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Enhancing production cost insights: integrating Cost Accounting and Regression Analysis

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MANAGEMENT SUMMARY

Company X, a global manufacturer of renewable energy plants, operates in a project-based environment where cost estimations are made before production begins. However, expenses frequently deviate from initial estimates, leading to financial discrepancies due to unforeseen production costs. The core issue is the absence of a cost accounting method that provides accurate insight into the production cost structure. Moreover, the absence of a systematic method for detecting budgeting inaccuracies leads to inefficiencies, necessitating a regression analysis to identify underlying patterns. Therefore, the research question arises:

How can implementing a new cost accounting method and regression analytics improve Company X's insight into production costs?

This study employs the Managerial Problem-Solving Method (MPSM) to systematically identify and address the core problem. A literature review evaluated various cost accounting and regression analysis methods. Regression analysis was applied to identify key cost drivers and assess cost estimation inaccuracies, while activity-based costing (ABC) was implemented to improve cost allocation. A cost price model was developed, incorporating ABC. Data was collected from internal company records, including production logs and financial reports, supplemented with expert interviews. The selected methods were validated through expert validation and statistical techniques, including cross-validation and goodness-of-fit measures.

The regression analysis showed that labour costs were systematically overestimated, while indirect costs were underestimated. The cost price model was validated using two sensitivity analyses. The One-Factor-at-a-Time (OFAT) sensitivity analysis, which measures the impact of individual variables by altering them while keeping others constant, indicated that material costs (13.13%), carbon steel labour (13.1%), and corporate overhead cost driver rate (9.12%) had the greatest impact on the cost price. The Morris sensitivity analysis, which examines relationships between variables, demonstrated that corporate overhead cost driver rate and internal assembly labour significantly influenced cost price due to their interaction with other cost factors.

The study confirms that implementing a structured cost accounting method, combined with a regression-based budget analysis, enhances insight into production costs at Company X. The transition towards ABC, along with a refined budgeting process supported by regression analysis, is essential for improving cost transparency and financial control.

However, the cost price model was not validated for accuracy due to insufficient data and should be tested once more data becomes available. Additionally, the regression analysis did not account for external factors affecting budget deviations, such as inflation, market volatility, or supplier issues. The dataset used for regression analysis was small. Another limitation is multicollinearity, which may have distorted coefficient estimates, reducing the reliability of findings.

Recommendations for Company X include implementing a refined cost accounting approach such as ABC to improve cost visibility and indirect cost allocation. Data collection should be enhanced by integrating existing Enterprise Resource Planning (ERP) systems with production data already captured at the factory floor into a centralised database. Lastly, labour estimation should adopt a dynamic approach, continuously monitoring real-time labour data and comparing it with estimates, allowing adjustments instead of relying on fixed labour standards updated quarterly.

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LIST OF ABBREVIATIONS

ABC	Activity-Based Costing
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
CI	Consistency Index
CR	Consistency Ratio
CS	Carbon Steel
EE	Elementary Effect
ERP	Enterprise Resource Planning
EU	European Union
FAT	Factory Acceptance Test
GAAP	Generally Accepted Accounting Principles
HR	Human Resource
I/O	Input/Output
IFRS	International Financial Reporting Standards
LOOCV	Leave-One-Out Cross-Validation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MFCA	Material Flow Cost Accounting
MLR	Multiple Linear Regression
MPSM	Managerial Problem Solving Method
OFAT	One-Factor-at-a-Time
PCA	Principal Component Analysis
PCR	Principal Component Regression
POs	Production Orders
RI	Random Index
RMSE	Root Mean Squared Error
SE	Standard Error
SRR	Sum of Squared Residuals
SS	Stainless Steel
SST	Sum of Squares Total

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TCP	Total Cost Price
TDABC	Time-Driven Activity-Based Costing
USA	United States of America
VDP	Variance Decomposition Proportions
VIF	Variance Inflation Factor
WSM	Weighting Scoring Model

1 INTRODUCTION

1.1 Organisational context

Company X is a global manufacturer of renewable energy plants operating in more than 30 countries. With a workforce of over 500 employees, the company specialises in designing, developing, and installing energy plants that convert organic materials, primarily waste, into renewable energy, such as biogas (Company X, 2025). Its diverse clientele includes municipalities and large energy-intensive industries seeking sustainable energy solutions. In addition to manufacturing plants for external clients, Company X also operates its own installations to generate and sell sustainable energy.

The company produces a range of energy plant types, each with a distinct configuration of components and specific input-output requirements. Depending on the design, an energy plant may consist of up to 600 individual components, which can vary significantly between plant types. Given the diverse requirements of its clients, Company X customises each installation to meet specific operational and regulatory needs. Its technological solutions contribute to sustainability by enabling industries, municipalities, and agricultural businesses to reduce waste and lower carbon emissions. To maintain efficiency and industry leadership, Company X invests in research and innovation.

1.2 Action problem

Company X operates in a project-based environment. The sales department plays a key role in negotiating plans with potential customers. Collaborating closely with the procurement and engineering teams, they calculate the estimated costs for each project. Once an agreement is finalised, the order is sent to the production company, Company Y, located abroad. At this facility, all materials are delivered, prepared, and assembled into operational sub-assemblies, ready to be installed at the customer's location into a fully operational energy plant. Projects are executed simultaneously, and in some cases, parts of the production process are even started before negotiations with a customer are officially closed.

For production, a basic cost allocation scheme is standardised. This allocation scheme is designed by Company X to streamline resource distribution and ensure financial accountability. However, the financial department occasionally observes that Company Y requires additional cash to sustain operations. Furthermore, Company Y cannot pinpoint the exact sources of these extra costs. Moreover, the predetermined costs are used to calculate the cost price, which serves as a basis for customer negotiations. Extra cash required by Company Y causes the production costs to exceed the initially budgeted amount. Consequently, the following action problem arises:

Unforeseen production costs arise, leading to budget overruns and financial discrepancies.

1.3 Problem identification

With the action problem clearly defined, the core problem can be identified. Identifying the core problem is essential because it provides a clear focus on what needs to be addressed to create lasting improvements. The core problem is identified by constructing a problem cluster, which traces all underlying causes back to the root cause, starting from the action problem. (Chevallier, 2016). The problem cluster can be found in Appendix A.1.
The action problem addresses costs that arise without Company X fully understanding their origins or impact. During and after the production processes, actual expenses occasionally exceed expectations. The sales department may negotiate a new project, and then the procurement and engineering departments determine the necessary activities and resources to manufacture a working plant. Ideally, by adding these activities and resources together, the organisation should arrive at a credible cost price for producing the unit. Yet, in reality, it seems more complicated. Some costs do not stem directly from the production process of a certain plant but rather originate in preparatory tasks or general materials that support multiple projects. Indirect costs such as utilities, facilities, and maintenance expenses often go unaccounted for when calculating a project's cost price. As a result, these essential costs remain hidden contributors that steadily decrease profit margins.
Tracing the problems upwards reveals the root cause, which we consider the core problem. The core problem, pictured in red in Appendix A.1, can be defined as *the absence of a cost accounting method that provides insight into the cost structure of the production process*. Without the knowledge gained from implementing a cost accounting method, Company X cannot realistically plan budgets, allocate resources, or make informed pricing decisions. The cost accounting method should allow Company X to capture not only direct, project-specific expenses but also indirect costs and overheads.
In addition to the absence of an accurate cost accounting method, another root cause is identified. There is no knowledge of what aspects of the budgeting process are inaccurate. It is critical to understand which types of costs consistently exceed initial budget estimates to improve these processes. To address this, a regression analysis can be employed, enabling the company to identify significant cost drivers and detect patterns or anomalies in spending. This analytical approach would allow Company Y to pinpoint the root causes of budget overruns, whether they are linked to particular stages of the production process, fluctuating material prices, or unforeseen operational challenges.
By integrating these formerly evasive costs into the overall financial picture and employing regression analysis to uncover key cost drivers, the company can establish a more reliable foundation for profitability, accountability, and strategic growth. This dual approach transforms Company X's cost management from a reactive exercise into a proactive, data-driven practice, ensuring that every aspect of the production process is clearly understood, correctly valued, and continuously optimised.

1.4 Gap between Norm and Reality

Currently, the company lacks a clear procedure for identifying production costs and associating them with specific activities or processes. Furthermore, the company does not have a clear view of budgeting inefficiencies. As a result, unexpected costs arise, causing actual expenses to deviate from the budgeted amounts, ultimately reducing the desired profit margin.
The norm is for the company to have a precise understanding of production costs and the ability to allocate them to specific projects. Furthermore, a validated method for doing so is desired as well. Achieving this would accurately determine the cost price and help maintain the intended profit margin.

1.5 Problem-solving approach

The main research question is based on Company X's core problem, as stated in Section 1.3. This research aims to provide an improved insight into the cost structure of the production process and is defined as:

How can implementing a new cost accounting method and regression analytics improve Company X's insight into production costs?

The methodology that is used for this research is the Managerial Problem-Solving Method (MPSM) by Heerkens and van Winden (2021). This is a general research design model that is widely used. It is a systematic approach that involves identifying the core problem, conducting thorough research into it, and solving it. Its creative techniques make it applicable in many situations (Heerkens & Van Winden, 2021). The methodology consists of the following seven phases:

Phase 1: Defining the problem
The first phase of the MPSM is problem identification. The problem is understood in terms of its context, stakeholders, and scope. Discovering underlying problems is essential here.

Phase 2: Formulating the approach
In this phase, the problem-solving approach is defined. It is important to discover the methods available for solving problems similar to this research's core problem. A systematic literature review is conducted to identify possible cost accounting methods. Furthermore, regression methods are investigated to define possible methods to discover budgeting inefficiencies.

Phase 3: Analysing the problem
During this phase, the problem is extensively analysed. This includes gathering the right data, clearly understanding the production process and cost structure of Company Y, discovering causes and consequences, and setting up constraints and requirements.

Phase 4: Formulating possible solutions
After analysing the problem, possible solutions are generated. There are a variety of them, so we can evaluate what the right strategy is afterwards. Criteria are established to assess the possible cost accounting methods. The characteristics of Company Y's production environment are stated when choosing a proper regression method.

Phase 5: Choosing the solution
After evaluating the possible solutions, the best-fitting method is chosen. This is done by evaluating them against the criteria established earlier. The right regression method is chosen based on the characteristics of the production environment of Company Y. It is decided in what programme both the solutions are generated.

