggesting they represent scalable and balanced best practices. This aligns with existing DEA literature, where projects appearing frequently in reference sets tend to demonstrate well-rounded performance in both inputs and outputs [64, 84].

When we shift to the BCC model, which accounts for variable returns to scale, we observe that while Projects 15 and 39 remain prominent benchmarks, their relative influence shifts slightly. This indicates that some projects find more relevant peers under the BCC assumptions, reflecting the model's enhanced flexibility in capturing scale effects. Such adaptability is crucial when evaluating heterogeneous projects that differ in size or operational scope [85].

Table 5.11 summarizes the frequency with which these key projects serve as references under both models, reinforcing the consistent benchmarking role of Projects 15 and 39. Their recurrent presence suggests that these projects share operational strengths-such as optimized workload management, efficient resource use, or superior output levels-making them ideal efficiency exemplars. These findings are also supported visually by the results provided by the *deaR* app, as discussed in Section 3.4, with detailed results available in Appendix B.4.

Table 5.11: Most frequently referenced DMUs in CCR and BCC Models

| **Reference Project** | **Times Referenced (CCR)** | **Times Referenced (BCC)** |
|---|---|---|
| Project 15 | 25 | 25 |
| Project 39 | 23 | 28 |
| Project 13 | 15 | 17 |
| Project 24 | 5 | 6 |
| Project 21 | 13 | 10 |
| Project 4 | 8 | 5 |

As commented, Projects 15 and 39 stand out as the most frequently referenced benchmarks in both the CCR and BCC models, highlighting their role as exemplary efficient units. Analyzing their key operational characteristics reveals why they serve as ideal peer projects for efficiency comparison. Table 5.12 shows the input and output details of both of these projects. The question is; *what is making these projects efficient and repeatedly used as benchmarks among the others?* The input and output values suggest that Project 15 achieves a high Stake amount (€12,500) while keeping Cost, Duration, and Workload very low. This balance between high output and minimal input is what makes it an efficient frontier project, particularly under the assumptions of the CCR model, which emphasizes CRS [1]. The probability of success is also an output; however, since it is fixed at 63% for many projects in the dataset, it behaves more like a qualifying criterion or filter rather than a variable output. As such, it contributes less to differentiating efficiency between projects.

On the other hand, Project 39 handles a much smaller Stake (€422.83), but it does so with exceptionally minimal inputs, the lowest in terms of Costs, Duration, and Workload across all projects. This configuration allows Project 39 to perform exceptionally well under the BCC model, which focuses on pure technical efficiency without penalizing for scale [2]. Even though the output magnitude (stake amount) is low, the efficiency in transforming inputs into outputs is maximized. In this sense, Project 39 serves as an ideal benchmark for similar small scale projects, showing how limited resources can still make proportionally strong outcomes.

In summary, Project 15 stands out because it demonstrates how a high-value project can be managed efficiently with minimal resources, making it a general purpose benchmark. Project 39, although much smaller, is a model of resource optimization at a smaller scale and is especially influential in guiding the performance improvement of other small or technically inefficient projects under the BCC framework.

Table 5.12: Comparison Between Project 15 and Project 39

| Attribute | Project 15 | Project 39 |
|---|---|---|
| Referenced (CCR / BCC) | 25 / 25 | 23 / 28 |
| Stake Amount | 12,500 | 422.83 |
| Probability | 63 | 81 |
| Duration | 6 | 3 |
| Costs | 412.35 | 30.53 |
| Workload | 6.17 | 0.80 |
| Scale | Medium | Very Small |
| Efficiency Type | Balanced at scale (CCR) | Pure technical (BCC) |

To further understand why Projects 15 and 39 are selected as benchmarks, it is useful to compare them to similar projects that are not referenced as frequently. Table 5.13 presents a comparison between Project 15 and Project 22, as well as between Project 39 and Project 25. These pairs are chosen based on similar scale or function: Project 22 has a similar stake output of €8,000 and moderate input levels, while Project 25, such as Project 39, is a small scale project with very small resource consumption.

Despite the apparent similarities, Project 22 is not referenced as frequently because it is less efficient in converting its inputs to outputs. Although it maintains the same probability of success (63%), its duration (12 vs. 6), cost (1,039.56 vs. 412.35), and workload (18.01 vs. 6.17) are all significantly higher than those of Project 15, while delivering a smaller stake amount. This imbalance reduces its relative efficiency in both CCR and BCC models.

Similarly, Project 25 shares the a small scale characteristics of Project 39 but fails to reach the same efficiency frontier. Although both projects use extremely limited resources, Project 25 handles only €83.33 in stake compared to Project 39, which is €422.83. With relatively comparable costs and workload, the lower output magnitude of Project 25 results in weaker performance under the BCC model, where technical efficiency dominates [2].

Table 5.13: Comparison of Benchmark Projects with Similar Non-Benchmark Projects

| Project | Stake (€) | Probability (%) | Duration | Cost (€) | Workload | Reference Count |
|---|---|---|---|---|---|---|
| **Project 15** | 12,500.00 | 63 | 6 | 412.35 | 6.17 | 25 (CCR), 25 (BCC) |
| Project 22 | 8,000.00 | 63 | 12 | 1,039.56 | 18.01 | 0 |
| **Project 39** | 422.83 | 81 | 3 | 30.53 | 0.80 | 23 (CCR), 28 (BCC) |
| Project 25 | 83.33 | 42 | 9 | 105.75 | 1.70 | 0 |

These comparisons highlight a key insight in DEA: efficiency is not just a matter of scale or absolute input levels, but rather how proportionally well inputs are transformed into outputs [1]. Projects such as 15 and 39 stand out because they push the boundaries of this transformation process, whereas others with superficially similar profiles fall short when examined under the idea of optimization.

### 5.3.5. Summary

As observed in the analysis, many projects do not operate under CRS, which implies that they are not functioning at an optimal scale. This conclusion is supported by two key findings: first, the RTS classifications indicate that only a small subset of DMUs are categorized as having constant returns to scale, while the majority exhibit either increasing or decreasing returns. Second, these results reflect that for most projects, scaling inputs up or down does not produce a proportional change in outputs. In other words, some projects are operating below an efficient scale and could benefit from expansion (increasing returns), while others have exceeded the optimal scale and are experiencing inefficiencies due to size (decreasing returns).

These scale inefficiencies highlight a limitation of the CCR model, which assumes that all units operate under CRS. While useful in some contexts, this assumption does not align well with the heterogeneous nature of the projects in our dataset. In contrast, the BCC model introduces flexibility by allowing for VRS, thereby distinguishing between pure technical efficiency and scale efficiency [2]. This enables a more adaptable and realistic evaluation, especially for projects that are technically efficient but not appropriately scaled.

The results reveal that efficiency scores under the BCC model are generally higher than those under CCR. This is expected, as the BCC model evaluates efficiency relative to similarly sized peers, whereas the CCR model penalizes projects that are not already operating at optimal scale. The lower scores observed under CCR for many projects thus reflect scale inefficiencies: issues not in how they operate, but in how much they operate. For instance, Project 1 demonstrates this distinction: Under the BCC model, it has a relatively low efficiency score and is identified as operating under increasing returns to scale. This suggests that, while its internal operations may be reasonably efficient, it is currently too small to realize full efficiency. A proportional increase in resources (e.g., budget, staff) could potentially produce more than proportional gains in output (e.g., stake amount), bringing the project closer to the efficiency frontier under CCR.

On the other hand, a project such as Project 8, which has a lambda sum greater than one and is classified under DRS, may be too large. Even though it performs adequately under BCC, the CCR model indicates that its scale may be counterproductive. In such cases, reducing input size might help improve overall efficiency by realigning operations to a more optimal scale. The BCC model also facilitates more realistic benchmarking through its reference sets (constructed using lambda values), which match inefficient units with efficient ones of comparable size. This avoids the issue of benchmarking small projects against disproportionately large or resource-rich units.

Projects such as Project 15 and Project 39 emerge as key reference units across multiple inefficient DMUs, under both CCR and BCC models. Their frequent appearance as benchmarks suggests that they demonstrate good operational efficiency. However, two additional factors should be considered when interpreting their prominence: the anonymization of data and project scale differences. First, due to the anonymization of project identifiers, the labels (e.g., “Project 15”) do not provide context regarding qualitative dimensions such as strategic priority, stakeholder involvement, or technical complexity. These omitted factors might affect real-world performance but are not captured in the DEA inputs and outputs. As a result, the model may disproportionately highlight numerically balanced projects as benchmarks. Second, there is a substantial scale difference between these projects. Project 15 appears to operate at a medium-to-large scale with efficient resource use, while Project 39 is extremely small, yet exhibits exceptionally high performance ratios. DEA models often favor such tightly managed small-scale units because their input-output ratios can be more easily optimized under strict constraints [85]. In addition, this could be making a strons effect, since as mentioned previously in Section 4, the sample should be uniform: the objects should be of the same type [15], and in our case, this condition was not fulfilled, since projects of different types and nature could have been considered and, for that reason, they may not be well comparable.

In summary, the variation in RTS across the dataset, combined with the improved discriminatory power and interpretability of results under the BCC model, reinforces its suitability for this context. It allows for a more tailored and scale-aware efficiency assessment, making it a more appropriate framework for analyzing project-level performance when scale heterogeneity and contextual ambiguity are present.

## 5.4. KPIS AND ACTIONABLE RESULTS

Taking into account the results obtained and the technical concepts analyzed, we developed a set of KPIs to interpret DEA outcomes in a project management context. The "Project Efficiency" KPI, based on CCR and BCC models (Section 5.4.1), provides a direct benchmark for ranking projects by performance. This approach aligns with prior studies where DEA models have been adapted for project selection, efficiency measurement, and performance benchmarking (e.g., [36, 37, 43, 53]). Our KPI framework can be viewed as an adapted and practical extension tailored specifically to project portfolio analysis. A related approach was proposed by Kuchta et al. [30], who developed a modified, stakeholder perspective-based DEA model to support the ranking of IT and R&D projects. In their study, DEA was not only used to compute efficiency scores, but also to generate managerial insights that help prioritize projects from different stakeholder perspectives. Inspired by this line of work, our KPI framework also extends DEA outcomes into actionable indicators to support project portfolio decisions. Additionally, the "Time Optimization Potential" (Section 5.4.2) and "Resource Waste Indicator" (Section 5.4.3) KPIs identify improvement margins in duration and workload. The "Best Practice Role Count" indicates which projects consistently serve as role models for others, while the "Scale Recommendation" KPI helps managers decide whether a project should be scaled up or down. The full set of KPIs is summarized in Table 5.14.

Table 5.14: Overview of the KPIs derived from DEA Results

| KPI Name | Based On | Formula / Logic | Managerial Implication | Suggested Visualization |
|---|---|---|---|---|
| **Efficiency Score** | DEA CCR and BCC models | Score $\in [0,1]$ from model output | Indicates overall performance relative to efficient frontier; useful for benchmarking and ranking projects | Ranked bar chart; traffic light rating; color-coded dashboard |
| **Target Gap (%)** | DEA Target vs. Actual Duration | $\frac{\text{Actual}-\text{Target}}{\text{Actual}} \times 100$ | Measures how much time could be saved to reach efficiency; supports project timeline optimization | Scatter plot (actual vs. target); histogram of gaps; sorted list |
| **Slack in Workload (hrs)** | DEA Slack Inputs | Excess input hours reported in slack output | Highlights avoidable effort; helps identify over-resourcing or process inefficiency | Box plot across projects; stacked bar by input types |
| **Peer Count (Reference Role)** | Lambda reference sets | Number of times project is used as peer | Identifies role-model projects that guide others toward efficiency; highlights best practices | Ranking chart; peer-reference network diagram |
| **RTS Classification** | RTS output from BCC model | IRS / CRS / DRS label per DMU | Suggests whether projects would benefit from scaling up or down; strategic sizing guidance | Pie chart of RTS types; efficiency vs. scale matrix |

The KPIs developed in this study are designed with minimal non-technical stakeholders in mind, particularly project managers who may not be familiar with DEA. Following the reasoning of Kuchta et al. [30], adapting the outputs of DEA into intuitive, stakeholder-friendly metrics helps bridge the gap between technical analysis and managerial decision-making. By presenting DEA results in a more accessible format, the KPIs increase the practical usability of the model and support more informed, transparent, and confident project selection decisions.