Phase 6: Implementing the solution
In this phase, the method is used to come up with results. Firstly, the models for both the cost price and budgeting evaluation are built. Here, we can see what happens with the cost structure using the available data and the chosen method. We also carry out the regression analysis. Both the solutions are validated.

Phase 7: Evaluate the solution and provide recommendations
First, the outcomes are evaluated. We can then compare the outcome with the desired situation mentioned at the beginning of this research. Afterwards, we conclude the study and give Company X recommendations.

1.5.1 Research Design

In this section, the research design is explained. It is a framework that outlines how the study is conducted. The plan specifies the methods and procedures used in collecting, analysing, and interpreting data. A well-constructed research design is essential to minimise bias and maximise data reliability, yield maximum information with minimal experimental error, and provide a clear structure for the entire research process (De Vaus, 2001).
This research follows a descriptive and explanatory approach, integrating qualitative methods for understanding production processes and quantitative methods for cost analysis. Understanding the production process is the first step towards determining the cost drivers. Through interviews with the production staff and managers, the research identifies the direct and indirect costs that significantly influence the overall production expenses. Key variables, as mentioned in Section 2.2, such as labour costs, material expenses and overhead allocation, are operationalised.
For the data collection, relevant cost data is obtained from internal company records such as production logs, financial reports and data from the Enterprise Resource Planning (ERP) system. Interviewing the production staff and management strengthens the dataset by providing insights and context.
Using insight from the systematic literature review that is conducted, the study evaluates the suitability of numerous cost accounting methods and regression methods. We establish criteria to find the method that fits the organisation's specific needs. These include accuracy, relevance to the production process, ease of implementation and alignment with the company's objective. The selected methods are adapted to the company's context using the collected data. The methods are tested and validated to ensure reliability and validity. This involves consulting with industry experts and statistical validation. By validating the method, its limitations become clear as well. For instance, the scalability of the method could be a limitation. Additionally, the limitations of this research are the availability and accuracy of cost data and biases in employee responses.

1.5.2 Research Questions

In this section, the research questions are established. These questions are based on the methodology and the research design. The research questions contribute towards answering the main research question mentioned in Section 1.5.

1. *What cost accounting methods are available for allocating direct and indirect costs in manufacturing environments?*
2. *Which regression models are available for investigating inaccurate cost estimation?*

The aim here is to identify and understand various cost accounting methods and regression models to establish a foundation for selecting the most appropriate methods for Company Y. These questions are answered in Chapter 2.

3. *What steps are involved in the production process at Company Y?*
4. *How do direct and indirect costs associated with the steps in the production process affect total production costs?*

Answering these questions enables the analysis of the production workflow and cost drivers. It provides insight into the cost structure and the challenges of establishing the right cost price. These two questions are addressed in Chapter 3.

5. *What cost accounting approach best fits Company Y's production methods and cost structure, and why?*

6. *Which regression models are most suitable for conducting a cost variance analysis in the context of Company Y?*

It is essential to evaluate potential methods and justify selecting the most suitable one or a combination of multiple. It ensures the alignment between the method(s) and the operational and company needs. These questions are answered in Chapter 4.

7. *How can the selected cost accounting and regression methods be adapted for implementation at Company X using its existing data?*

The objective is to determine how the selected cost accounting method can be effectively adapted to Company X's operational context, utilising the data collected earlier in the research. This process involves developing a structured implementation plan that details how the cost accounting method can be integrated into existing operations while addressing practical challenges. Key adjustments and feasibility considerations are identified to ensure a realistic and scalable approach. The regression analysis is done on collected data to identify potential budgeting weaknesses. These aspects are thoroughly examined in Chapter 5.

8. *How can the validity and reliability of the selected methods be assessed at Company X?*

It is necessary to establish validation procedures for the selected method to ensure that the new cost insights are accurate and trustworthy. The validation methods should align with the available resources. This is addressed in Chapter 5 as well.

9. *What new insights into production costs are gained from applying the selected cost accounting method to Company X's situation?*

10. *What recommendations can be made for Company X based on the new cost insights for improving cost management and decision-making?*

Answering these last two questions, the goal is to provide actionable suggestions derived from the findings. It helps the company use the new insight to optimise its operations. This is addressed in the final part of this thesis, Chapter 6.

1.5.3 Scope

The scope of this research is intentionally limited to two standard types of energy plants, Product A and B. Each type has many customisation options to fulfil the customer's needs. The limitation ensures in-depth analysis and actionable recommendations within the time constraints of a bachelor's thesis. These product types sell the most, so its practical relevancy is the highest. By focusing solely on direct and indirect production costs, the study aims to provide a granular understanding of the production's cost structure without dilution from unrelated cost factors such as sales or transport. This focus aligns closely with the core problem identified, addressing the gap in cost accounting methods and budget efficiency to offer insights tailored to Company X's production.

1.5.4 Deliverables

As a result of the research conducted at Company X, there are several deliverables. First, a **detailed report** including recommendations on how to implement a cost accounting method to enhance insight into production costs. It also outlines the cost accounting method selection process and the rationale behind the choice. Furthermore, it includes an identification of cost estimation errors and recommendations on how to solve these errors. All of these recommendations are accompanied by practical guidelines. Secondly, it includes a **cost price model**, made in Excel, that incorporates a cost accounting method to improve cost allocation and enhance visibility into the production's cost structure.

2 THEORETICAL FRAMEWORK

The theoretical framework of this study establishes the foundation for evaluating and implementing cost accounting and regression methods within Company X's production processes. Through a systematic literature review, the chapter delves into the principles of cost accounting and regression analysis, offering a comprehensive understanding of how these methods can provide insights into cost structures and drivers. By integrating regression analysis, the study expands its focus to include predictive and diagnostic tools, allowing for the identification of significant cost drivers and patterns. This enhanced theoretical base enables the design of more effective cost accounting models tailored to Company X's operational and financial needs.

2.1 Cost Accounting

Cost accounting is a specialised branch of accounting that plays a key role in business management. Whereas financial accounting focuses on providing financial information to external stakeholders, such as investors and regulators, cost accounting has a more internal focus and is designed to help managers understand, control, and optimise costs associated with a company's operations. By analysing the cost structure of products, services, or processes, companies can make informed decisions to enhance efficiency and profitability (Horngren et al., 2018).
Cost accounting involves identifying, measuring, analysing, and reporting costs. The first step involves identifying the purpose of cost accounting and the specific cost objects, such as products, services, or departments. Costs are then classified based on their nature (direct or indirect), behaviour (fixed or variable), and purpose (product or period costs) (Hansen & Mowen, 2006). Direct costs are assigned directly to cost objects, while indirect costs are allocated using cost drivers. A cost driver is a characteristic or activity that causes costs to be incurred. It is a measurable factor that directly influences the costs of a specific activity, product, or service. The data is then analysed to calculate total and unit costs to identify inefficiencies (Hansen & Mowen, 2006).
The primary objective of cost accounting is to accurately determine the cost of production or service delivery, helping management control expenditures and make strategic decisions (Horngren et al., 2018). The scope of cost accounting goes beyond the mere calculation of costs. It contains cost control, cost reduction, and cost analysis, forming the foundation for budgeting, pricing, and financial planning. This function is essential in manufacturing industries, service sectors, and even non-profit organisations, as it provides insights into resource utilisation and cost efficiency.

2.2 Cost Types

Certain types of costs are often mentioned in cost management and cost accounting. Based on their nature, we can categorise costs into three distinctions: direct or indirect, fixed or variable, and product or period (Hansen & Mowen, 2006). This section explains these types of costs.

2.2.1 Direct vs. Indirect costs

Direct costs are expenses that can be directly attributed to the production of specific goods or services a business sells. These costs are easily traceable and directly linked to the creation of a product or delivery of service (Horngren et al., 2018). Direct costs typically include raw materials used for manufacturing, direct labour costs involved, and equipment or machinery that is specifically used for that production process.
Indirect costs are expenses that cannot be directly attributed to a specific project, product or service. According to Horngren (2018), indirect costs are defined as costs that cannot be traced to the cost object. The costs incurred benefit multiple activities or projects. Indirect costs include rent, utilities, and maintenance, but also indirect labour and material expenses. The terms *indirect costs* and *overhead* are often used interchangeably. However, they have distinct meanings in cost management and accounting. Overhead costs is a subset of indirect costs that refer to the *expenses of an ongoing business* that cannot be directly tied to creating a product. It focuses on keeping the business running. These are costs like rent, utilities and office supplies (Hansen & Mowen, 2006).

2.2.2 Fixed vs. Variable costs

According to Hansen and Mowen (2006), "fixed costs are costs that in total are constant within the relevant range as the level of the activity driver varies" (p. 68). In other words, fixed costs remain unchanged over a specific period, regardless of fluctuations in production or sales levels. These costs do not vary with output and are incurred irrespective of the volume of goods produced or sold. Examples include factory rent and insurance premiums (Drury, 2018).
In contrast, variable costs change in direct proportion to production levels (Hansen & Mowen, 2006). For instance, in a bakery, expenses such as flour and packaging materials fluctuate based on output. The fundamental distinction between these cost types lies in their relationship with production levels: fixed costs decrease per unit as output increases, whereas variable costs remain directly proportional to production volume (Horngren et al., 2018).

2.2.3 Product vs. Period costs

Product costs are the costs incurred in the manufacturing of goods or the provision of services (Hansen & Mowen, 2006). These costs are capitalised as inventory and are only recognised as expenses, specifically as the cost of goods sold, once the product is sold. According to Hansen and Mowen (2006), "period costs are expensed in the period in which they are incurred. Thus, none of these costs can be assigned to products or appear as part of the reported values of inventories on the balance sheet" (p. 40). Period costs include selling, administrative, and general expenses, such as advertising, executive salaries, and office rent. Unlike product costs, which are directly tied to production and inventoried until the sale of goods, period costs are expensed immediately in the income statement during the period in which they occur. In summary, product costs are inventoriable and directly associated with the production process, whereas period costs are recognised as expenses immediately and pertain to the overall business operations rather than manufacturing.