### 5.4.1. Efficiency Score: Project Efficiency

The first KPI we propose is based on the DEA efficiency score derived from both the CCR and BCC models. As previously discussed, the efficiency score ranges from 0 to 1 and reflects how effectively a project (DMU) converts inputs into outputs compared to its most efficient peers [55]. A score of 1 indicates that the project is efficient, while a score below 1 suggests that the project could improve by proportionally reducing its inputs or increasing its outputs. This type of KPI aligns with existing approaches where DEA efficiency scores are used to support project selection, evaluation, and benchmarking in various project management contexts. For instance, Toloo and Mirbolouki [37] and Frączkowski et al. [43] used DEA-based efficiency scores to rank projects and identify best practices. As mentioned, Kuchta et al. [30] explicitly adapted DEA to create stakeholder-oriented rankings for IT and R&D projects, proposing an approach that also aims to make DEA results more understandable to non-technical stakeholders, similar in spirit to our traffic light visualization (see Figure 5.14 and Table 5.15). Moreover, Hedayat et al. [36] demonstrated how DEA efficiency scores can inform improvement actions in project-based organizations. Project managers can use this score to benchmark their project's overall efficiency. Low scores signal inefficiencies that may be caused by excessive workload, long durations or resource misallocation. This allows managers to investigate areas for operational improvement. Additionally, this score can be used to rank projects, offering a clear way to highlight top performers, and giving priority to top performers.

To facilitate interpretation and communication, results can be visualized using bar plots or efficiency score distributions. For instance, a horizontal bar chart sorted from highest to lowest score can clearly show the relative performance of each project. Alternatively, grouping projects by efficiency bands (e.g., 1.0, 0.9–0.99, <0.9) in a stacked column chart can give a quick overview of the distribution of performance levels across the portfolio can make it easier to communicate findings to stakeholders.

As an example, Figure 5.13 provides a representative visualization of this KPI. In the figure, the projects with the highest bars (score = 1) are the most efficient. If the orange bar (BCC) is higher than the blue bar (CCR), it indicates that the project performs better under VRS, suggesting that its current scale of operation may be negatively impacting efficiency.

Projects with low scores show significant potential for improvement, either by reducing inputs or increasing outputs.

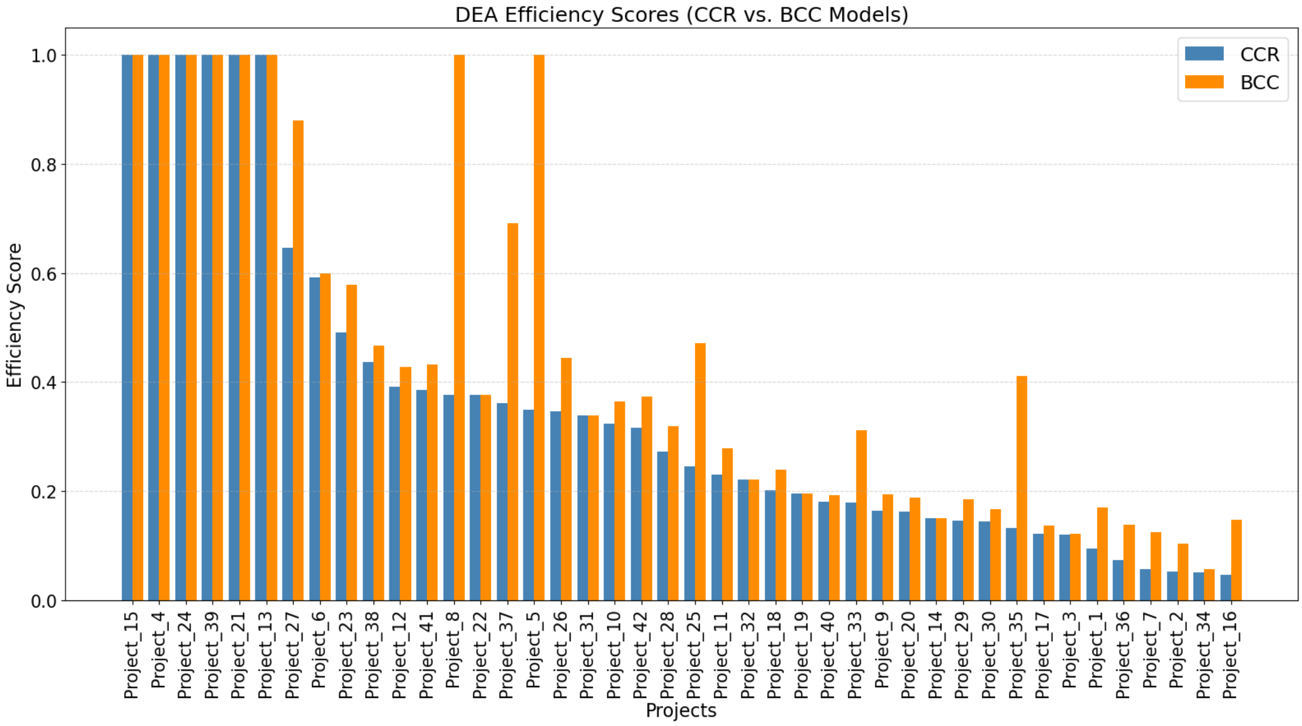



Figure 5.13: Example of visual representation for Project Efficiency KPI based on the efficiency score

While DEA efficiency scores provide valuable benchmarking data, they can be difficult to interpret for stakeholders unfamiliar with the method. To address this, we introduced a simplified traffic light visualization in Figure 5.14 that translates the scores into intuitive performance categories. This makes the results more accessible for project managers and facilitates faster, more informed decision-making without requiring technical knowledge of DEA. This table categorizes projects into three levels of efficiency using a simple traffic light logic:

- **Green**: Efficient - Projects operating at best practice levels.
- **Orange**: Moderate - Projects with some room for improvement.
- **Red**: Low - Projects with significant inefficiencies.

Figure 5.14 helps project managers identify which projects are leading in performance and which may require closer analysis or support, without needing to understand the technical details of DEA.

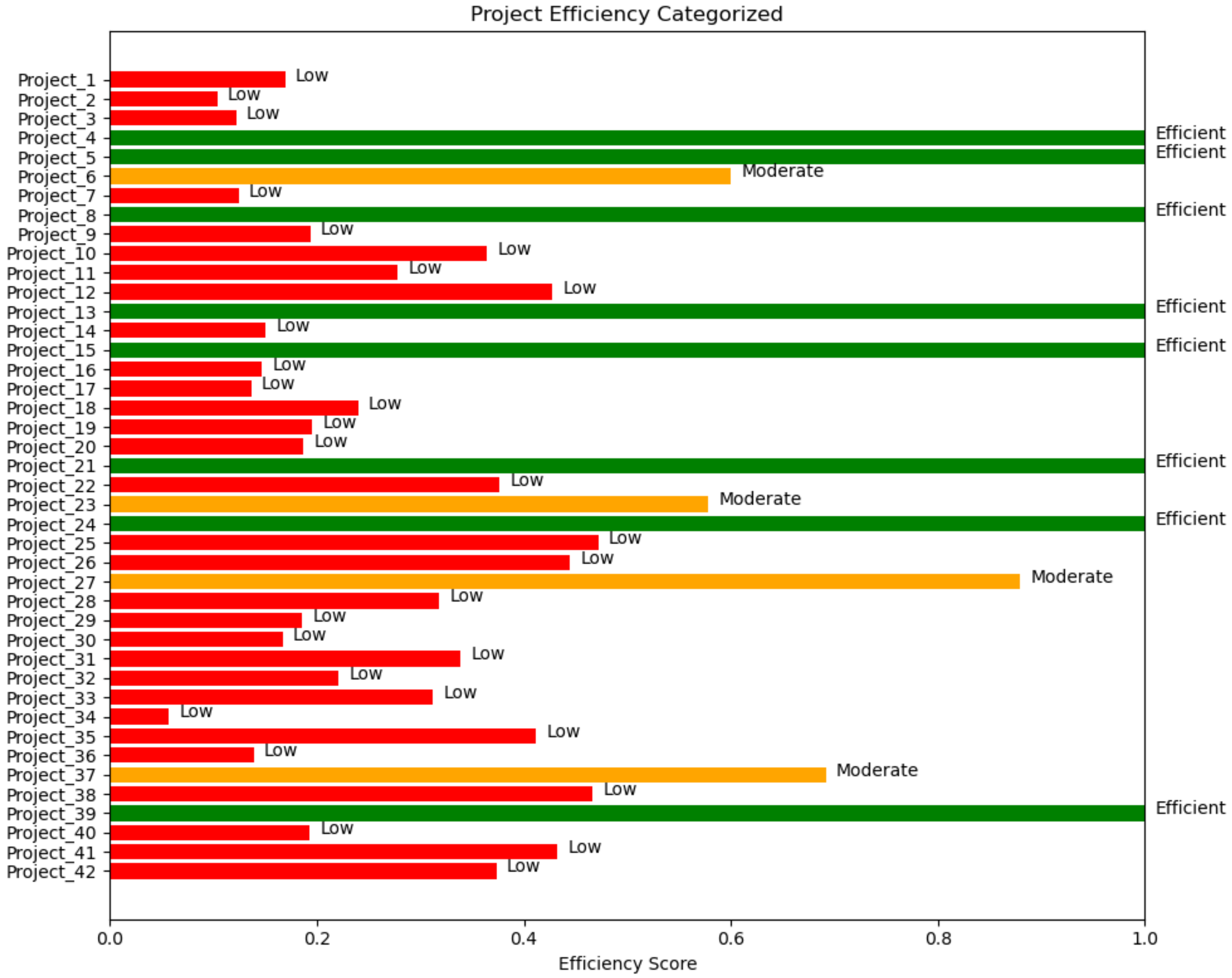



Figure 5.14: Example of visual representation for Project Efficiency KPI based on the efficiency score adapted to different stakeholders (BCC Model)

Table 5.15: Summary example for Project Efficiency Categories Based on DEA Scores (BCC Model)

| Project | Category | Color |
|---|---|---|
| Project 4 | Efficient | Green |
| Project 5 | Efficient | Green |
| Project 8 | Efficient | Green |
| Project 13 | Efficient | Green |
| Project 15 | Efficient | Green |
| Project 21 | Efficient | Green |
| Project 24 | Efficient | Green |
| Project 39 | Efficient | Green |
| Project 27 | Moderate | Orange |
| Project 6 | Moderate | Orange |
| Project 23 | Moderate | Orange |
| Project 12 | Moderate | Orange |
| Project 25 | Moderate | Orange |
| Project 26 | Moderate | Orange |
| Project 28 | Moderate | Orange |
| Project 31 | Moderate | Orange |
| Project 33 | Moderate | Orange |
| Project 35 | Moderate | Orange |

| Project | Category | Color |
|---|---|---|
| Project 37 | Moderate | Orange |
| Project 38 | Moderate | Orange |
| Project 41 | Moderate | Orange |
| Project 42 | Moderate | Orange |
| Project 1 | Low | Red |
| Project 2 | Low | Red |
| Project 3 | Low | Red |
| Project 7 | Low | Red |
| Project 9 | Low | Red |
| Project 10 | Low | Red |
| Project 11 | Low | Red |
| Project 14 | Low | Red |
| Project 16 | Low | Red |
| Project 17 | Low | Red |
| Project 18 | Low | Red |
| Project 19 | Low | Red |
| Project 20 | Low | Red |
| Project 22 | Low | Red |
| Project 29 | Low | Red |
| Project 30 | Low | Red |
| Project 32 | Low | Red |
| Project 34 | Low | Red |
| Project 36 | Low | Red |
| Project 40 | Low | Red |

### 5.4.2. Target Gap: Time Optimization Potential (%)

This KPI measures the percentage deviation between the actual duration of a project and the efficient target duration estimated through the DEA model. As an example, if the DEA model indicates that a project could be completed in 120 days but it actually took 150 days, the resulting gap would be +25%. Thus, a high value suggests that the project could have been completed faster without affecting output quality, indicating potential inefficiency in scheduling or resource allocation. It highlights inefficiencies in scheduling and time management. It facilitates the detection of opportunities for improved planning. The idea of using DEA to analyze time-related inefficiencies in projects is supported by several studies. For example, Razavi Hajiagha et al. [53] used DEA to evaluate project efficiency with respect to time and cost performance. Similarly, [43] incorporated project duration as a key factor in their DEA-based project success assessment. [30] demonstrated the value of DEA-based rankings for IT and R&D projects, where project completion time was one of the central performance dimensions. By explicitly translating the DEA-estimated target duration into a "Time Optimization Potential" KPI, our approach builds on this previous work and provides project managers with an actionable indicator to identify and address scheduling inefficiencies in their project portfolio.

Moreover, the KPI seeks for the continuous improvement of project scheduling practices, which is a core principle in both project control literature (e.g., [86]) and professional standards such as the PMI's PMBOK Guide [24]. Project managers can use this KPI to reassess time planning and identify where better project controls could shorten delivery timelines. Additionally, from a managerial perspective, analyzing it encourages more accurate timeline estimations and the adoption of practices that enable meeting planned deadlines, thereby contributing to more efficient project management and reduction of avoidable delays. A scatter plot comparing actual versus target durations or a histogram of gap percentages across projects can highlight trends and outliers.

As done before, a simplified representation for users not familiarized with DEA can be seen in Figure 5.15. This pie chart shows the percentage of projects classified by their time-saving opportunity based on actual versus efficient target durations:

- Efficient (0–10%): Projects completed close to the optimal timeline; little room for improvement.
- Moderate Delay (10–25%): Some delay present; moderate potential to improve scheduling and resource allocation.
- High Delay (>25%): Significant inefficiencies detected; major opportunities to optimize project duration.

This visual quickly conveys how widespread time inefficiencies are across your portfolio of projects, making it easy for managers and non-expert stakeholders to grasp the overall status at a glance.

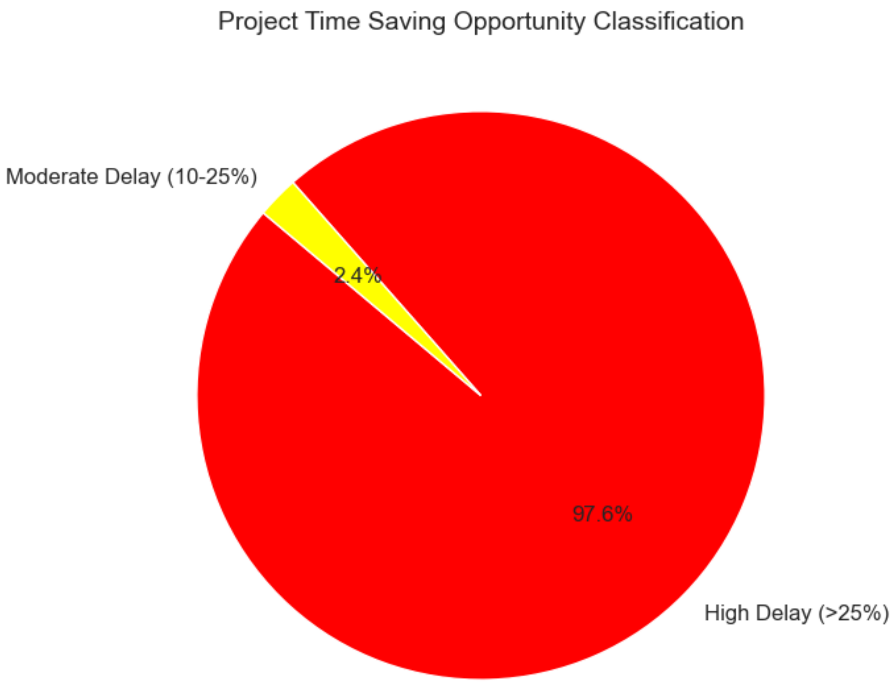



Figure 5.15: Example of adapted visual representation for Time Optimization Potential

Table 5.16 complements the pie chart by listing each project, its actual time-saving gap (%) and its classification. It provides a detailed view of which projects fall into which category, which can act as an easy reference for managers to prioritize follow-up actions. In addition, it adds transparency into the exact gap percentages supporting the color-coded classification.

Table 5.16: Project Time Saving Opportunity Classification

| Project | Gap % | Class |
|---|---|---|
| Project_24 | 96.83 | High |
| Project_13 | 96.83 | High |
| Project_39 | 96.30 | High |
| Project_6 | 96.30 | High |
| Project_10 | 95.95 | High |
| Project_12 | 95.93 | High |
| Project_41 | 95.88 | High |
| Project_28 | 95.45 | High |
| Project_18 | 95.43 | High |
| Project_26 | 95.24 | High |
| Project_34 | 95.11 | High |
| Project_17 | 95.01 | High |
| Project_9 | 94.78 | High |
| Project_42 | 94.67 | High |
| Project_19 | 94.42 | High |
| Project_30 | 93.91 | High |
| Project_32 | 93.70 | High |
| Project_33 | 93.31 | High |
| Project_37 | 92.86 | High |
| Project_25 | 92.86 | High |
| Project_22 | 92.83 | High |
| Project_1 | 91.21 | High |
| Project_15 | 90.48 | High |
| Project_20 | 89.30 | High |
| Project_40 | 88.98 | High |
| Project_3 | 88.80 | High |
| Project_2 | 88.47 | High |
| Project_38 | 87.78 | High |

| Project | Gap % | Class |
|---|---|---|
| Project_36 | 87.66 | High |
| Project_21 | 87.65 | High |
| Project_14 | 87.16 | High |
| Project_11 | 86.75 | High |
| Project_35 | 86.28 | High |
| Project_23 | 80.74 | High |
| Project_29 | 80.07 | High |
| Project_27 | 70.69 | High |
| Project_4 | 58.02 | High |
| Project_5 | 49.21 | High |
| Project_16 | 48.58 | High |
| Project_7 | 42.12 | High |
| Project_31 | 30.40 | High |
| Project_8 | 19.05 | Moderate |

Figure 5.16 displays a distribution plot illustrating the spread of time optimization gaps across all projects. This type of graph helps project managers quickly assess how common different levels of inefficiency are in terms of project duration. By examining the shape of the distribution, managers can identify whether most projects are clustered around low gap values, indicating consistent time management, or if there is a long tail of projects with large deviations, pointing to isolated but significant time inefficiencies. The visual format makes it easy to spot issues or recurring trends, enabling more targeted interventions in scheduling practices or re-

source allocation across the portfolio.

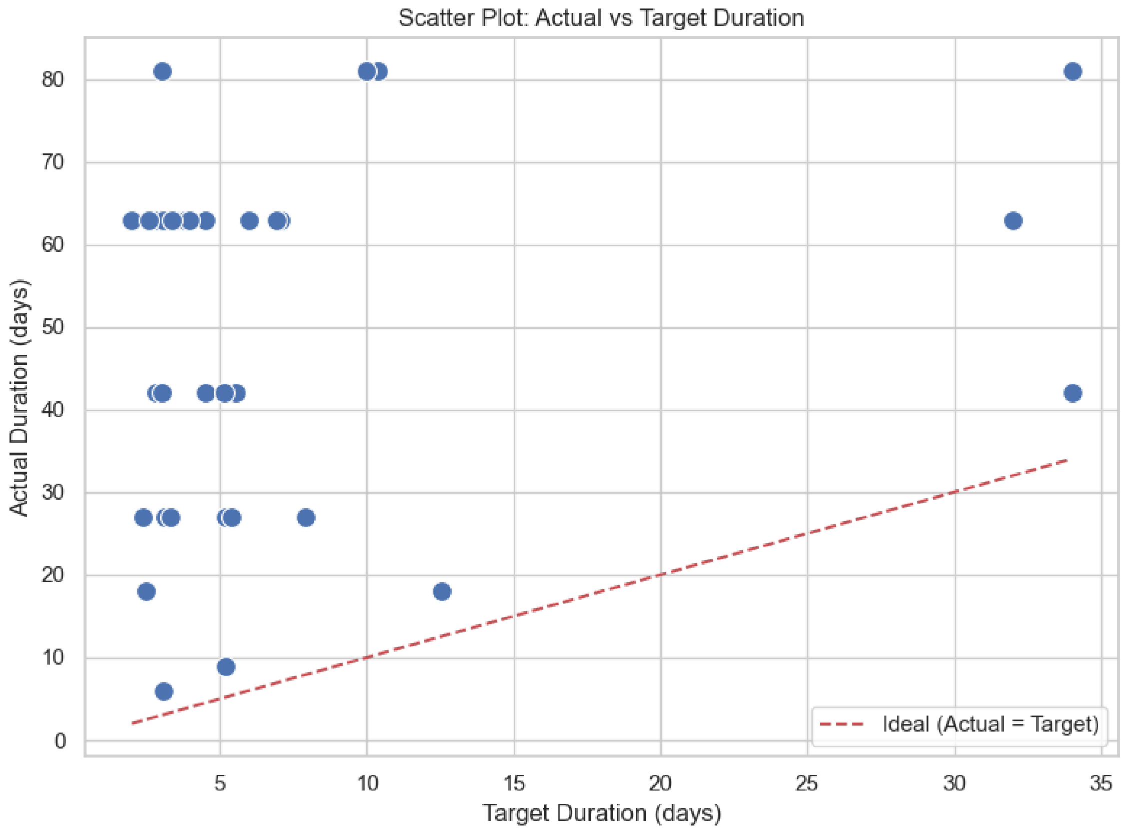



Figure 5.16: Visual representation for Time Optimization Potential

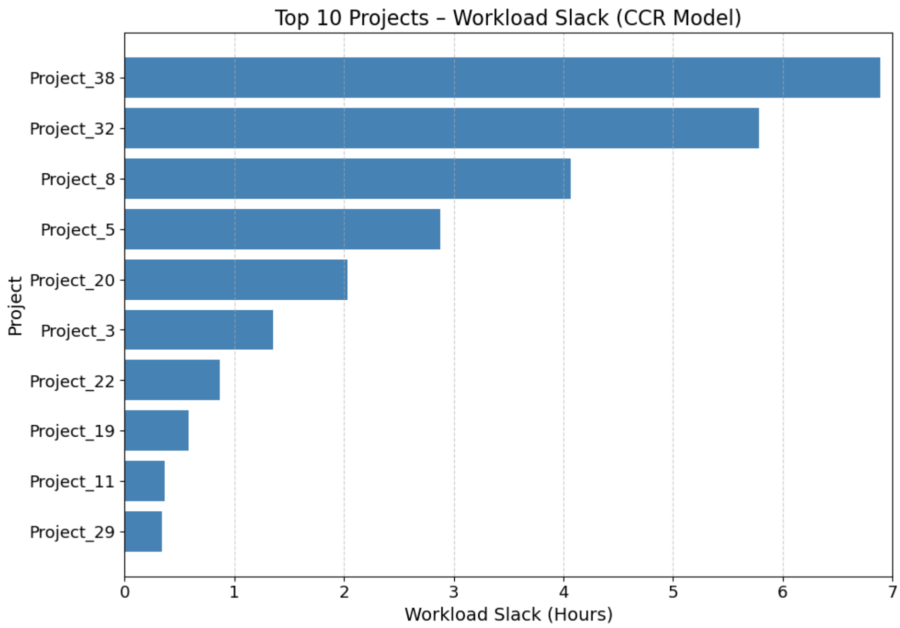
### 5.4.3. Slack in Workload: Resource Waste Indicator (Hours)

This KPI is derived from the input slacks reported by DEA. It quantifies the excess workload (in hours) that could have been avoided for each project while still producing the same outputs. Slack represents resource inefficiency [64]. A high slack value implies overstaffing, inefficient task allocation or unnecessary work being performed.

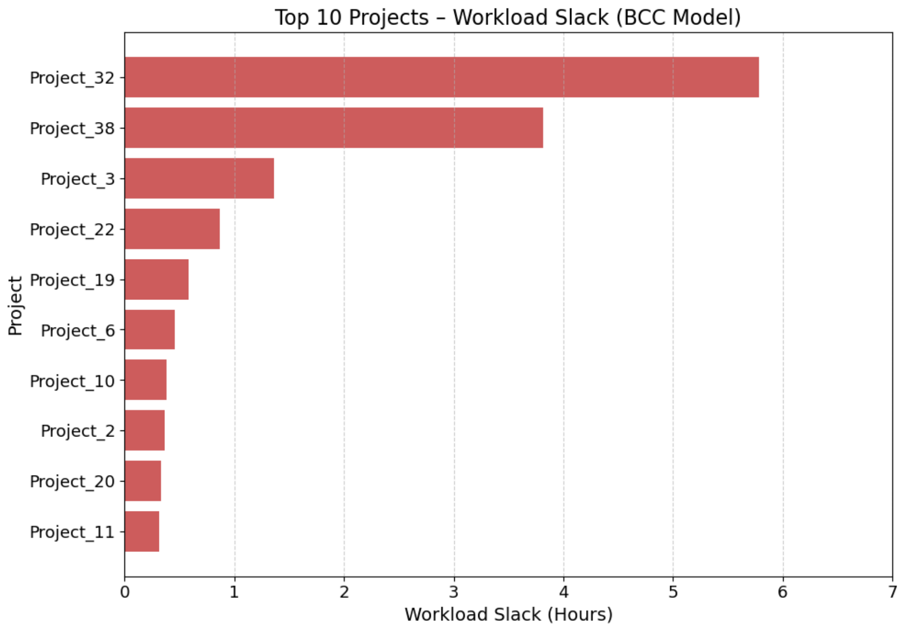
The identification of slack is aligned with the principles of lean project management, where eliminating waste and improving flow are key goals [86]. Monitoring slack in resources contributes directly to continuous improvement cycles and supports better workload balancing, reducing burnout risk and enhancing team productivity [24]. In addition, the literature on project performance management emphasizes the importance of detecting and addressing resource over consumption as a driver of project cost and schedule overruns [86–88]. Thus, integrating this KPI can be a valuable tool for improving resource efficiency and aligning project management practices with the best performance benchmarks.