2.3 Cost Accounting Methods

This section discusses different cost accounting methods. Important aspects of cost accounting methods are in which manner they allocate costs, how they align with financial regulations, scalability, and granularity of a method, which also affects ease of implementation. Each method has its own characteristics, so it adjusts according to the needs of specific industries or companies. The methods included in this section are relevant because they align with the research's objectives and might be useful for implementation at Company Y. The methods mentioned in this section can be divided into three categories, which are shown in Figure 2.1. Volume-based methods allocate overhead based on production volume or labour hours, while activity-based approaches link overhead to specific organisational activities. Process-based costing methods look at production processes or jobs as a whole, often dealing with batches of goods or tailored products. The methods discussed are summarised at the end of the section in Table 2.1.

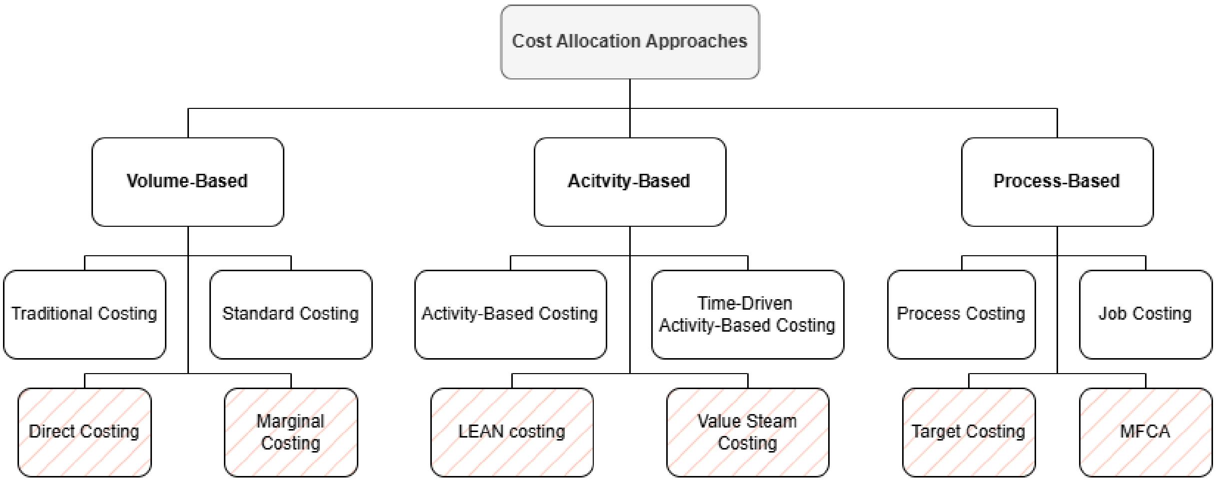

Figure 2.1: Cost Allocation Approaches

A few cost accounting methods are excluded from this study. These are hatched red in Figure 2.1. Material Flow Cost Accounting (MFCA), LEAN costing and Value Stream Costing are excluded because they focus on waste reduction. Although MFCA can be considered as an activity-based method if focused on specific activities, it generally is process based. Direct costing is not included because it does not include indirect costs. Marginal costing is not included because it does not include fixed costs. Fixed costs and indirect costs are both needed in this study. Lastly, target costing is not assessed in this study either, as it is a market-driven approach which starts with a sales price and determines what the maximum costs can be. This is not truly about costs.

2.3.1 Traditional Costing

Traditional costing, also known as full costing or absorption costing, is a cost accounting method that has been widely used among organisations for many years. Traditional costing is a method that incorporates all manufacturing costs, both direct and indirect expenses. It uses four main components to determine the total cost of production. It covers direct materials, direct labour, both variable and fixed manufacturing overhead. According to Horngren (2018), traditional costing systems allocate overhead to products based on the volume of resources used in production. It uses a single overhead rate which makes it more simplistic compared to other cost accounting methods. The overhead rate is a metric that represents the proportion of the overhead costs relative to a specific allocation measure, such as direct labour or machine hours. Traditional costing often fails to account for product diversity. With a greater variety of products, the method

using broad averages can lead to misallocation of costs (Horngren et al., 2018). This lack of specificity makes it difficult to efficiently adapt to different products.
Companies often use traditional costing as it complies with Generally Accepted Accounting Principles (GAAP) and International Financial Reporting Standards (IFRS) for external financial reporting (Horngren et al., 2018). These are accounting rules, standards, and procedures used to guide financial reporting. Where GAAP is mainly used in the United States, IFRS is used in the EU. Financial institutions and investors accept the method and, therefore, is better for facilitating financing and increasing confidence in financial statements.

2.3.2 Standard Costing

According to Drury (2018), standard costing is a method that involves establishing predetermined costs, known as standard costs, for the products or services. This is done for direct materials, direct labour, and overhead. These predetermined costs are based on historical data, operational efficiency, market conditions or industry benchmarks. The standard costs are compared with the actual costs for variance analysis. The organisation can take action by studying the reasons for variances. Standard Costing is a widely used method in manufacturing environments for cost control, performance evaluation and decision-making.
Standard costing particularly benefits companies with repetitive and predictable production processes, such as manufacturing (Drury, 2018). The automotive industry and the healthcare sector often use this method. Standard costing is much less complex than other cost accounting methods, such as activity-based costing (ABC). By using predetermined costs as benchmarks, detailed cost tracking is not essential. This makes the method less resource-intensive. Using the industry benchmarks when determining the standard costs gives a more reliable image of whether the costs are aligned with expected standards. Other methods, like ABC, allocate costs more accurately but lack a comparison with the expected standard.
Although it is easy to implement compared to other methods, standard costing is not flexible (Drury, 2018). Working with predetermined costs is challenging in dynamic industries where cost changes occur frequently in technology, energy, or maintenance. Additionally, labour availability could be an uncertain factor. If these predetermined standards are outdated, the variance analysis with its interpretations is not valid.

2.3.3 Activity-Based Costing

ABC is a method for assigning overhead and indirect costs, such as manufacturing overhead and administrative costs, to products, services or customers more precisely than traditional costing methods. As of today, the degree of automation within manufacturing is increasing, the proportion of overhead costs is also increasing. Because of this, ABC is gaining popularity. Instead of using averages, ABC identifies activities that are performed to produce a certain product. Then, it assigns all the costs necessary to perform that activity. Thereafter, product costs can be calculated through the degree to which they use these activities. Based on the intensity of these activities, the method allocates overhead costs proportionally (Kaplan, 1997).
ABC is particularly useful for companies that have a complex product mix. These are companies that produce a wide range of products, varying in product complexity, batch sizes, customization and resources (Horngren et al., 2018). Furthermore, companies prefer ABC over traditional costing methods when they are dealing with a high percentage of overhead costs. Traditional costing methods primarily focus on direct costs and allocate overhead in a less precise way. In contrast, ABC establishes a relationship between all costs (both direct and indirect) and the activities that drive those costs. In other words, ABC connects overhead costs to production activities, making the total cost of a product more accurately reflect the true resources it consumes (Noreen, 1991). However, there is a risk of making the system overly complex, which

reduces the scalability. By adding more activities and cost drivers, it leads to difficulty when updating them (Noreen, 1991).

2.3.4 Time-Driven Activity-Based Costing

Time-driven activity-based costing (TDABC) is a simplified version of ABC that uses time as the primary cost driver. It rather focuses on the time required to perform an activity than the detailed composition of cost data of which an activity consists. Like ABC, TDABC begins with defining all the activities or processes in an organisation that consume resources. The focus here is to understand what needs to be done to deliver the product eventually. Once the activities are defined, the next step is determining how much time is needed to perform these activities. This is done by measuring or estimating the time of executing such an activity under normal operating circumstances. The typical workload is included, and exceptional cases are preferred to be excluded. Afterwards, the cost per unit of time is calculated. This involves adding up all the costs associated with the resources needed for the activity and dividing it by total available time capacity, for example, total working hours in a period (Kaplan & Anderson, 2007). So, at its core, TDABC focuses on two key parameters:

- The cost of supplying resource capacity
- The time required to perform activities or transactions

Using time as the primary cost driver is less complicated and, therefore, less time-consuming than ABC as it streamlines the process of assigning costs. This also makes it easier to update the method after implementation and makes it more scalable (Kaplan & Anderson, 2007). It simplifies the process compared to ABC while providing more insight regarding organisational efficiency and resource utilisation. Therefore, TDABC is a well-suited method for firms looking for a less complex and less costly implementation than ABC. ABC often relies on extensive employee surveys and subjective time allocations (Hoozée & Hansen, 2018). While TDABC simplifies cost allocation by applying standardised time-driven rates, it may be less effective in cases where resource consumption varies significantly across different activities. In contrast, ABC offers a more precise allocation method by capturing the complexity of cost behaviour, making it particularly suitable for environments where tracking resource usage is not straightforward. This ensures that overhead costs are assigned based on the actual activities performed, leading to more accurate cost insights and improved decision-making in budgeting and pricing strategies (Hoozée & Hansen, 2018). TDABC is particularly interesting for companies that rely on the time spent on certain job processes, such as healthcare. Furthermore, if demand for certain activities fluctuates much and quickly, a time-based approach is more flexible.

2.3.5 Process Costing

Process costing is a method designed for industries that produce large quantities of homogeneous products through continuous production processes. In process costing, costs are accumulated for each production stage or department. These costs cover direct materials, direct labour, and manufacturing overhead, which are then averaged over the total units produced within a given period (Drury, 2018). A unique aspect of process costing is its treatment of partially completed goods. To ensure accurate cost allocation, companies calculate the degree of completion for these goods and convert them into equivalent units. This ensures that costs are distributed proportionally between finished goods and work-in-progress inventory. It simplifies cost accounting by grouping costs by process rather than individual units, reducing administrative burden and streamlining cost tracking. This makes it a more practical choice compared to complex methods like ABC. By averaging costs across all units, process costing ensures consistent and accurate cost allocation, crucial for pricing decisions and inventory valuation. Process

costing includes both variable and fixed overheads, providing a complete picture of production expenses. Process costing is inherently scalable because it is designed for industries that produce large volumes of identical or similar units (Drury, 2018). Additionally, it simplifies financial reporting by using average costs per unit, ensuring compliance with standards like GAAP or IFRS. Process costing also aids cost control by identifying variances in material usage or labour efficiency, enabling organisations to optimise operations.
Process costing does have several disadvantages compared to other costing methods. Unlike job costing, which tracks specific job costs, it averages costs, leading to inaccuracies for diverse or custom products (Hansen & Mowen, 2006). Its overhead allocation lacks the precision of ABC, and it struggles to identify inefficiencies or non-value-adding activities. Process costing is unsuitable for dynamic or non-homogeneous production environments and can obscure cost variations within production stages. Additionally, calculating equivalent units for work-in-progress can be complex (Soudatti, 2024). Overall, it provides less detailed insights, making it less flexible for decision-making than alternatives like ABC.