Project managers can make use of this KPI to improve task assignment, reduce overtime, or reevaluate the necessity of specific tasks. It can be visualized using a boxplot to show variability across projects or a stacked bar chart if comparing slack across multiple input dimensions such as hours or costs.

Figure 5.17 presents the top 10 projects with the highest workload slack under the CCR (a) and BCC (b) models. Each bar quantifies hours that could have been avoided without reducing project output, highlighting inefficiencies in task distribution or resource planning. These visualizations are useful for project managers to identify and investigate potential overstaffing, bottlenecks, or redundant activities.




(a) Top 10 workload slack projects under the CCR model




(b) Top 10 workload slack projects under the BCC model

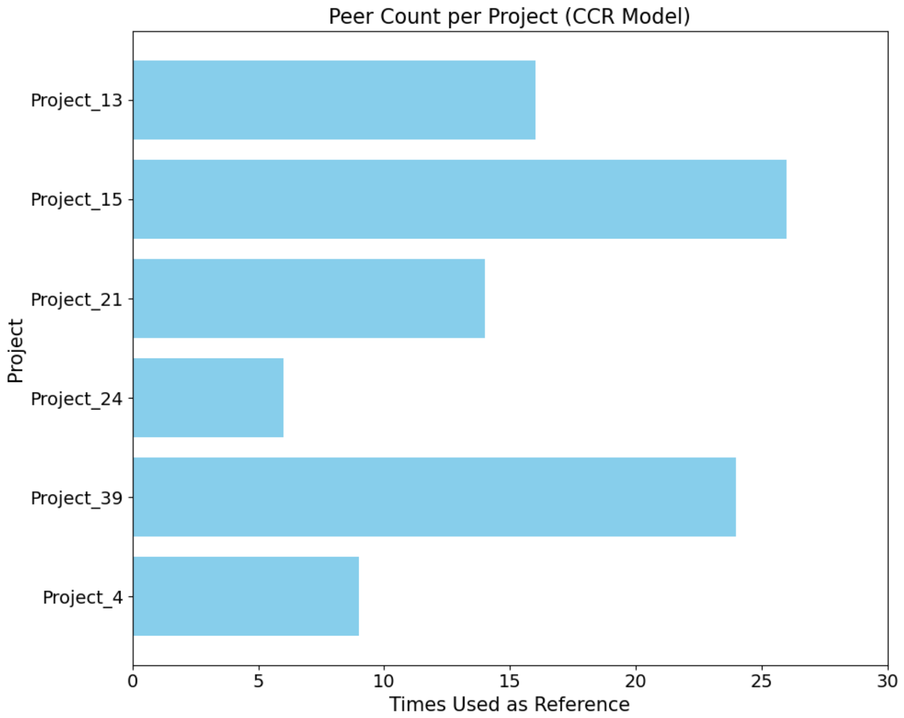
Figure 5.17: Visual comparison of the most inefficient projects (in terms of workload slack) under both DEA models

#### 5.4.4. Peer Count (Reference Role): Best Practice Role Count

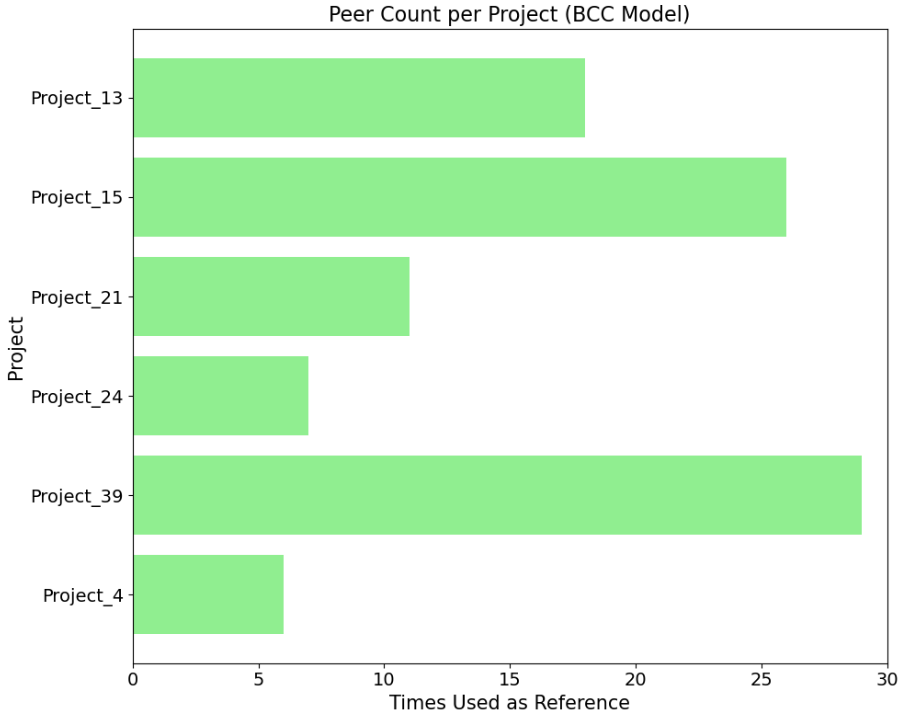
This KPI counts the number of times each project is used as a reference (peer) for inefficient projects in the DEA model, based on the reference set (lambdas). A high count indicates that the project is frequently considered a role model or best practice benchmark for others. It reflects strong relative performance and suggests that the project operates in a way others could emulate [2, 79].

Benchmarking in project management is a recognized approach for continuous performance improvement, enabling organizations to identify leaders, share effective practices, and elevate overall portfolio performance [86]. By highlighting which projects frequently serve as benchmarks, this KPI helps project managers focus on key success factors and encourages knowledge transfer across projects [24]. Project managers can use this KPI to identify leaders within the portfolio and explore what makes these projects successful. Visualization ideas include a ranking bar chart of peer counts or a network diagram showing which projects serve as references for others.

Figure 5.18 is a horizontal bar chart that visualizes the Peer Count for each project, separately under the CCR and BCC DEA models. Each bar represents how many times a project was used as a reference (i.e., best practice peer) for inefficient projects, based on the non-zero values in the lambda matrix. Projects with taller bars are those most frequently cited as benchmarks, making them key examples of efficiency. This visualization makes it easy to identify standout performers and assess how influential each project is in shaping efficiency standards across the portfolio.




(a) Peer count under the CCR model.




(b) Peer count under the BCC model.

Figure 5.18: Peer count (reference role) of each project in CCR and BCC models. Projects that are frequently used as references are considered best practice benchmarks.

### 5.4.5. RTS Classification: Scale Recommendation

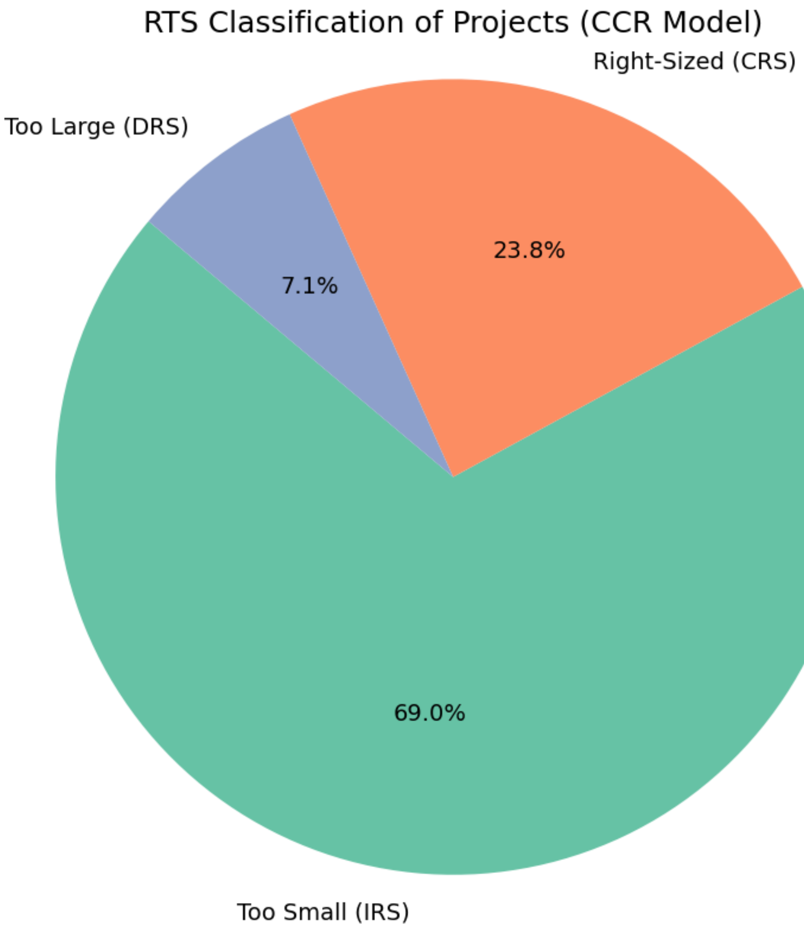
This KPI classifies each project according to its RTS under the BCC model.The final KPI we propose translates the technical DEA concept of RTS into more intuitive terms for decision-makers. It classifies each project based on how changes in scale (such as increasing budget or team size) would affect its efficiency. The actual classification falls into the theory described in Subsection 5.3.3:

- Projects labeled "Too small" (IRS) are operating under conditions where increasing their scale (such as adding resources) would likely improve performance. The project could benefit from scaling up.
- "Too large" (DRS) suggests that the project may be oversized, and reducing its scope or resources could lead to better outcomes.
- "Right-sized" (CRS) means the project is at an optimal scale, and further adjustments in size are unlikely to improve efficiency.

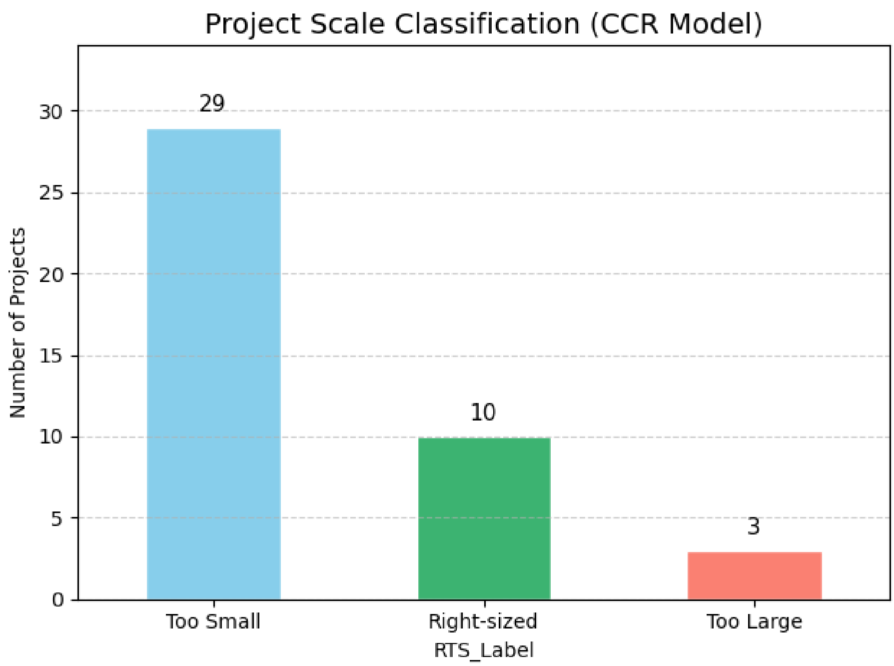
This idea fits well with common project portfolio management practices, which focus on using resources wisely and making sure projects support overall business goals [26]. In addition, effective scaling of projects either through expansion or downsizing is a recognized way to improve project performance and cost-effectiveness [24].

By classifying projects under this RTS framework, managers could gain a structured approach to resource reallocation decisions and can better balance the portfolio to maximize overall value. Visualization could include a pie chart or a stacked bar chart that illustrates the proportion of projects under each category.

Figure 5.19 presents the classification of projects under the RTS concept from the CCR DEA model. These visualizations help managers understand whether individual projects are operating at an efficient scale. The pie chart (Figure 5.19a) shows the proportional distribution of projects in each scale category, offering a visual sense of how widespread each condition is across the portfolio. This relative perspective is particularly helpful for quickly assessing the overall balance or imbalance in project sizing. Together, these visualizations support decision-makers in identifying structural inefficiencies. Projects categorized as “Too Small” or “Too Large” might be prioritized for restructuring or resource adjustment, while “Right-Sized” projects can serve as internal benchmarks of scale efficiency.




(a) Number of projects by scale classification (CCR).




(b) Proportion of projects by scale classification (CCR).

Figure 5.19: Visual classification of projects under the Returns to Scale (RTS) framework based on the CCR DEA model. The bar chart shows the count of projects in each RTS category, while the pie chart highlights the proportional distribution. These views help identify whether projects are too small, too large, or operating at an optimal scale.

## 5.5. SOFTWARE FUNCTIONAL AND NON-FUNCTIONAL REQUIREMENTS

For the proposed DEA-based project efficiency framework to be successfully implemented in practice, several practical propositions are recommended and should be addressed. This section summarizes the main requirements and outlines how the approach could be implemented into existing project portfolio management processes.

Firstly, high-quality and consistent project data is essential. The framework relies on input variables such as cost, duration, and workload, as well as output variables such as stake amount and probability of success. These must be available in the organization's systems and accurately reflect project characteristics prior to execution. In this study, data integration was achieved through automated scripts combining information from estimation packs and the demand management system. Similar processes would need to be established in practice, or some other sustainable way in order to make this assessment a recurrent practice. An idea is to make use of the FAIR data principles - ensuring data is findable, accessible, interoperable, and reuseable - to guide the management and structuring of project data. Adopting these principles would supports reliable DEA assessments and fosters long-term data governance and system scalability [89].

Equally important is the selection of appropriate input and output variables. As emphasized in the literature, it is crucial that the variables used in the DEA model reflect the strategic priorities of the organization and the specific nature of the projects being evaluated [39, 68]. In real-world testing of this framework, we observed that this point is particularly important: not all projects in a portfolio are strictly comparable in nature. Some projects that appeared less efficient according to the DEA results were still considered highly valuable to the organization for strategic or non-quantifiable reasons. This highlights the need for flexibility: the model should allow stakeholders to adjust the variables depending on their evaluation goals and the specific context of the portfolio. That is why, is strongly recommended to have communication with stake holders and make use of their knowledge when it comes to choosing the parameters. Moreover, the variables should be chosen carefully to ensure they fairly represent the diversity of the projects being analyzed.

From a tooling perspective, the approach does not require complex infrastructure. DEA models can be run using open source tools such as the *deaR Shiny App* (which could not be the best option due to company confidentiality and company privacy, especially if trying to avoid anonymization of data) or integrated into existing analytics platforms through R or Python libraries, which could be potentially easier for companies. The analysis can be performed periodically (e.g., monthly, quarterly) depending on the organization planning or cycles and the team that will take care of it. In addition, it could be used to inform project selection, prioritization, and portfolio reviews.

Finally, successful implementation also depends on fostering a culture that embraces efficiency-focused and data-driven decision-making. As emphasized by Bourne et al. [90], without organizational buy-in and cultural alignment, even well-designed performance measurement systems often fail to deliver lasting impact. DEA-based KPIs such as slack indicators, RTS classifications, and peer counts should be introduced gradually and incorporated into existing portfolio dashboards and project review meetings.

Another key aspect is to carefully consider who the target users of these KPIs are. In this study, we deliberately designed the DEA-based KPIs (such as slack indicators, RTS classification and peer counts) to be understandable and actionable for project managers, portfolio managers, and decision-makers within the organization. The selection of KPIs was also influenced by the nature of the chosen variables, ensuring that the results would be relevant to the company's actual interests and strategic goals. As highlighted in the literature by Kuchta et al. [30], aligning performance measurement with the needs and expectations of key stakeholders is critical for ensuring adoption and practical impact. It is essential to design KPIs with a clear understanding of who will use them, and how they will support actual decision processes. Moreover, through discussions with employees, it became clear that for this framework to be used effectively in practice, it is essential to ensure that the people interpreting the KPIs understand the broader project context. DEA is ultimately a quantitative tool, and while it provides valuable efficiency insights, it does not fully capture the strategic importance or unique qualitative aspects of each project. Therefore, when KPIs are presented (e.g., during review or meetings), it is crucial to complement the numerical results with input from stakeholders who are familiar with the specific projects and their context. This helps avoid the risk of misinterpreting the results or undervaluing projects that may appear inefficient in the model but are strategically important to the company. Similar recommendations are made in other studies, highlighting the importance of combining quantitative performance measures with qualitative judgment and stakeholder input to achieve more balanced and informed decisions [75, 90].

By addressing these practical requirements, specially the flexibility in variable selection and the importance of stakeholder alignment, organizations can better integrate the DEA-based framework into their portfolio management processes and make more informed and data-driven project selection decisions.

# 6

# CONCLUSION

This thesis explored how DEA can be used as a proactive decision-support tool to evaluate and select the most efficient projects before execution. In doing so, it responded to the growing need among organizations for systematic, data-driven project evaluation methods in the early stages of the project life cycle, especially in contexts with limited resources and multiple competing proposals [91].The primary research question was:

*How can DEA be used as a proactive decision-support tool to evaluate and select the most efficient projects before execution?*

To answer this, the study designed and validated a DEA-based project selection framework using both CCR and BCC models, tested on a real-world dataset with estimated pre-project values. Several key findings emerged in response to the specific research sub-questions:

At the heart of this work was the exploration of how DEA's well-established CCR and BCC models could be adapted for pre-project assessment using estimated inputs and outputs. Inputs such as cost, time, and workforce, alongside projected outputs including expected benefits and deliverable quality, were carefully identified and validated as suitable metrics readily available during planning. By applying the models to a real-world dataset, the framework successfully distinguished between efficient and less efficient project candidates, demonstrating DEA's potential beyond retrospective evaluation.

The CCR model assumes that projects operate under CRS, meaning that efficiency is measured by how well projects turn inputs into outputs compared to the best-performing projects overall [1]. On the other hand, the BCC model allows for VRS, which makes it better suited for situations where projects differ in size or resource availability [2]. When comparing the two, the CCR model tends to show a wider range of efficiency scores, while the BCC model provides a more detailed assessment by taking into account inefficiencies related to the project scale. This comparison reveals a trade-off: the CCR model is simpler and easier to interpret, but the

BCC model offers a more detailed evaluation, especially when project sizes vary. This comparison was reflected in the results, where the BCC model identified more projects as efficient by accounting for differences in scale, offering a more detailed evaluation. In contrast, the CCR model, assuming constant returns to scale, showed a broader range of efficiency scores but was less sensitive to variations in project size.

A notable contribution of the study was the translation of DEA outputs into intuitive KPIs and visual tools designed to bridge the gap between technical complexity and managerial decision-making. Indicators such as Efficiency Scores, Peer Comparisons and RTS were developed and communicated through accessible visualizations. This approach enhances transparency and usability, allowing stakeholders without technical expertise in DEA to better understand and use the efficiency assessments in their project selection decisions.

In addition, due to the need for practical applicability, this research also established a comprehensive set of requirements to guide the design of the DEA-based project evaluation framework. These requirements ensure that the model can handle the complexities of projects in their early stages, such as limited data availability and mixed qualitative and quantitative indicators while remaining accessible and interpretable to non-expert users. Requirements cover modeling flexibility (supporting multiple inputs and outputs, and both input- and output-oriented perspectives), data considerations (handling small datasets and ensuring consistent indicator definitions), result interpretation (clear and understandable reporting), and tool usability (user-friendly interfaces, exportable results, and visualizations). Privacy and data integrity concerns were also addressed, emphasizing secure internal execution options for sensitive data. Together, these requirements provide a foundation for a strong, adaptable, and user-centered DEA framework that supports real-world project selection decisions.

Overall, the thesis confirms that DEA can be effectively repurposed as a forward-looking tool in project management, enabling organizations to prioritize projects with the highest potential for efficient resource utilization before committing to execution. The proposed framework thus supports improved resource allocation, objective decision-making, and strategic alignment within project portfolios.

This thesis ultimately bridges the gap between project management theory, quantitative evaluation through DEA, and the practical conditions necessary for implementation. The foundation of project management, particularly the Iron Triangle of time, cost, and scope, shaped the choice of input and output variables, ensuring alignment with established success criteria. DEA provided a mechanism to assess the relative efficiency of projects based on these variables, offering a structured and objective alternative to intuitive or politically driven selection processes. However, for such a model to be sustainable in practice, it must be grounded in realistic data and system requirements. This includes ensuring consistent access to high-quality pre-project data, user-friendly interfaces, and secure, interpretable results that align with organizational processes. The connection between these three pillars — project management principles, DEA methodology, and model usability — is what enables the framework to move from academic theory to actionable practice.

## 6.1. PRACTICAL AND SCIENTIFIC CONTRIBUTIONS

From a practical standpoint, this research provides a structured framework that facilitates the application of DEA methods for the evaluation and selection of early-stage projects. Although no new DEA model was developed, this study proposes a set of KPIs and requirements that make DEA results more accessible and useful for decision-makers, who often lack technical expertise in the methodology. It also provides practical guidance on how to analyze DEA results, such as efficiency scores and improvement targets—and proposes related KPIs to help translate these outputs into clear, actionable measures for project evaluation and management.

The framework supports evaluation in contexts with limited or qualitative data, which is common in early-stage projects and improves transparency in interpreting efficiency scores and improvement targets. Additionally, it offers recommendations for securely handling sensitive data, enabling internal execution of analyses without compromising confidentiality.

Scientifically, this research contributes to bridging the gap between data-driven methods and managerial decision-making in innovation management. While DEA has been widely applied as a post analysis tool, its use for evaluating early-stage projects remains limited (see Section A.1). This study advances the integration of DEA into this domain by proposing a structured framework that outlines the different steps and requirements to make the method both usable and understandable. By applying DEA to ongoing projects and comparing the CCR and BCC models, the research sheds light on how different RTS assumptions influence project evaluation. It also provides practical guidance on how to interpret DEA outputs, such as efficiency scores, peer benchmarks and improvement targets. It proposes a set of related KPI to support actionable insights and informed decision-making. These contributions offer a foundation for future research and encourage broader adoption of DEA in project management contexts.

## 6.2. LIMITATIONS AND FUTURE RESEARCH RECOMMENDATION

Despite the valuable contributions, this research has some limitations that should be taken into account:

- **Dependence on existing DEA models:** The framework uses established CCR and BCC models, which may limit adaptability to different contexts or specific needs, as no custom model was developed.
- **Qualitative and limited data:** Some indicators are qualitative and financial data were partially unavailable due to the early stage of the projects. While the KPIs were carefully selected to mitigate this, it may still affect result precision.
- **Limited empirical validation:** The framework has been applied to a single case study. Further validation across multiple organizations and sectors would strengthen its generalizability and practical relevance.

- **Strategic relevance:** The model emphasizes quantitative efficiency and may overlook the strategic or qualitative value of certain projects. Some projects deemed less efficient still held high strategic importance for the organization.