2.3.6 Job Costing

Job costing is a cost accounting method used to track and allocate costs associated with producing specific products or services. It is especially useful for industries where the products or services are custom-made or each project is unique. In job costing, costs are assigned to individual jobs or batches of products rather than the overall production process. The three main cost categories tracked are direct materials, direct labour, and overhead (Horngren et al., 2018). Job costing is often used in made-to-order environments or where products are customised or produced in relatively small batches rather than mass production. This method is beneficial for companies that track costs for each client engagement, such as consultancies or accountants. The high level of detail allows accurate cost tracking, but makes scaling difficult (Horngren et al., 2018).
Additionally, there is an activity-based approach to job costing. This is a refined approach to job costing that integrates the principles of ABC. Within a job, the method assigns costs to specific activities or tasks. It differs from normal job costing as it is not based on broad measures such as direct labour or machine hours without considering the specific activities causing those costs. For example, in construction, activity-based job costing could separate costs for excavation, formwork, and concrete pouring as distinct activities. In contrast, normal job costing would take these together under a single cost code (Fayek, 2001). In short, by combining ABC with job costing, benefits of ABC such as improved cost tracking and standardisation across projects are complemented. However, disadvantages such as increased effort for data gathering and complexity in implementation are also part of the combination.

Table 2.1: Overview Cost Accounting Methods

Method	Description	Key Features	Best Suited For
Traditional Costing	Allocates all manufacturing costs, including direct and indirect, using a single overhead rate.	• Simple to implement • Uses broad averages • Complies with GAAP/IFRS • Less accurate for diverse products	• Organisations with uniform products • Financial reporting and regulatory compliance

Continued on next page

Table 2.1: Overview Cost Accounting Methods (Continued)

Method	Description	Key Features	Best Suited For
Standard Costing	Uses predetermined costs (standards) for materials, labour, and overhead to compare with actual costs.	• Enables variance analysis • Good for cost control • Less complex but lacks flexibility	• Repetitive production processes • Stable industries (automotive, healthcare)
ABC	Assigns overhead and indirect costs based on activities that drive costs rather than broad measures.	• More precise than traditional costing • Tracks cost drivers at activity level • Suitable for complex product mixes • Can be complex and expensive to implement	• Companies with high overhead costs • Businesses with diverse product lines
TDABC	A simplified version of ABC that uses time as the primary cost driver to allocate overhead.	• Easier to update than ABC • Uses standardised time-driven rates • Balances precision and scalability	• Time-intensive industries (e.g., healthcare) • Businesses seeking a simplified ABC approach
Process Costing	Allocates costs based on production processes, averaging costs across homogeneous units.	• Simplifies cost tracking • Uses equivalent units for unfinished goods • Not suitable for custom products	• High-volume, continuous production industries (chemicals, food, pharmaceuticals)
Job Costing	Allocates costs to individual jobs or projects rather than mass production processes.	• Tracks direct materials, labour, and overhead per job • High level of cost tracking detail • Not easily scalable	• Custom manufacturing • Service industries (consulting, construction)

2.4 Regression

Regression analysis is a statistical technique widely used to model and analyse the relationships between a dependent variable, often called the outcome or response variable, and one or more independent variables, referred to as predictors, regressors or explanatory variables. This method is fundamental in understanding complex data patterns, estimating causal effects, and predicting future outcomes (Montgomery et al., 2012). Its versatility makes it essential across various fields, including economics, engineering, and production management. In the domain of production, regression analysis is particularly relevant for estimating costs, analysing productivity, and optimising resource allocation.

2.4.1 Simple Linear Regression

The simplest form of regression analysis is simple linear regression, where the relationship between a single independent variable X and a dependent variable Y is examined. The model can be expressed as Equation (2.1).

$$Y = \alpha + \beta X + \epsilon \tag{2.1}$$

where α is the intercept or constant. It represents the mean value of the response variable when all the predictor variables in the model are set to zero. β represents the slope of the line (indicating the effect of X on Y), and ϵ stands for the error term capturing unexplained variability (Montgomery et al., 2012). This approach is often used in production to explore how one factor, such as labour hours, influences costs. For instance, if labour hours increase by one unit, the corresponding change in production costs can be quantified by β (Chatterjee & Hadi, 2006).

2.4.2 Multiple Linear Regression

When analysing multiple variables simultaneously, multiple linear regression (MLR) becomes necessary. This model extends simple linear regression to include several independent variables, thereby significantly enhancing its explanatory strength. Unlike simple regression, which attributes changes in the dependent variable to a single factor, multiple regression allows for the inclusion of multiple predictors, providing a more comprehensive view of the factors influencing the outcome. For example, in a manufacturing setting, production costs might depend not only on labour hours but also on material costs, energy consumption, and machine maintenance. Incorporating these variables into a multiple regression model makes it possible to separate their individual effects and identify the most impactful cost drivers. This comprehensive approach ensures a deeper understanding of the production process and supports more informed decision-making (Chatterjee & Hadi, 2006). Here, $X_1, X_2, \ldots, X_k$ represent different predictors, each contributing to the variation in Y, as can be seen in Equation (2.2).

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \epsilon \tag{2.2}$$

2.4.3 Multicollinearity

Multicollinearity implies near-dependence among the independent variables. According to Chatterjee (2006), “the presence of near-linear dependencies can dramatically impact the ability to estimate regression coefficients” (p. 117). It refers to the situation where there is a high correlation between the independent variables in the model. This can impose unstable and unreliable estimates of the coefficients. Furthermore, it creates difficulty in interpreting the individual effects of correlated predictors.

There are a few possibilities for detecting multicollinearity. One key diagnostic tool for this is the Variance Inflation Factor (VIF) (Kim, 2019). It is calculated according to Equation (2.3).

$$VIF = \frac{1}{1 - R^2} \tag{2.3}$$

Where R^2 is the coefficient of determination from regressing one explanatory variable on all others. A VIF between 5 and 10 indicates multicollinearity and a VIF above 10 indicates severe multicollinearity. However, VIF cannot identify which specific predictors cause multicollinearity. A correlation matrix is a way of diving deeper into the multicollinearity of individual variables. The correlation matrix displays the pairwise (between two variables) correlation coefficient, r.

Equation (2.4) calculates r (Chatterjee & Hadi, 2006).

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{2.4}$$

Where x_i, y_i are the data points of variables X and Y and $\bar{x}, \bar{y}$ are the mean values of variables X and Y. If two or more predictors have high correlations (r above 0.8), they are likely to be multicollinear. A crucial note is that a low pairwise correlation does not mean there is no multicollinearity (Alin, 2010).

Variance Decomposition Proportions (VDP) can be used to detect multicollinearity for specific variables. VPDs are calculated from the eigenvectors and show how much variance in a regression coefficient is inflated due to multicollinearity (Kim, 2019). Eigenvalues and eigenvectors are calculated from the correlation matrix. Each eigenvalue represents a component's contribution to the total variance. A very small eigenvalue indicates that some predictors are highly correlated. Then, the Condition Index (k) is calculated. k values above 30 suggest multicollinearity. Equation (2.5) calculates k, where λ_{max} is the maximum eigenvalue and λ_s refers to the sth eigenvalue.

$$k_s = \sqrt{\frac{\lambda_{\text{max}}}{\lambda_s}} \tag{2.5}$$

Apart from detecting multicollinearity, there are a few techniques used to handle multicollinearity in regression models. Examples are Ridge regression, Lasso regression, and Principal Component Regression (PCR). Ridge regression reduces multicollinearity by adding a penalty to the regression model that shrinks the size of the coefficients. This prevents any one predictor from dominating the model due to its correlation with others, resulting in more stable and reliable predictions. However, it keeps all predictors in the model. Lasso regression, like Ridge, includes a penalty, but it tends to shrink some coefficients to exactly zero. This means it not only reduces the effect of correlated predictors but also eliminates less important variables entirely, which simplifies the model. PCR tackles multicollinearity by transforming the original predictors into a set of uncorrelated components using Principal Component Analysis (PCA). The regression is then performed on these components, ensuring that the predictors used are not correlated, though at the cost of interpretability (Herawati et al., 2018).

2.4.4 Validation Strategies

Validation methods are essential in assessing how well regression models generalise to unseen data. These techniques play a critical role in counteracting the "optimism principle", whereby models tend to perform better on the data used for training than on future observations due to overfitting (Picard & Cook, 1984). Overfitting arises when a model captures not only the underlying patterns but also noise or random fluctuations, leading to poor generalisation. The result is that the model performs well on training data but not on unseen data (Montesinos López & Crossa, 2022). Cross-validation helps avoid overfitting by ensuring the model does not overly adapt to training data (Cheng et al., 2017). Below are two widely used validation methods described, highlighting their purpose, mechanics, and relevance.

Data splitting involves dividing a dataset into two subsets: one for training and one for validation or testing. A typical split allocates 70% of the data for model training, leaving 30% to test the model's predictive performance. This approach evaluates the extent to which the model generalises to unseen data by reserving the validation set as an unbiased estimate of predictive error (Martens & Dardenne, 1998). However, this method has limitations, particularly for small datasets, where the reduced sample size in the training subset can lead to increased variability in parameter estimates (Picard & Cook, 1984).

Cross-validation addresses the limitations of data splitting by repeatedly dividing the data into training and validation subsets. A common form, k-fold cross-validation, partitions the data into

k subsets (or folds), with each subset serving as the validation set in turn, while the remaining folds are used for training. The performance metrics are averaged across iterations, providing a more reliable estimate of the model's generalisation ability. For small datasets, leave-one-out cross-validation (LOOCV) is particularly advantageous, as it uses each observation as its own validation set, ensuring maximal use of available data (Martens & Dardenne, 1998).

2.4.5 Performance Metrics

While Section 2.4.4 focuses on ensuring that the model's performance is reliable and generalisable, this section focuses on evaluating model quality. Performance metrics for regression evaluate how well a regression model predicts continuous outcomes. The choice of metrics depends on the context and the importance of specific types of errors. Common metrics are described in this section.