Regardless of the progress made in this research, several recommendations can be made to further improve the practical and scientific value of the DEA-based evaluation framework. First, future work could focus on validating and refining the framework across a wider range of real-world innovation projects, allowing KPIs and methodological requirements to be tailored more precisely to the specific needs and contexts of different organizations. Such efforts would help bridge the gap between theoretical DEA applications and managerial decision-making practices. Furthermore, it would be valuable to explore the integration of DEA with other evaluation or simulation methods, particularly to improve robustness in situations characterized by the lack of data or high uncertainty, areas where traditional project selection methods often fall short. A direct comparison between DEA-based project assessments and traditional selection techniques could give interesting findings about the relative strengths and limitations of each approach, thereby informing better decision support tools. Additionally, developing comprehensive training materials and visualization tools would enhance understanding and interpretation of DEA results among multidisciplinary teams, facilitating wider adoption. It would also be valuable to connect the framework with machine learning or artificial intelligence techniques, enabling the system to generate actionable recommendations automatically and reduce the need for expert interpretation. This could be implemented through intuitive dashboards that guide users with data-driven insights and suggested actions based on project efficiency evaluations. Lastly, designing detailed guidelines to ensure secure and confidential implementation of DEA in environments handling sensitive data would safeguard data integrity without limiting the applicability of the framework. Looking ahead, it would be particularly interesting to develop a comprehensive, tailor-made DEA model specifically designed for project efficiency measurement, complete with embedded KPIs and automated interpretation features to provide actionable insights seamlessly.

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# A

# Appendix A: Systematic Literature Review



Table A.1: Table reporting all the articles that have been examined to conduct the research and highlighting their main features

| Author | Settings | Main Purpose | Technique | Metrics for evaluation | DMUs | Inputs | Outputs |
|---|---|---|---|---|---|---|---|
| [1] | General (DMUs)/Public program | Ways of assessing the efficiency of DMU's in public programs. Proposes CCR Model | CCR Model | Efficiency Score | – | – | – |
| [4] | Multi-Project Environment | Investigates the use of DEA to evaluate project performance, particularly in multi-project environments where projects are one-time events. Uses Earned Value Management System (EVMS) and Multidimensional Control System (MPCS) to reduce inputs/outputs | Not specify | Efficiency Score | Projects | Cost, work content, level of monitoring, level of uncertainty | Design yield, operations yield, training yield, documentation yield, project management yield, SPI – scheduling index, CPI – cost index |

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| Author | Settings | Main Purpose | Technique | Metrics for evaluation | DMUs | Inputs | Outputs |
|---|---|---|---|---|---|---|---|
| [50] | Spain's wood-based industry | Evaluates the relationship between productive efficiency and innovation activity using DEA | DEA models (CCR & BCC) | Efficiency Scores, innovation indices | Wood base firms | Employees, shareholder's funds, loans, R&D expenditures, R&D partnerships | Sales, Profits before taxes, Patents, Product innovations, Process innovations |
| [54] | General | Proposes a structured procedure for applying DEA in efficiency analysis across various domains | DEA Models | – | – | – | – |
| [2] | General (DMUs) | Introduces the BCC model, extending DEA to account for variable returns to scale (VRS) | BBC Model | Efficiency Score | – | – | – |
| [51] | Defense industry | Evaluates the efficiency of defense companies using DEA | DEA models (CCR & BCC) | Efficiency Score | Companies defense-sector | Labor (number of employees), capital (Euros), price of labor (percent), price of capital (percent), input prices | Cash flow (Euros), sales (Euros), value added (Euros) |
| [55] | General | Foundational DEA theory and applications | DEA | Various | – | – | – |
| [35] | General | Introduces the concept of productive efficiency and lays the foundation for DEA | DEA | Efficiency Score | – | – | – |
| [14] | General | Develops a DEA-based indicator to quantify and assess the negative impacts of project risks | DEA | Risk Impact Scores, Efficiency Scores | Risk factors | – | Negative effects |
| [43] | IT Projects | Proposes a model for selecting IT projects that maximizes their probability of success | DEA | Success Probability, Efficiency Scores | Projects | – | – |
| [18] | General | Analyzes how to select appropriate benchmarking paths in DEA for better efficiency improvement | DEA | Efficiency Scores, Benchmarking Paths | – | – | – |
| [46] | IT Projects | Uses DEA to evaluate the success of IT projects by analyzing efficiency and performance factors | DEA | Efficiency Scores, Success Metrics | Projects | Cost, duration, team size, external and internal expenses, potential loss to the organization | Financial benefits, improvement of internal process control, new skills, intangible benefits, customer satisfacion, function points implemented |
| [42] | General Projects | Uses DEA to select and prioritize projects based on efficiency and resource utilization | DEA | Efficiency Scores | – | – | – |
| [40] | Software Projects | Uses DEA to assess the efficiency of software development projects | DEA | Efficiency Scores | Projects | Dummy variable (1) | Project size/ Total cost, Project size/ Project duration |
| [44] | NASA/Lean Six Sigma Projects | Assessing the efficiency of Lean Six Sigma projects using Data Envelopment Analysis (DEA) | DEA | Efficiency Score, Resource Utilization, Project Performance | Projects | Critical Success Factors (CSFs) , Total Team Hours (TTH) | Process Sigma, Cost avoidance |

*Continued on next page*

| Author | Settings | Main Purpose | Technique | Metrics for evaluation | DMUs | Inputs | Outputs |
|---|---|---|---|---|---|---|---|
| [53] | General/Banking Industry | Proposes a bi-level DEA model to improve efficiency measurement and target setting in hierarchical decision-making environments | Bi-Level DEA Model | Efficiency Score, Target Setting | – | – | – |
| [52] | General (DMUs) | Introduces a multiobjective optimization approach to compute the efficient frontier in DEA, improving efficiency analysis | Multiobjective Optimization, DEA | Efficiency Score | – | – | – |
| [45] | Lean Management Projects | Evaluates the efficiency of Lean Management projects using DEA to compare performance | CCR Model | Efficiency Score | Projects | Project costs, project preparation time, cost of modifications and changes at the workplace, cost of resources helping reduce time required for changeover | Reduction in external set-up time, reduction in internal set-up time, reduction in set-up errors, reduction in production lead time, reduction in unnecessary movements, increase in work safety, increase in machine utilization rate, increased productivity, reduction in inventory of spare parts and accessories, changeover time, First Time Through (FTT), Overall Equipment Effectiveness (OEE) |
| [38] | Construction Industry | Proposes a combined ANP-DEA approach to improve decision-making in selecting projects | Analytic Network Process (ANP) + Data Envelopment Analysis (DEA) | Efficiency Scores, Project Ranking | Projects | – | – |
| [30] | IT and R&D Projects | Proposes a modified DEA model incorporating stakeholders' perspectives for ranking IT and R&D projects | Modified DEA | Efficiency Scores, Stakeholder Considerations, Project Ranking | Projects | Budget, duration, number of full professors, number of associate professors, number of assistant professors | Number of high-quality publications, number of international conference presentations, number of monographs, number of patents, number of scientific degrees and titles |
| [15] | IT Projects | Examines how DEA can be applied to IT project evaluation, focusing on selecting appropriate inputs and outputs based on organizational needs | DEA | Efficiency Scores, Input-Output Selection Criteria | Projects | Overrun of time, overrun of budget, size of the team, trust among the team | Compliance with scope, project succes, client satisfaction |
| [39] | Projects General | Analyzes project efficiency using DEA, focusing on resource utilization and performance measurement | CCR Model | Efficiency Scores, Input-Output Ratios | Projects | Labour, material, project duration | Contract value |

*Continued on next page*

| Author | Settings | Main Purpose | Technique | Metrics for evaluation | DMUs | Inputs | Outputs |
|---|---|---|---|---|---|---|---|
| [6] | General | Discusses considerations before selecting an appropriate DEA model, addressing methodological choices and implications (such as inputs or outputs) | DEA | – | – | – | – |
| [37] | Projects General | Proposes a DEA-based method for selecting the most efficient projects | DEA | Efficiency Scores, Project Ranking | Proposals | Costs of software, training, supporting | Time reduction, improvement in management capabilities |
| [19] | General | Systematic review of DEA applications in benchmarking from 2003 to 2020, identifying trends and gaps in research | DEA | – | – | – | – |
| [13] | R&D Projects | Proposes an integrated DEA and Balanced Scorecard approach for evaluating R&D projects | DEA, Balanced Scorecard | Efficiency Scores, Performance Indicators | Projects | Investments | Discounted cash flow, customer focus feedback, performance improvement, congruence, importance synergy, propriety position, platform for growth, durability, probability of success |
| [49] | General | Develops a framework integrating explainable AI to enhance target setting in DEA-based decision-making | DEA Target Setting + AI | Efficiency Score, AI Interpretability | Hospitals | Labor, facility, active-bed | Inpatients, outpatients, starred, bed-day, occupancy-rate |
| [36] | Projects General | To assess the efficiency of project-based organizations using a two-level DEA approach | Two-Level DEA | Efficiency Score, Resource Allocation, Project Performance | Projects | Project cost, compliance with the goals and strategies, effect of political and economic factors, complexity of technical and technology, function of people-time project, experience of project manager | SPI, CPI, levels of customer satisfaction from the quality project, income levels of project personnel, increase in technical skills of project personnel, profitability of the project for the contractor, improvement of the project's image for the contractor, delay in payment to contractors |
| [41] | Technology Transfer Projects | To assess the performance of technology transfer projects using DEA technique | DEA | Efficiency Score, Project Performance, Resource Utilization | Companies | Implementation/Investment cost, experience, training | Operations per year |
| [48] | Construction Industry | To evaluate and optimize tunnel construction projects by combining DEA and simulation methods | DEA + Simulation | Efficiency Score, Performance Metrics | Projects | – | – |

*Continued on next page*

| Author | Settings | Main Purpose | Technique | Metrics for evaluation | DMUs | Inputs | Outputs |
|---|---|---|---|---|---|---|---|
| [47] | Real State Projects | Introduces a DEA-based model to enhance decision-making in venture capital investments within real estate projects | DEA | Efficiency Scores, Investment Decision Metrics | Projects | – | – |

# B

# Appendix B: Results

## B.1. SLACK VALUES FOR CCR AND BCC MODELS

Table B.1: Slack values for CCR Model

| Project | Duration | Costs | Workload | Stake Amount | Probability |
|---|---|---|---|---|---|
| Project_1 | 0 | 807.66 | 0.00 | 0.00 | 0.00 |
| Project_2 | 0 | 0.00 | 0.23 | 0.00 | 0.00 |
| Project_3 | 0 | 0.00 | 1.36 | 0.00 | 1.47 |
| Project_4 | 0 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_5 | 0 | 81.87 | 2.88 | 0.00 | 54.60 |
| Project_6 | 0 | 17.45 | 0.00 | 183.93 | 0.00 |
| Project_7 | 0 | 0.00 | 0.08 | 0.00 | 0.00 |
| Project_8 | 0 | 187.11 | 4.06 | 0.00 | 92.40 |
| Project_9 | 0 | 0.00 | 0.05 | 0.00 | 0.00 |
| Project_10 | 0 | 0.00 | 0.34 | 0.00 | 0.00 |
| Project_11 | 0 | 0.00 | 0.37 | 0.00 | 0.00 |
| Project_12 | 0 | 0.00 | 0.28 | 0.00 | 0.00 |
| Project_13 | 0 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_14 | 0 | 0.00 | 0.04 | 0.00 | 0.00 |
| Project_15 | 0 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_16 | 0 | 0.00 | 0.10 | 0.00 | 2.16 |
| Project_17 | 0 | 0.00 | 0.11 | 0.00 | 0.00 |
| Project_18 | 0 | 2.20 | 0.00 | 0.00 | 0.00 |
| Project_19 | 0 | 0.00 | 0.58 | 0.00 | 0.00 |
| Project_20 | 0 | 110.82 | 2.03 | 0.00 | 0.00 |
| Project_21 | 0 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_22 | 0 | 0.00 | 0.87 | 0.00 | 0.00 |
| Project_23 | 0 | 0.00 | 0.34 | 0.00 | 0.76 |
| Project_24 | 0 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_25 | 0.65 | 10.04 | 0.00 | 135.91 | 0.00 |
| Project_26 | 0.78 | 16.34 | 0.00 | 287.67 | 0.00 |
| Project_27 | 0 | 0.00 | 0.02 | 0.00 | 0.00 |
| Project_28 | 0 | 0.00 | 0.07 | 0.00 | 0.00 |
| Project_29 | 0 | 0.00 | 0.34 | 0.00 | 7.66 |
| Project_30 | 0 | 10.48 | 0.00 | 0.00 | 0.00 |
| Project_31 | 0 | 0.00 | 0.27 | 0.00 | 62.66 |
| Project_32 | 0 | 378.37 | 5.78 | 0.00 | 0.00 |
| Project_33 | 0 | 5.58 | 0.00 | 0.00 | 0.00 |
| Project_34 | 0 | 9.20 | 0.00 | 0.00 | 0.00 |
| Project_35 | 0 | 0.00 | 0.05 | 0.00 | 0.00 |
| Project_36 | 0 | 2.77 | 0.00 | 0.00 | 0.00 |
| Project_37 | 0.58 | 11.18 | 0.00 | 0.00 | 0.00 |
| Project_38 | 0 | 409.33 | 6.88 | 0.00 | 8.40 |
| Project_39 | 0 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_40 | 0 | 1.56 | 0.00 | 0.00 | 0.00 |
| Project_41 | 0 | 3.51 | 0.00 | 0.00 | 0.00 |
| Project_42 | 0 | 0.00 | 0.00 | 0.00 | 0.00 |