First, the Mean Absolute Error (MAE) is explained. MAE is calculated as the average of the absolute differences between predicted and actual values, providing a clear measure of the average magnitude of errors in the original units of the target variable. Its primary advantage lies in its interpretability, as it directly indicates how far off predictions are, on average (Azadi & Karimi-Jashni, 2016). Additionally, MAE is less sensitive to large outliers than metrics that square the errors, making it a more robust measure in datasets with extreme values (Khan et al., 2022). However, since it relies on absolute differences, MAE does not strongly penalise rare, large errors, nor does it emphasise reducing variance in the errors. Equation (2.6) calculates the MAE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2.6}$$

Root Mean Squared Error (RMSE), by contrast, involves squaring each prediction error, averaging these squared errors, and then taking the square root of the result. This process increases the penalty for larger deviations, making RMSE particularly effective in scenarios where large errors are especially undesirable (Chicco et al., 2021). However, this sensitivity to outliers can also be a disadvantage, as it strengthens their influence on the metric. RMSE is less intuitive than MAE due to the squaring step. RMSE is determined with Equation (2.7).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2.7}$$

Mean Absolute Percentage Error (MAPE) expresses the absolute error as a percentage of the actual value, computed by dividing the absolute error by the actual value, averaging the result, and multiplying by 100 to express it as a percentage (Chicco et al., 2021). This metric is especially valuable for understanding errors in relative terms rather than absolute terms, making it suitable for comparing predictive performance across datasets with different scales. However, MAPE has limitations. It becomes undefined or misleading when actual values include zeros or very small numbers, and it disproportionately weights instances with smaller actual values. The MAPE is mathematically expressed in Equation (2.8).

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{2.8}$$

Selecting the appropriate metric depends on the objectives of the analysis and the specific characteristics of the dataset. MAE and RMSE focus on measuring absolute errors and their squared counterparts, respectively. MAPE provides insight into relative errors and is particularly useful when comparing performance across scales. Each metric has unique advantages and limitations in terms of interpretability, sensitivity to outliers, and applicability across data scales.

2.4.6 Goodness-of-fit

In this section, goodness-of-fit metrics are discussed. These measure evaluate how well the regression model fits the data. The two measures discussed in this section are the R^2 and the adjusted R^2. R^2 measures the proportion of the total variation in the dependent variable that is explained by the regression model (Akossou & Palm, 2013). R^2 is mathematically expressed in Equation (2.9).

$$R^2 = 1 - \frac{\text{SSR}}{\text{SST}} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2.9}$$

Where the SSR is the sum of squared residuals, the unexplained variability, and the SST is the sum of squares, the total variability. Residuals are the differences between the observed values and the predicted values by a regression model (Montgomery et al., 2012).
However, adding more independent variables to a model will never decrease R^2 as it can only stay the same or increase, even if the added variables are only weakly related to the dependent variable. Therefore, R^2 tends to get larger as you keep adding predictors, even if those predictors do not genuinely improve the model. This is where the adjusted R^2 comes in. The adjusted R^2 modifies the R^2 to account for the number of predictors in the model, and the sample size. Equation (2.10) determines the adjusted R^2.

$$\text{Adjusted } R^2 = 1 - \left(\frac{\text{SSR}/(n-k-1)}{\text{SST}/(n-1)}\right) \tag{2.10}$$

The adjusted R^2 penalises the model for adding independent variables that do not improve the model's explanatory function (Cheng et al., 2014). The penalty depends on the number of independent variables (k) and the sample size (n). Because of this, the adjusted R^2 is able to decrease when predictors are added. This metric is often used to compare models with different predictors (Chatterjee & Hadi, 2006).

2.4.7 Evaluating the coefficients

Where Sections 2.4.5 and 2.4.6 focus on metrics which measure the performance of the overall model, this section focuses on statistical tools to conclude the precision and contribution of individual coefficients in a certain model, also known as inferential statistics. Widely used tools are calculating the t-value, p-value and the standard error (SE) of the coefficients. This section describes how these are calculated, how they are related to each other and what they mean in the context of regression.
Earlier, the RMSE is mentioned, also known as the standard error of the estimate. This measures the overall variability of the regression's residuals. The standard error of a regression coefficient measures how much variability there is in the estimated coefficient for each predictor (Montgomery et al., 2012). This essentially reflects how precise the estimate of the true effect is. To calculate the SE of a coefficient, firstly, the variance-covariance matrix of the coefficient estimates is calculated (Adeboye et al., 2014). This quantifies the variances of individual coefficient estimates and the covariances between pairs of coefficients. As can be seen in Equation (2.11), it is derived from the residual variance (σ^2) and the inverse of the design matrix ($(X'X)^{-1}$), which is a matrix of the predictors, including the intercept.

$$\text{Var}(\hat{\beta}) = \sigma^2(X'X)^{-1} \tag{2.11}$$

The residual variance is estimated by dividing the SSR by the sample size (n) minus the number of predictors (k) minus 1. This is shown in Equation (2.12).

$$\hat{\sigma}^2 = \frac{\text{SSR}}{n-k-1} = \frac{\sum(y_i - \hat{y}_i)^2}{n-k-1} \tag{2.12}$$

The standard error of a coefficient is calculated by the square root of the corresponding diagonal element of this matrix (Adeboye et al., 2014). This is determined in Equation (2.13).

$$\text{SE}(\hat{\beta}_j) = \sqrt{\sigma^2 \cdot (X'X)^{-1}_{jj}} \tag{2.13}$$

A lower SE implies that the estimate of the corresponding coefficient is more precise, while a higher SE suggests that the estimation is more uncertain. A large standard error would indicate that one should be cautious about the reliability of that independent variable's effect (Siegel, 2016).
The t-statistic is highly correlated to the standard error, as can be seen from the Equation (2.14). It is basically the ratio of the coefficient to its standard error (Siegel, 2016). It can be seen as dividing the slope by the uncertainty. The t-value says something about the statistical significance of each predictor. The t-value is mathematically expressed in Equation (2.14).

$$t = \frac{\hat{\beta}_j}{\text{SE}(\hat{\beta}_j)} \tag{2.14}$$

A larger (absolute) t-value indicates that the coefficient is like to be significantly different from zero (Montgomery et al., 2012). A smaller value means that the coefficient is not clearly distinguishable from zero which means it may not have a large effect, statistically speaking. It is, in that case, not playing a substantial role in predicting the outcome.
Lastly, the p-value is derived from the t-value. It quantifies the probability of observing the estimated coefficient under the null hypothesis that β_i is zero (Montgomery et al., 2012). It essentially determines the probability (under the assumption that the true effect is zero) of getting a t-value as large or larger than the one observed, under a t-distribution with the appropriate degrees of freedom under the null hypothesis.
A low p-value means that it is unlikely that the observed t-value occurred by random chance if the true coefficient were zero (not contributing) (Siegel, 2016). In other words, a low p-value suggests that the independent variable is statistically significant in explaining the dependent variable. The p-value is usually considered low if it is under 0.05, but this depends on the chosen significance level. The p-value does not say, however, how large the effect of the predictor is in practical terms. Furthermore, multicollinearity, discussed in Section 2.4.3, inflates the standard errors, reducing the t-values and increasing the p-values (Siegel, 2016).

2.4.8 Regression Applications

Regression analysis finds extensive application in production management. A key area is cost prediction, where historical data is used to estimate future production costs. For example, if historical data suggests that material costs and energy consumption significantly impact production costs, a multiple regression model can provide precise forecasts. Additionally, regression is invaluable for process optimisation, as it identifies critical factors affecting productivity, enabling managers to make informed decisions to enhance efficiency (Montgomery et al., 2012).
A variance analysis is another critical application of regression analysis. MLR can provide a nuanced interpretation of how individual differences contribute to the overall outcome (Plonsky & Oswald, 2016). It could be used to identify discrepancies between expected and actual costs. By modelling cost drivers, regression helps quantify the contributions of various factors to these variances. Outlier detection within regression analysis further aids in identifying unusual cost spikes, which might indicate inefficiencies or errors. Scenario analysis using regression models enables the simulation of changes in key drivers, providing valuable insights into their potential impact on costs (Chatterjee & Hadi, 2006).
In conclusion, regression analysis is a robust and adaptable tool that offers deep insights into relationships within production data. Its applications in cost prediction, process optimisation,

and variance analysis make it an effective tool for production management. By leveraging regression models, organisations can achieve data-driven decision-making, leading to enhanced efficiency, cost control, and strategic growth.

2.5 Summary

This chapter establishes the theoretical foundation for understanding and managing production costs within the company while exploring how regression analysis can diagnose inefficiencies and inaccuracies in budgeting. The chapter begins by introducing cost accounting, which provides managers with tools to analyse and optimise costs by focusing on internal financial processes rather than solely on external reporting. Within this method, costs are categorised based on their behaviour, such as direct or indirect, fixed or variable, or product or period costs. This lays the groundwork for advanced cost tracking and decision-making.

Building on this foundation, the chapter examines several cost accounting methodologies applicable in different production environments. Traditional costing applies a single overhead rate across all manufacturing costs, ensuring compliance with financial reporting standards but often lacking precision in overhead allocation. Activity-based costing (ABC) improves overhead distribution by tracing costs to specific activities, making it particularly relevant when overhead forms a substantial proportion of total costs. Time-driven activity-based costing (TDABC) refines this approach by using time as the primary cost driver, enabling more flexible and easily adjustable cost allocation in response to demand fluctuations. Job costing is suited to custom and made-to-order production, tracking expenses at an individual project level, while standard costing establishes predetermined benchmarks for materials, labour, and overhead, facilitating variance analysis. In contrast, process costing is most suitable for large-scale, standardised production, where costs are averaged across continuous production cycles. Each method offers distinct advantages, but all serve to enhance cost visibility and resource allocation, ultimately contributing to more effective budgeting and pricing strategies.

In addition to cost accounting approaches, the chapter explores regression analysis as a statistical tool for modelling relationships between costs and their drivers. Simple and multiple regression models provide varying levels of complexity in assessing how independent variables, such as labour hours, material costs, or machine usage, affect total production costs. The predictive accuracy of these models is evaluated using performance metrics such as R^2, adjusted R^2, mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). Validation techniques, including data splitting and cross-validation, mitigate overfitting and ensure model generalisation to future datasets. Additionally, inferential statistical measures, such as t-values and p-values, assess the significance of each cost driver, while diagnostic methods, such as the variance inflation factor (VIF), check for multicollinearity to prevent inflated variance in the estimates.