Table B.2: Slack values for BCC Model

| Project | Duration | Costs | Workload | Stake Amount | Probability |
|---|---|---|---|---|---|
| Project_1 | 0.00 | 1456.99 | 0.00 | 0.00 | 36.00 |
| Project_2 | 0.00 | 0.00 | 0.37 | 0.00 | 45.66 |
| Project_3 | 0.00 | 0.00 | 1.36 | 0.00 | 6.88 |
| Project_4 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_5 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_6 | 0.00 | 49.32 | 0.46 | 183.40 | 0.00 |
| Project_7 | 1.76 | 9.66 | 0.00 | 0.00 | 72.00 |
| Project_8 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_9 | 0.00 | 0.00 | 0.05 | 0.00 | 14.78 |
| Project_10 | 0.00 | 0.00 | 0.38 | 0.00 | 8.59 |
| Project_11 | 0.00 | 0.00 | 0.32 | 0.00 | 35.34 |
| Project_12 | 0.00 | 0.00 | 0.30 | 0.00 | 6.71 |
| Project_13 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_14 | 0.00 | 0.00 | 0.04 | 0.00 | 0.00 |
| Project_15 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_16 | 0.00 | 0.00 | 0.08 | 0.00 | 68.99 |
| Project_17 | 0.00 | 0.00 | 0.12 | 0.00 | 10.01 |
| Project_18 | 0.00 | 3.08 | 0.00 | 0.00 | 13.58 |
| Project_19 | 0.00 | 0.00 | 0.58 | 0.00 | 0.00 |
| Project_20 | 0.00 | 0.00 | 0.33 | 0.00 | 21.00 |
| Project_21 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_22 | 0.00 | 0.00 | 0.87 | 0.00 | 0.00 |
| Project_23 | 0.00 | 0.00 | 0.16 | 0.00 | 53.52 |
| Project_24 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_25 | 1.25 | 19.35 | 0.00 | 339.50 | 39.00 |
| Project_26 | 1.00 | 21.01 | 0.00 | 381.63 | 18.00 |
| Project_27 | 0.00 | 13.03 | 0.00 | 0.00 | 54.00 |
| Project_28 | 0.00 | 0.00 | 0.07 | 0.00 | 12.30 |
| Project_29 | 0.00 | 0.00 | 0.28 | 0.00 | 49.87 |
| Project_30 | 0.00 | 14.38 | 0.00 | 0.00 | 16.92 |
| Project_31 | 0.00 | 0.00 | 0.27 | 0.00 | 63.00 |
| Project_32 | 0.00 | 378.37 | 5.78 | 0.00 | 0.00 |
| Project_33 | 0.00 | 10.92 | 0.00 | 0.00 | 34.77 |
| Project_34 | 0.00 | 11.22 | 0.00 | 0.00 | 10.95 |
| Project_35 | 0.00 | 0.00 | 0.11 | 0.00 | 51.61 |
| Project_36 | 0.00 | 15.04 | 0.00 | 0.00 | 53.26 |
| Project_37 | 1.15 | 21.63 | 0.00 | 189.50 | 39.00 |
| Project_38 | 0.00 | 212.45 | 3.82 | 0.00 | 21.00 |
| Project_39 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Project_40 | 0.00 | 6.25 | 0.00 | 0.00 | 18.00 |
| Project_41 | 0.00 | 4.22 | 0.00 | 0.00 | 8.56 |
| Project_42 | 0.00 | 1.16 | 0.00 | 0.00 | 15.04 |

## B.2. TARGET VALUES FOR CCR AND BCC MODELS

Table B.3: Target values for the CCR Model

| DMU | Duration | Costs | Workload | Stake Amount | Probability |
|---|---|---|---|---|---|
| Project_1 | 1.31 | 311.23 | 4.83 | 1666.67 | 27 |
| Project_2 | 1.59 | 84.73 | 1.33 | 2137.31 | 27 |
| Project_3 | 6.93 | 362.27 | 5.45 | 12997.22 | 64.47 |

| DMU | Duration | Costs | Workload | Stake Amount | Probability |
|---|---|---|---|---|---|
| Project_4 | 34.00 | 262.59 | 3.76 | 15538.89 | 81 |
| Project_5 | 11.20 | 769.73 | 11.52 | 23333.33 | 117.6 |
| Project_6 | 2.96 | 61.35 | 1.24 | 423.36 | 81 |
| Project_7 | 3.20 | 26.03 | 0.38 | 1500.00 | 9 |
| Project_8 | 12.80 | 879.69 | 13.16 | 26666.67 | 134.4 |
| Project_9 | 2.78 | 76.77 | 1.38 | 1833.33 | 63 |
| Project_10 | 2.27 | 146.49 | 2.38 | 600.00 | 63 |
| Project_11 | 4.61 | 164.93 | 2.53 | 7416.67 | 42 |
| Project_12 | 2.35 | 178.51 | 2.84 | 950.00 | 63 |
| Project_13 | 2.00 | 282.95 | 4.33 | 333.33 | 63 |
| Project_14 | 10.40 | 228.45 | 3.57 | 10714.74 | 81 |
| Project_15 | 6.00 | 412.35 | 6.17 | 12500.00 | 63 |
| Project_16 | 0.96 | 39.81 | 0.60 | 1666.67 | 8.16 |
| Project_17 | 2.81 | 144.31 | 2.35 | 2166.67 | 63 |
| Project_18 | 2.41 | 81.24 | 1.45 | 771.78 | 63 |
| Project_19 | 3.52 | 847.76 | 13.15 | 5333.33 | 63 |
| Project_20 | 3.88 | 296.94 | 4.47 | 8000.00 | 42 |
| Project_21 | 10.00 | 356.56 | 5.43 | 16666.67 | 81 |
| Project_22 | 4.51 | 391.05 | 5.91 | 8000.00 | 63 |
| Project_23 | 4.41 | 118.37 | 1.79 | 5666.67 | 27.76 |
| Project_24 | 2.00 | 1172.71 | 18.34 | 1000.00 | 63 |
| Project_25 | 1.56 | 15.83 | 0.41 | 219.25 | 42 |
| Project_26 | 2.33 | 23.74 | 0.62 | 328.87 | 63 |
| Project_27 | 5.81 | 74.90 | 1.14 | 3833.33 | 27 |
| Project_28 | 2.45 | 99.51 | 1.71 | 952.67 | 63 |
| Project_29 | 4.24 | 155.29 | 2.36 | 7121.96 | 34.66 |
| Project_30 | 3.30 | 74.19 | 1.34 | 2666.67 | 63 |
| Project_31 | 12.52 | 345.01 | 5.23 | 16475.71 | 80.66 |
| Project_32 | 3.97 | 798.04 | 12.35 | 6666.67 | 63 |
| Project_33 | 1.61 | 53.17 | 0.95 | 533.33 | 42 |
| Project_34 | 2.71 | 128.11 | 2.11 | 1833.33 | 63 |
| Project_35 | 0.79 | 62.29 | 0.97 | 676.67 | 18 |
| Project_36 | 1.77 | 34.80 | 0.61 | 1400.00 | 27 |
| Project_37 | 1.58 | 16.05 | 0.42 | 233.33 | 42 |
| Project_38 | 4.80 | 329.88 | 4.94 | 10000.00 | 50.4 |
| Project_39 | 3.00 | 30.53 | 0.80 | 422.83 | 81 |
| Project_40 | 6.49 | 141.14 | 2.27 | 6401.06 | 63 |
| Project_41 | 2.31 | 148.76 | 2.41 | 733.33 | 63 |
| Project_42 | 2.85 | 76.32 | 1.37 | 2000.00 | 63 |

Table B.4: Target values for the BCC Model

| DMU | Duration | Costs | Workload | Stake Amount | Probability |
|---|---|---|---|---|---|
| Project_1 | 2.37 | 561.83 | 8.71 | 1666.67 | 63.00 |
| Project_2 | 3.11 | 166.20 | 2.70 | 2137.31 | 72.66 |
| Project_3 | 7.06 | 369.06 | 5.58 | 12997.22 | 69.88 |
| Project_4 | 34.00 | 262.59 | 3.76 | 15538.89 | 81.00 |
| Project_5 | 32.00 | 2433.13 | 41.12 | 23333.33 | 63.00 |
| Project_6 | 3.00 | 30.53 | 0.80 | 422.83 | 81.00 |
| Project_7 | 5.21 | 47.07 | 1.01 | 1500.00 | 81.00 |
| Project_8 | 34.00 | 2833.68 | 45.76 | 26666.67 | 42.00 |
| Project_9 | 3.29 | 90.86 | 1.65 | 1833.33 | 77.78 |
| Project_10 | 2.55 | 164.80 | 2.68 | 600.00 | 71.59 |
| Project_11 | 5.57 | 199.27 | 3.19 | 7416.67 | 77.34 |
| Project_12 | 2.56 | 195.12 | 3.11 | 950.00 | 69.71 |
| Project_13 | 2.00 | 282.95 | 4.33 | 333.33 | 63.00 |
| Project_14 | 10.40 | 228.45 | 3.57 | 10714.74 | 81.00 |
| Project_15 | 6.00 | 412.35 | 6.17 | 12500.00 | 63.00 |
| Project_16 | 3.08 | 128.32 | 2.17 | 1666.67 | 74.99 |
| Project_17 | 3.14 | 161.55 | 2.64 | 2166.67 | 73.01 |
| Project_18 | 2.88 | 96.48 | 1.72 | 771.78 | 76.58 |
| Project_19 | 3.52 | 847.76 | 13.15 | 5333.33 | 63.00 |
| Project_20 | 4.49 | 471.79 | 7.18 | 8000.00 | 63.00 |
| Project_21 | 10.00 | 356.56 | 5.43 | 16666.67 | 81.00 |
| Project_22 | 4.51 | 391.05 | 5.91 | 8000.00 | 63.00 |
| Project_23 | 5.20 | 139.51 | 2.35 | 5666.67 | 80.52 |
| Project_24 | 2.00 | 1172.71 | 18.34 | 1000.00 | 63.00 |
| Project_25 | 3.00 | 30.53 | 0.80 | 422.83 | 81.00 |
| Project_26 | 3.00 | 30.53 | 0.80 | 422.83 | 81.00 |
| Project_27 | 7.91 | 88.95 | 1.58 | 3833.33 | 81.00 |
| Project_28 | 2.87 | 116.47 | 2.00 | 952.67 | 75.30 |
| Project_29 | 5.38 | 196.96 | 3.15 | 7121.96 | 76.87 |
| Project_30 | 3.83 | 83.94 | 1.56 | 2666.67 | 79.92 |
| Project_31 | 12.53 | 345.12 | 5.23 | 16475.71 | 81.00 |
| Project_32 | 3.97 | 798.04 | 12.35 | 6666.67 | 63.00 |
| Project_33 | 2.81 | 91.24 | 1.65 | 533.33 | 76.77 |
| Project_34 | 3.08 | 144.79 | 2.40 | 1833.33 | 73.95 |
| Project_35 | 2.47 | 193.57 | 3.08 | 676.67 | 69.61 |
| Project_36 | 3.33 | 55.85 | 1.16 | 1400.00 | 80.26 |
| Project_37 | 3.00 | 30.53 | 0.80 | 422.83 | 81.00 |
| Project_38 | 5.13 | 577.65 | 8.82 | 10000.00 | 63.00 |

| DMU | Duration | Costs | Workload | Stake Amount | Probability |
|---|---|---|---|---|---|
| Project_39 | 3.00 | 30.53 | 0.80 | 422.83 | 81.00 |
| Project_40 | 6.94 | 146.53 | 2.43 | 6401.06 | 81.00 |
| Project_41 | 2.59 | 166.70 | 2.71 | 733.33 | 71.56 |
| Project_42 | 3.36 | 88.94 | 1.62 | 2000.00 | 78.04 |