In a real-world budgeting context, these regression techniques enable the company to quantify inefficiencies by comparing predicted cost outcomes with actual expenses. This data-driven approach supports continuous improvement by allowing managers to separate the causes of cost overruns, address them proactively, and enhance budgetary decision-making. By integrating cost accounting methods with regression analysis, the company can refine its financial planning, optimise resource allocation, and improve cost estimation accuracy.

3 CURRENT SITUATION

This chapter provides an overview of the current cost accounting and production processes at Company Y, forming the basis for identifying areas of improvement. It begins with an analysis of the production process, detailing the key stages involved in manufacturing Products A and B, including fabrication, assembly, insulation, and quality control. The cost structure is then examined, categorising costs into direct, indirect, and overhead costs, and explaining their allocation across different business units. Following this, the product costing approach is outlined, describing how costs are incorporated into project quotations using predefined cost benchmarks. Finally, the chapter identifies limitations in cost accounting and budgeting that hinder accurate cost estimation, establishing the groundwork for the following chapters.

3.1 Production Process

This section outlines the key steps in producing Products A and B based on observations, interviews, and production logs. The production process is a structured series of activities ensuring the final product meets functional and operational requirements. This process starts with preparing the container, which forms the framework of the energy plant. Afterwards, the process logically flows from painting, assembly, insulation, and quality checks before shipping the product for delivery. The production process is depicted in Figure 3.1.

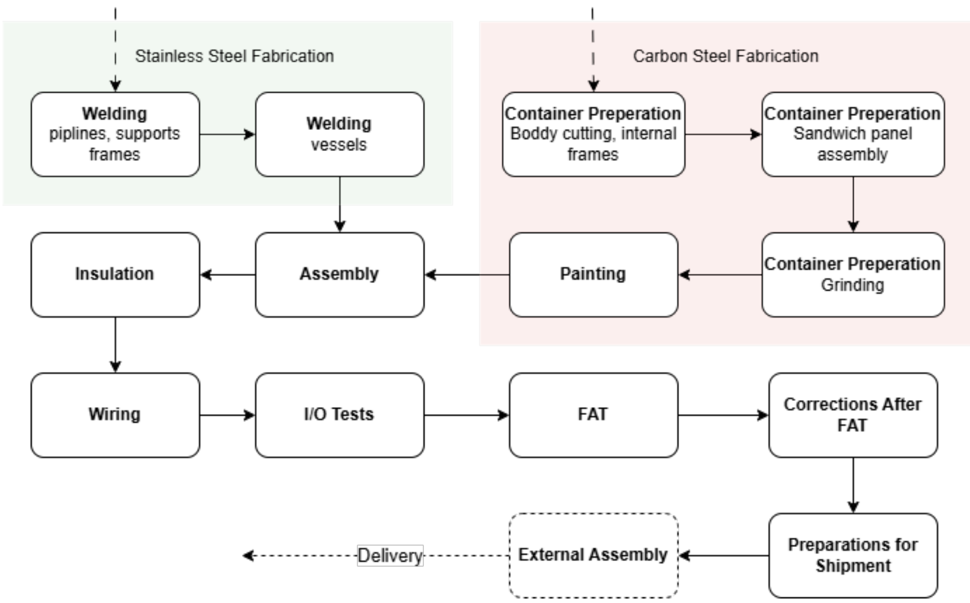

Figure 3.1: Production Process

Computer panels at each production phase collect essential data. When production staff begin a task, they log in, enter the project number, and register the task's start along with the materials used. Upon completion, they finalise the task in the system. This process generates data on task duration per project and the materials consumed.
The process begins with the fabrication phases of stainless steel (SS) and carbon steel (CS), where carbon steel is also referred to as black steel. At this stage, the focus is on welding key structural components, such as pipelines, supports, and container frames. The CS and SS phases can be performed simultaneously. The SS fabrication phase mostly includes manufacturing all pipes, vessels and valves for the container. All these instruments are cut and welded according to the specific project order. Furthermore, outside frames are made to support the total construction. Skilled welders carefully construct these parts using precision tools to guarantee strong, reliable connections.
During the CS fabrication phase, the focus lies on preparing the container itself and the frames to support the construction inside the container. Here, the container body is cut and welded with internal frames to accommodate its components. Sandwich panels are assembled onto the container. These panels play a critical role in providing insulation, structural rigidity, and protection against external environmental factors. Thereafter, the container is prepared for painting. This includes grinding, which smooths out surfaces and edges in readiness for the next step, the painting phase. A specialised machine applies protective coatings to prevent corrosion and wear. Moreover, it provides proper branding on the container. Due to limited in-house capacity, external partners are sometimes contracted for painting.
During the assembly phase, pipes, valves, and instrumentation are installed inside the container. These components are integral to the container's functionality, as they allow for the regulation, transportation, and management of materials such as gases or fluids. During the insulation phase, insulation skids are installed inside the container to enhance its thermal efficiency and operational safety. At this stage, the reboiler skid is also insulated to maintain optimal performance.
With insulation completed, the focus shifts to wiring. This phase involves installing electrical wiring, including connections for the reboiler skid. The wiring ensures that all instrumentation, sensors, and control systems are powered and interconnected, facilitating automated operations and monitoring. Proper wiring is critical to the container's ability to function as part of a renewable energy system.
Once wiring is complete, the container undergoes Input/Output (I/O) tests. During these tests, all electrical and mechanical systems are thoroughly examined to verify that they are functioning correctly. Input and output signals are checked to ensure that control systems communicate effectively with instrumentation, providing reliable data and system performance.
The next step in the process is the Factory Acceptance Test (FAT). This is a comprehensive evaluation to confirm that the container meets all functional and quality specifications. FAT ensures that the product performs as intended and meets the client's requirements before it leaves the factory. If any issues are identified during FAT, they are addressed in the corrections after FAT phase, where technicians resolve problems and retest systems to ensure compliance.
The final phase of the production process is shipment preparation. At this stage, the large subassemblies are prepared for transport to their installation site. Proper packaging and handling ensure the product arrives safely.
The production processes of Products A and B are carefully planned and executed by a sequence of activities that ensure quality, reliability, and functionality. From initial fabrication and preparation to assembly, testing, and shipment, each phase contributes to the creation of a container that meets the strict demands of Company X's renewable energy installations. This process, from start to end, takes about eighteen weeks. This structured approach guarantees a durable and efficient product ready for sustainable energy production.

3.2 Cost Structure

This section outlines the cost structure of Company Y, and how it aligns with certain cost accounting approaches. The cost structure at Company Y, which foresees the production of Company X, is organised to account for the financial resources required in production activities. It categorises costs into three primary types: direct costs, indirect costs, and overhead costs. This organisation allows resources to be allocated across the different production units and support functions.

Costs are attributed to specific manufacturing activities within Company Y's operations. These activities are divided into four main business units, which form Company Y's cost structure. These are the Carbon Steel, Stainless Steel, (Internal) Assembly, and the Electricity activities. Each unit handles distinct production tasks, as mentioned in Section 3.1. The carbon steel unit focuses on preparing the container body, including cutting, constructing internal frames, and painting. The stainless steel unit is responsible for welding components such as pipes, valves, and vessels. The internal assembly unit integrates these components, adding insulation suited to the container's operational environment. The electricity unit manages wiring and the installation of control panels to ensure system functionality. The direct costs associated with these units include raw materials like steel sheets and welding rods, as well as labour costs. Labour expenses are split into salaries for full-time employees and payments for subcontractors. Subcontractors are engaged when additional expertise or capacity is required, such as for certified welding or painting tasks that exceed internal capacity. For example, the painting process, which requires much space and one to two weeks of time, is frequently outsourced to avoid production delays.

Indirect costs include expenses that support production but are not directly linked to a specific product. These costs originate within the business unit itself, such as grinding tools and adhesives, which are indirect materials used specifically by workers in the carbon steel department. As these materials are exclusively utilised by a particular business unit, they are automatically allocated to that unit. Other indirect costs, such as utilities for machinery operation and maintenance expenses, follow a similar allocation process. Indirect labour costs, including employee benefits and performance bonuses, are also included. The allocation of costs from other departments, such as quality management, is addressed separately later in the text, as these are distributed based on the time spent supporting each business unit.

Departmental costs are also integrated into the cost structure, capturing the contributions of various support functions. These costs are distributed over the business units based on the number of employees, with this number established by examining how much time each department spends on the four main business units. The rate for dividing these indirect costs over the business units is calculated quarterly. The departments include project coordination, quality management, warehousing, engineering support, internal logistics, and standardisation. Project coordination handles scheduling and resource allocation. Quality management ensures that products meet required standards through inspections and testing. Warehousing manages inventory and storage of raw materials and finished goods. Engineering support provides technical guidance for addressing complex production tasks. Logistics oversees the transportation of materials and products, while standardisation ensures compliance with regulatory and customer requirements.

Overhead costs contain operational expenses that cannot be directly traced to production activities. These include administrative salaries, office maintenance, legal services, and IT infrastructure costs. Overhead is allocated to business units based on the square metres of facility space occupied by each unit. This allocation method ensures that operational expenses are distributed across units according to their use of shared resources.

The company's cost allocation system primarily follows a standard costing approach. Within this framework, direct costs, including raw materials and labour, are directly assigned to individual business units. Indirect costs, such as utilities, maintenance, and departmental support, are allocated based on measurable factors like time spent or headcount. Overhead costs are distributed according to criteria such as the facility space occupied. Although certain elements align with ABC, particularly in allocating departmental support using time-based measures, the overall system remains a standard costing approach. Overhead rates are predetermined, periodically recalculated and systematically applied to production units.

3.3 Product Costing

The product costing method used by Company Y, on behalf of Company X, is designed to incorporate all relevant costs into the cost price of a single project. The company makes a distinction between direct costs and indirect costs. Company Y's approach aligns with the principles of the standard costing method. Predetermined costs for labour and indirect cost rates are used to prepare project quotations. After each quarter, a cost variance analysis is conducted to identify deviations from the initial estimates. These variances inform updates to the rates used in subsequent cost calculations. This section describes how all relevant costs are incorporated into a single project and is based on interviews with both the production and financial management, and financial tools used by Company Y.

Direct costs are divided into four categories: labour costs, material costs, subcontractors, and indirect costs. For each project, the materials required are determined using a predefined list of standard plant types available for clients. These plants vary based on regional regulations, such as those in the USA and EU, as well as additional options selected by the client. These options cater to the operational environment and specific requirements of the plant. For example, a plant in Mexico may need enhanced cooling components compared to one in Alaska. Approximately half of the materials are ordered specifically for each project, while the other half is sourced from stock, leveraging cost efficiency in bulk purchasing. Labour costs are determined by the production coordination department, which assesses the manpower required for the project. This includes both the availability of internal staff and the need for subcontractors, which may arise from capacity constraints or the requirement for specialised expertise. Subcontractors are often engaged for tasks such as certified welding or painting that exceed the company's in-house capabilities.

Indirect costs are allocated to the four main business units: Carbon Steel, Stainless Steel, Internal Assembly, and Electricity. Once distributed to these units, the indirect costs are assigned to individual projects based on the number of hours spent by each business unit on the project. A standard rate for indirect costs is recalculated quarterly, reflecting deviations observed in the previous quarter. Indirect costs contain items such as grinding tools and adhesives that are specific to a particular business unit and are automatically allocated to that unit. The allocation of costs from other departments, such as quality management, is addressed separately, based on the proportion of time spent supporting each business unit.

Each project is divided into approximately seventeen production orders, with a detailed quotation prepared for each. This quotation includes direct material, direct labour, subcontractor, and indirect costs for each of the four main business units. Materials are listed by Company X and procured by either Company X or Company Y. Labour requirements and subcontractor involvement are determined using historical data and managerial estimates. For the Carbon Steel and Stainless Steel business units, labour costs are calculated based on the weight of the materials being processed. The indirect costs for each business unit are integrated into the cost price by applying a specific rate to the material, labour, and subcontractor costs. This rate is based on historical data and updated quarterly to reflect observed deviations. Additionally, a margin rate is applied to each business unit's costs to calculate the final project cost. Like the indirect cost rate, the margin rate is reviewed and adjusted quarterly to align with current financial data.

3.4 Room for Improvement

Currently, there are several aspects of the cost accounting process at Company Y that require attention for improvement. These areas are critical to aligning the costing methodology more closely with the dynamic and complex production environment of the company and to enhancing the overall accuracy and utility of the cost accounting system.

One significant area for improvement lies in the standard costing method currently in use. While standard costing is highly effective in environments with stable, repetitive operations where processes are clearly defined, it is less suitable for the dynamic production environment of Company Y. As noted by Drury (2018), the standard costing method flourishes in settings where it is feasible to establish realistic and consistent cost benchmarks. However, Company Y's operations involve producing customised installations, making it challenging to rely on predetermined costs. The customisation and variability inherent in the production process necessitate a more flexible approach to product costing that can accommodate frequent changes and unique project requirements. Furthermore, the data collected by the computer panels is not yet used effectively. This data is very valuable for shifting towards a more flexible approach.

Another area with considerable potential for improvement is the budgeting process. At the moment, the company is primarily focused on revising cost benchmarks for future production. While this practice ensures that benchmarks are periodically updated, it overlooks the opportunity to investigate the root cause of the miscalculations. By analysing the components of the quotation process that consistently fail to accurately estimate costs, the company could identify specific inefficiencies or recurring issues. Addressing these inefficiencies would improve the accuracy of cost-price estimations, leading to lower cost variances and helping the company maintain profitability.

Optimising both the cost accounting method and the budgeting process offers a pathway to enhancing the product costing procedure. A more tailored approach to cost accounting would ensure that all relevant costs are incorporated into the cost price of a single project more precisely. This enhancement would not only strengthen profitability by providing a clearer understanding of cost structures but also facilitate better decision-making in financial planning and strategic development. By addressing these areas, Company Y can establish a more adaptive and effective framework for managing production costs.

3.5 Summary

This chapter provides an overview of Company Y's current operational and financial practices, highlighting the production process, cost structure, product costing method, and areas needing improvement. The production process encompasses all tasks required to assemble and prepare customised renewable energy plants, ranging from cutting and welding metal frames to performing insulation, wiring, and quality checks. Production data are partially collected on the factory floor through computer panels, creating a foundation for more detailed cost tracking in the future. Regarding the cost structure, the chapter outlines how direct costs, such as materials and labour, are traced to specific business units, while indirect costs, such as utilities and maintenance, are allocated based on operational metrics like hours or headcount. Overhead expenses are distributed according to facility space usage. Although some elements resemble ABC principles, the overarching method remains standard costing, relying on periodically updated overhead rates. The chapter concludes by noting limitations in the current cost allocation and budgeting process. These shortcomings are especially problematic in a custom manufacturing environment, as standard costing does not capture the variability inherent in different projects.

4 SELECTING COSTING & REGRESSION METHODS

Selecting the most appropriate cost accounting method is critical for effective financial management in a complex manufacturing environment. This chapter evaluates various cost accounting methods and regression techniques to address Company Y's specific challenges, such as handling customised products, low production volumes, and extensive production cycles. By incorporating regression analysis into the evaluation process, the study ensures a data-driven approach to identifying cost drivers and assessing the budgeting process. The implementation of these methods support the development of a tailored solution that aligns with Company X's strategic objectives and operational realities.

4.1 Establishing Criteria

When determining the most suitable cost accounting method, it is vital to establish a set of criteria that reflect both the operational characteristics and strategic priorities of the organisation. The following criteria have been identified, based on interviews with employees, as critical for Company X.

Production characteristics: consisting of the sub-criteria *low production volume*, *customised products*, and *extensive production cycles*.

Scalability: the ability to adapt if production scales up or diversifies. This is important if the cost accounting method needs to be applied to other products at Company X or if the production volume increases in the future. Company X is always innovating for new products.

Implementation feasibility: ease of adoption, including compatibility with existing ERP systems or Excel tools.

Accuracy and detail: precision in allocating direct and indirect costs to improve decision-making.

Strategic alignment: supporting business goals of Company X, which is mainly improving budgeting and financial planning to maintain profitability.

Another criterion that might seem relevant is compliance with financial standards such as the GAAP and IFRS. However, the goal of this cost accounting model is to support internal decision-making. In contrast, compliance with financial standards is necessary for external reporting requirements, as investors and financial institutions rely on these reports. This is why this criterion is not included in the selection.

4.2 Weighting the Criteria

This section explores what weighting method fits best in selecting the right cost accounting method for Company X. The weighting of criteria is executed including a consistency check is shown thereafter. With the proper weights determined, the right cost accounting method can be chosen.

4.2.1 Selecting a proper weighting method

To ensure that the right cost accounting method is chosen in this chapter, the right method to assess the weight of the criteria established in Section 4.1 is vital. A few factors influence the decision to choose the right weighting approach (Ayan et al., 2023).

The weighting process must balance complexity with available time and resources. When deadlines are tight or expertise is limited, a simpler approach ensures clarity and efficiency. In contrast, more detailed methods yield deeper insights when sufficient resources are available. The number of criteria also influences complexity. Smaller sets are easier to manage, while larger sets require a structured and systematic approach to ensure fair evaluation and accurate weighting. The type of data used is also crucial. Quantitative data supports evidence-based decisions, while qualitative inputs, like expert opinions, need structured interpretation. Stakeholder involvement influences the process, as collaboration becomes essential when multiple perspectives are considered (Odu, 2019). Maintaining consistency and objectivity reduces bias, increases confidence in results and aligns with strategic objectives.

Based on the factors that influence the decision described above, the Analytic Hierarchy Process (AHP) emerges as the most suitable weighting method. AHP is the most suitable method for the following reasons. With a manageable number of seven criteria, AHP provides sufficient depth without becoming overly resource-intensive. It facilitates an organised comparison process, ensuring that all criteria are appropriately weighted based on their relative importance (Odu, 2019). AHP accommodates both types of inputs, translating qualitative judgments into numerical weights while incorporating measurable data where available. AHP includes built-in consistency checks, which evaluate whether judgments made during pairwise comparisons are logically consistent. This feature reduces the likelihood of subjective bias and ensures the reliability of the weighting process. For a decision as critical as selecting a cost accounting method, maintaining consistency is crucial to building confidence in the results (Toloie-Eshlaghy et al., 2011). The criteria and their relevance to Company X's operations require a method that can handle nuanced trade-offs between operational efficiency, strategic goals, and scalability. AHP's flexibility in weighting and ranking criteria ensures that the process aligns closely with the company's specific needs and priorities.

4.2.2 Assigning Weight to Criteria

AHP is a structured decision-making method designed to evaluate and prioritise multiple criteria or alternatives. It simplifies complex decisions by breaking them into a hierarchy that consists of the overall goal, the criteria, sub-criteria, and alternatives. For this study, the overall goal is selecting the cost accounting method, then we have the criteria, including production characteristics as sub-criteria, and the alternatives, namely the costing methods (ABC, Job costing, etc.) (Saaty, 1990). AHP relies on pairwise comparisons to assess the relative importance of each criterion and the performance of alternatives with respect to those criteria. Through this process, numerical weights are calculated for each criterion, and overall scores are determined for each option based on their relative importance. In this comparison, there are nine different scales of importance from one criterion to the other. The value 1 means that they are equally important, 3 means the one is moderately important over the other one, 5 stands for strong importance all the way up to 9, which indicates extreme importance (Taherdost, 2017). The two pairwise comparisons for the criteria and sub-criteria can be found in Tables 4.1 & 4.2. These scores were given based on interviews with production and finance employees.

Table 4.1: Criteria Pairwise Comparison

Criteria	Production	Scalability	Implementation	Accuracy	Strategic	Average Weight
Production characteristics	1	5	4	1	5	0.380
Scalability	0.20	1	0.33	0.20	0.50	0.058
Implementation feasibility	0.25	3	1	0.33	2	0.135
Accuracy and detail	1	5	3	1	4	0.342
Strategic alignment	0.20	2	0.50	0.25	1	0.085

Table 4.2: Sub-criteria Pairwise Comparison

Sub-criteria	Low production volume	Customised products	Extensive production cycles	Average weight
Low production volume	1	0.20	0.33	0.106
Customised products	5	1	3	0.633
Extensive production cycles	3	0.33	1	0.260

Each column is normalised by dividing each cell by its total column value. Thereafter, the average weight of each row is calculated, which can be found in Tables 4.1 & 4.2 as well. The average weight of the sub-criteria is multiplied by the average weight of the production characteristics to calculate the final weights of the sub-criteria.
One of the key features of AHP is its built-in consistency check, which ensures that the judgments made during the pairwise comparisons are logical and unbiased. This makes the method particularly effective in reducing subjectivity. The Consistency Ratio (CR) is calculated by the following steps (Saaty, 1990):

1. The pairwise comparison matrix (Tables 4.1 & 4.2) is multiplied by the weight vector (average weight column in Tables 4.1 & 4.2) to calculate a consistency vector.