## B.3. RETURN TO SCALE VALUES FOR CCR AND BCC MODELS

Table B.5: Return values under CCR model

| DMU | Lambsum | RTS |
|---|---|---|
| Project_1 | 0.42858 | Increasing |
| Project_2 | 0.37906 | Increasing |
| Project_3 | 0.92508 | Increasing |
| Project_4 | 1 | Constant |
| Project_5 | 1.86667 | Decreasing |
| Project_6 | 1.02642 | Decreasing |
| Project_7 | 0.11111 | Increasing |
| Project_8 | 2.13333 | Decreasing |
| Project_9 | 0.80953 | Increasing |
| Project_10 | 0.88055 | Increasing |
| Project_11 | 0.52567 | Increasing |
| Project_12 | 0.90482 | Increasing |
| Project_13 | 1 | Constant |
| Project_14 | 1 | Constant |
| Project_15 | 1 | Constant |
| Project_16 | 0.10716 | Increasing |
| Project_17 | 0.86439 | Increasing |
| Project_18 | 0.82305 | Increasing |
| Project_19 | 1 | Constant |
| Project_20 | 0.66667 | Increasing |
| Project_21 | 1 | Constant |
| Project_22 | 1 | Constant |
| Project_23 | 0.34278 | Increasing |
| Project_24 | 1 | Constant |
| Project_25 | 0.51852 | Increasing |
| Project_26 | 0.77778 | Increasing |
| Project_27 | 0.33333 | Increasing |
| Project_28 | 0.83705 | Increasing |
| Project_29 | 0.43237 | Increasing |
| Project_30 | 0.7832 | Increasing |

| DMU | Lambsum | RTS |
|---|---|---|
| Project_31 | 0.99578 | Increasing |
| Project_32 | 1 | Constant |
| Project_33 | 0.54767 | Increasing |
| Project_34 | 0.85355 | Increasing |
| Project_35 | 0.2645 | Increasing |
| Project_36 | 0.33333 | Increasing |
| Project_37 | 0.51852 | Increasing |
| Project_38 | 0.8 | Increasing |
| Project_39 | 1.00000 | Constant |
| Project_40 | 0.77778 | Increasing |
| Project_41 | 0.88128 | Increasing |
| Project_42 | 0.80709 | Increasing |

Table B.6: Return to Scale values under BCC model

| DMU | Lambsum | RTS |
|---|---|---|
| Project_1 | 1.00000 | Variable |
| Project_2 | 1.00000 | Variable |
| Project_3 | 1.00000 | Variable |
| Project_4 | 1.00000 | Variable |
| Project_5 | 1.00000 | Variable |
| Project_6 | 1.00000 | Variable |
| Project_7 | 1.00000 | Variable |
| Project_8 | 1.00000 | Variable |
| Project_9 | 1.00000 | Variable |
| Project_10 | 1.00001 | Variable |
| Project_11 | 1.00000 | Variable |
| Project_12 | 1.00000 | Variable |
| Project_13 | 1.00000 | Variable |
| Project_14 | 1.00000 | Variable |
| Project_15 | 1.00000 | Variable |
| Project_16 | 1.00000 | Variable |
| Project_17 | 0.99999 | Variable |
| Project_18 | 1.00000 | Variable |
| Project_19 | 1.00000 | Variable |
| Project_20 | 1.00000 | Variable |
| Project_21 | 1.00000 | Variable |
| Project_22 | 1.00000 | Variable |
| Project_23 | 1.00000 | Variable |
| Project_24 | 1.00000 | Variable |

| DMU | Lambsum | RTS |
|---|---|---|
| Project_25 | 1.00000 | Variable |
| Project_26 | 1.00000 | Variable |
| Project_27 | 1.00000 | Variable |
| Project_28 | 1.00000 | Variable |
| Project_29 | 1.00000 | Variable |
| Project_30 | 1.00001 | Variable |
| Project_31 | 0.99999 | Variable |
| Project_32 | 1.00000 | Variable |
| Project_33 | 1.00000 | Variable |
| Project_34 | 1.00000 | Variable |
| Project_35 | 1.00000 | Variable |
| Project_36 | 1.00000 | Variable |
| Project_37 | 1.00000 | Variable |
| Project_38 | 1.00000 | Variable |
| Project_39 | 1.00000 | Variable |
| Project_40 | 1.00000 | Variable |
| Project_41 | 1.00001 | Variable |
| Project_42 | 1.00000 | Variable |

## B.4. REFERENCE VALUES FOR CCR AND BCC MODELS

| DMU | Project_13 | Project_15 | Project_21 | Project_24 | Project_39 | Project_4 |
|---|---|---|---|---|---|---|
| Project_1 | 0.1173 | 0.1145 | 0 | 0.1969 | 0 | 0 |
| Project_2 | 0.0417 | 0.1640 | 0 | 0 | 0.1733 | 0 |
| Project_3 | 0 | 0.5810 | 0.3441 | 0 | 0 | 0 |
| Project_4 | 0 | 0 | 0 | 0 | 0 | 1 |
| Project_5 | 0 | 1.8667 | 0 | 0 | 0 | 0 |
| Project_6 | 0.1189 | 0 | 0 | 0 | 0.9075 | 0 |
| Project_7 | 0 | 0 | 0.0044 | 0 | 0.0153 | 0.0914 |
| Project_8 | 0 | 2.1333 | 0 | 0 | 0 | 0 |
| Project_9 | 0.0193 | 0.1236 | 0 | 0 | 0.6666 | 0 |
| Project_10 | 0.4404 | 0.0221 | 0 | 0 | 0.4180 | 0 |
| Project_11 | 0 | 0.0322 | 0.4190 | 0 | 0.0745 | 0 |
| Project_12 | 0.5209 | 0.0508 | 0 | 0 | 0.3331 | 0 |
| Project_13 | 1 | 0 | 0 | 0 | 0 | 0 |
| Project_14 | 0 | 0 | 0.5208 | 0 | 0.3580 | 0.1212 |
| Project_15 | 0 | 1 | 0 | 0 | 0 | 0 |
| Project_16 | 0 | 0.0286 | 0.0785 | 0 | 0 | 0 |
| Project_17 | 0.2389 | 0.1509 | 0 | 0 | 0.4746 | 0 |
| Project_18 | 0.1674 | 0.0363 | 0 | 0 | 0.6194 | 0 |
| Project_19 | 0.0412 | 0.3792 | 0 | 0.5796 | 0 | 0 |
| Project_20 | 0 | 0.6377 | 0 | 0.0290 | 0 | 0 |
| Project_21 | 0 | 0 | 1 | 0 | 0 | 0 |
| Project_22 | 0.3414 | 0.6285 | 0 | 0.0301 | 0 | 0 |
| Project_23 | 0 | 0 | 0.3018 | 0 | 0 | 0.0410 |
| Project_24 | 0 | 0 | 0 | 1 | 0 | 0 |
| Project_25 | 0 | 0 | 0 | 0 | 0.5185 | 0 |
| Project_26 | 0 | 0 | 0 | 0 | 0.7778 | 0 |
| Project_27 | 0 | 0 | 0.1049 | 0 | 0.0969 | 0.1316 |
| Project_28 | 0.2156 | 0.0512 | 0 | 0 | 0.5703 | 0 |
| Project_29 | 0 | 0.0202 | 0.4122 | 0 | 0 | 0 |
| Project_30 | 0 | 0.0244 | 0.1256 | 0 | 0.6332 | 0 |
| Project_31 | 0 | 0 | 0.8888 | 0 | 0 | 0.1069 |
| Project_32 | 0 | 0.4928 | 0 | 0.5072 | 0 | 0 |
| Project_33 | 0.1054 | 0.0258 | 0 | 0 | 0.4165 | 0 |
| Project_34 | 0.2174 | 0.1235 | 0 | 0 | 0.5126 | 0 |
| Project_35 | 0.1424 | 0.0478 | 0 | 0 | 0.0742 | 0 |
| Project_36 | 0 | 0 | 0.0690 | 0 | 0.2552 | 0.0091 |
| Project_37 | 0 | 0 | 0 | 0 | 0.5176 | 0.0009 |
| Project_38 | 0 | 0.8000 | 0 | 0 | 0 | 0 |
| Project_39 | 0 | 0 | 0 | 0 | 1 | 0 |
| Project_40 | 0 | 0 | 0.3154 | 0 | 0.3996 | 0.0627 |
| Project_41 | 0.4327 | 0.0331 | 0 | 0 | 0.4155 | 0 |
| Project_42 | 0 | 0.1319 | 0.0040 | 0 | 0.6711 | 0 |

Table B.7: Reference values under CCR model

| DMU | Project_13 | Project_15 | Project_21 | Project_24 | Project_39 | Project_4 |
|---|---|---|---|---|---|---|
| Project_1 | 0.6070 | 0.0932 | 0 | 0.2999 | 0 | 0 |
| Project_2 | 0.3192 | 0.1443 | 0 | 0 | 0.5365 | 0 |
| Project_3 | 0 | 0.6179 | 0.3147 | 0 | 0.0674 | 0 |
| Project_4 | 0 | 0 | 0 | 0 | 0 | 1 |
| Project_5 | 0 | 0 | 0 | 0 | 0 | 0 |
| Project_6 | 0 | 0 | 0 | 0 | 1 | 0 |
| Project_7 | 0 | 0 | 0 | 0 | 0.9287 | 0.0713 |
| Project_8 | 0 | 0 | 0 | 0 | 0 | 0 |
| Project_9 | 0.0616 | 0.1172 | 0 | 0 | 0.8211 | 0 |
| Project_10 | 0.5041 | 0.0184 | 0 | 0 | 0.4775 | 0 |
| Project_11 | 0 | 0.2034 | 0.2793 | 0 | 0.5173 | 0 |
| Project_12 | 0.5795 | 0.0479 | 0 | 0 | 0.3726 | 0 |
| Project_13 | 1 | 0 | 0 | 0 | 0 | 0 |
| Project_14 | 0 | 0 | 0.5208 | 0 | 0.3580 | 0.1212 |
| Project_15 | 0 | 1 | 0 | 0 | 0 | 0 |
| Project_16 | 0.2291 | 0.1047 | 0 | 0 | 0.6662 | 0 |
| Project_17 | 0.2973 | 0.1466 | 0 | 0 | 0.5561 | 0 |
| Project_18 | 0.2151 | 0.0305 | 0 | 0 | 0.7544 | 0 |
| Project_19 | 0.0412 | 0.3792 | 0 | 0.5796 | 0 | 0 |
| Project_20 | 0.2550 | 0.6235 | 0 | 0.1216 | 0 | 0 |
| Project_21 | 0 | 0 | 1 | 0 | 0 | 0 |
| Project_22 | 0.3414 | 0.6285 | 0 | 0.0301 | 0 | 0 |
| Project_23 | 0 | 0.0268 | 0.3029 | 0 | 0.6703 | 0 |
| Project_24 | 0 | 0 | 0 | 1 | 0 | 0 |
| Project_25 | 0 | 0 | 0 | 0 | 1 | 0 |
| Project_26 | 0 | 0 | 0 | 0 | 1 | 0 |
| Project_27 | 0 | 0 | 0.0790 | 0 | 0.7803 | 0.1407 |
| Project_28 | 0.2711 | 0.0459 | 0 | 0 | 0.6831 | 0 |
| Project_29 | 0 | 0.2293 | 0.2419 | 0 | 0.5288 | 0 |
| Project_30 | 0 | 0.0600 | 0.0935 | 0 | 0.8465 | 0 |
| Project_31 | 0 | 0 | 0.8890 | 0 | 0.0043 | 0.1066 |
| Project_32 | 0 | 0.4928 | 0 | 0.5072 | 0 | 0 |
| Project_33 | 0.2242 | 0.0108 | 0 | 0 | 0.7650 | 0 |
| Project_34 | 0.2729 | 0.1188 | 0 | 0 | 0.6082 | 0 |
| Project_35 | 0.6073 | 0.0255 | 0 | 0 | 0.3671 | 0 |
| Project_36 | 0 | 0.0409 | 0.0297 | 0 | 0.9294 | 0 |
| Project_37 | 0 | 0 | 0 | 0 | 1 | 0 |
| Project_38 | 0 | 0.7826 | 0 | 0.2174 | 0 | 0 |
| Project_39 | 0 | 0 | 0 | 0 | 1 | 0 |
| Project_40 | 0 | 0 | 0.3160 | 0 | 0.6281 | 0.0559 |
| Project_41 | 0.4950 | 0.0294 | 0 | 0 | 0.4756 | 0 |
| Project_42 | 0.0335 | 0.1308 | 0 | 0 | 0.8357 | 0 |

Table B.8: Reference values under BCC model