2. The estimate of the eigenvalue associated with each row is calculated by dividing the consistency vector by the weight vector. Thereafter, λ_{max} is calculated as the average of all the estimated eigenvalues.

3. Thereafter the Consistency Index (CI) is determined by Equation (4.1) where λ_{max} is the largest eigenvalue and n is the number of criteria (Taherdost, 2017).

$$CI = \frac{\lambda_{\text{max}} - n}{n - 1} \tag{4.1}$$

4. Then the Consistency Ratio (CR) is calculated with Equation (4.2).

$$CR = \frac{CI}{RI} \tag{4.2}$$

Random Index (RI) is a benchmark based on the number of criteria. In this case, with five main criteria, the RI is 1.12. For the three sub-criteria, the RI is 0.58. A CR of less than 0.1 is considered acceptable. The RI of the criteria table turns out to be 0.02 and the RI of the sub-criteria table turns out to be 0.03. Both of these values indicate that the pairwise judgements are comfortably consistent (Saaty, 1990). Full calculations can be found in Appendix A.2.
Implementing AHP, consistent weights for each criterion were established. These are used for the cost accounting method selection process in Section 4.3. The *low production volume* has a weight of 0.040. The *customised products* criterion has a weight of 0.241, while the *extensive production cycle*s criterion has a weight of 0.099. *Scalability* weighs 0.053, *implementation feasibility* weighs 0.135, *accuracy and detail* weighs 0.342, and *strategic alignment* weighs 0.085.

4.3 Evaluating Cost Accounting Methods

In this section, the cost accounting method for the costing model is chosen. This is done with the weighted criteria of the previous section. Normally, AHP is continued for the alternatives level (the cost accounting methods) to come to the final conclusion. For each criterion, a pairwise comparison is made by evaluating all the possible cost accounting methods against each other. The pairwise comparison between the cost accounting methods is, in this case, too detailed. Instead, a simpler method is chosen to reduce subjectivity. The last step of choosing the cost accounting method is done through a Weighting Scoring Model (WSM). It is described as simpler compared to AHP, as it does not require a pair-wise comparison (Chourabi et al., 2019). It can be mathematically expressed as Equation (4.3).

$$\text{Total Score} = \sum_{i=1}^{n} (w_i \cdot s_i) \tag{4.3}$$

where w_i is the weight of criterion i and s_i is the score for criterion i. The score can, in this case, be either 0 or 1. A score of 0 means that the cost accounting does not sufficiently support that criterion, and a score of 1 means that the method does sufficiently support the criterion.
With the criteria and alternatives defined, we immediately move on to the scoring of the alternatives based on the criteria. The scoring of the costing methods is grounded in the theoretical framework outlined in Chapter 2. The results are shown in Table 4.3.

Table 4.3: Scores Alternatives

Scores	Low volume	Customised	Long cycles	Scalability	Implementation	Accuracy	Strategic
Traditional	0	0	0	0	1	0	0
ABC	1	1	1	1	0	1	1
TD ABC	1	1	1	1	0	1	1
Job	1	1	1	0	1	1	1
Standard	0	0	0	1	0	0	1
Process	0	0	0	1	1	0	0

Traditional costing allocates overhead using a single rate or a limited set of rates, typically based on direct labour or machine hours. This method is straightforward to implement and compatible with spreadsheets or ERP systems, making it accessible for basic cost management (Horngren et al., 2018). However, its simplicity is a disadvantage when dealing with diverse product complexities or customised production in low volumes. In such cases, costs are often inaccurately distributed, which can mislead financial planning and undermine budgeting. Scalability, while technically feasible, becomes increasingly inaccurate as product diversity grows, making traditional costing unsuitable for Company X's dynamic production environment.

ABC enhances accuracy by linking costs to activities, such as setups or inspections, and allocating expenses based on the extent of activity utilisation by each product. This approach is particularly valuable for environments like Company X's, where products are customised, and production cycles are lengthy. Modern ERP systems often support ABC, which improves managerial decision-making by offering detailed cost insights (Kaplan, 1997). However, the method's data-intensive nature increases implementation complexity and future supervision. Despite this, the strategic value of ABC lies in its ability to align overhead allocation with actual resource consumption, supporting Company X's goal of budget refinement. ABC is particularly effective when it is easy to track which activities contribute to specific products, even if the exact resource usage within those activities is harder to determine (Hoozée & Hansen, 2018).

TDABC simplifies ABC by using time as the primary cost driver, requiring only the cost of resource capacity and the time taken for activities (Kaplan & Anderson, 2007). This method is well-suited to capturing time variations in producing customised products with lengthy cycles, as seen in Company X's operations. Compared to ABC, TDABC is easier to implement and update, as it eliminates the need for detailed activity data. However, there are disadvantages when applied to Company X's situation. TDABC relies heavily on a reliable time-tracking system and is sensitive to measurement errors. If employees forget to record time spent on specific production orders or frequently switch between tasks, inaccuracies can arise. Furthermore, some cost pools may not be effectively measured using time as a cost driver, making TDABC impractical for certain areas (Hoozée & Hansen, 2018). While TDABC is more accurate when tracking resource usage across activities, it is less effective in linking these activities to individual product costs. Despite its data intensity, TDABC provides a scalable and efficient tool for cost tracking, aligning with Company X's strategic objectives of financial accuracy and efficient resource utilisation.

Job costing tracks costs on a project basis, recording direct materials, labour, and overhead for each unique job (Horngren et al., 2018). This method excels in environments like Company X's, which are characterised by low production volumes and high customisation. While it provides precise direct cost tracking, its scalability becomes challenging with increasing job complexity or volume. By integrating activity-based elements, job costing can enhance overhead allocation accuracy (Fayek, 2001), making it a viable option for Company X's emphasis on project-specific cost insights.

Standard costing, which is mainly used currently by Company X, relies on predetermined cost standards for materials, labour, and overhead, comparing these to actual costs to identify variances in budgeted amounts (Drury, 2018). While effective in stable, high-volume production settings, it is less suitable for Company X's customised and evolving product environment. Frequent updates are required to maintain accuracy, diminishing the simplicity of this approach. This is also necessary if the production is scaled up, but it is feasible. Additionally, standard costing lacks the granularity needed to handle complex overhead allocation, limiting its value for detailed cost management in innovative, project-based environments.

Process costing aggregates costs across continuous production flows, yielding average costs per unit (Drury, 2018). This method is ideal for homogeneous, high-volume production but fails to differentiate costs in customised or varied production environments like that of Company X. Its inability to provide detailed cost allocation makes it unsuitable for improving cost precision in complex manufacturing settings. While process costing is less suited for diverse product lines, it handles increased production volumes effectively (Soudatti, 2024). Its straightforward implementation and compatibility with ERP or Excel systems further enhance its appeal as a cost management method.

By multiplying the scores in Table 4.3 with the weights established in Section 4.2.2, we can calculate the total weighted scores for each method. ABC and TDABC both come out highest with a score of 0.865. Job costing is close, with a score of 0.808. Process, standard and traditional costing are less suitable, with scores of 0.292, 0.143 and 0.135, respectively. Given Company Y's production environment, the most suitable options are TDABC and standard ABC. Both methods offer flexibility and scalability for capturing cost variations across activities, aligning with the company's strategic objectives of improving cost accuracy and financial planning. However, there is a disadvantage to TDABC compared to ABC when looking at the situation of Company Y. TDABC uses time as the main cost driver. It would be very impractical to measure some cost pools with time as a cost driver. Furthermore, as mentioned earlier, TDABC needs to rely on a reliable time-tracking system and is very sensitive to mistakes. TDABC is more accurate when it is easy to track how resources are used in different activities, but it is harder to track how those activities contribute to individual products. ABC is more accurate when it is easy to track which activities contribute to specific products, even if it is difficult to see exactly how resources are used in those activities. So, in manufacturing, one might know exactly how much time and effort each step in production takes per product, but it is harder to measure the exact resource cost for each activity. In conclusion, ABC is more suitable than TDABC in the context of Company X. This cost accounting method is thereby implemented in this study.

4.4 Improving the budgeting process through regression

In this section, a regression method is selected to identify areas of improvement in the budgeting process of Company Y. Regression analysis is a powerful tool for identifying and addressing inaccuracies in the quotation process. Examining relationships between cost components and total variance provides a systematic way to understand why cost estimates deviate from actual values. One key advantage of regression analysis is its ability to pinpoint which factors in the quotation process contribute most to inaccuracies. Independent variables, such as labour costs, material expenses, or subcontractor fees, can be assessed for their impact on the dependent variable, such as the total cost incurred. This helps identify whether specific elements are consistently over or underestimated, offering actionable insights to refine the process. For instance, the model can reveal if complex projects systematically underestimate labour costs or if indirect costs are disproportionately allocated. These insights are invaluable for reducing discrepancies and ensuring more accurate cost forecasting. First, we need to translate the current situation into characteristics that enable us to find the right regression method for solving this problem. We start with finding out what variables we will use. Then, we investigate what data characteristics are present, how the model is balanced, and how the regression analysis aligns with the research objectives. To conclude, the regression method used for this study is determined.

To find out what needs to be improved in the budgeting process, we need to establish what influences the additional costs. Where the actual total cost is our dependent variable, we also have independent variables. These variables are our cost drivers. There are five main cost components which are just for budgeting a single project. These are **material** costs, **labour** costs, **subcontractors** costs, **indirect** costs (excluding overhead) and **overhead** costs. These five cost components form the independent variables.

The data set contains 71 data points before cleaning the dataset. We also need to make sure that the function of the regression method is aligned with the research objective. The research objective is to find out what part of the estimated costs is structurally badly estimated. This means that we need to find out what independent variable has the highest impact on the overall cost deviation of production.

Taking these characteristics of the current situation into consideration, MLR is most suitable. The situation explores a single continuous dependent variable and multiple predictors. The rule of thumb is that each predictor needs a minimum of ten data points (Stevens, 1996), which is the case. MLR is useful for understanding the relationship between variables and quantifying how each independent variable affects the dependent variable. This is exactly the relationship that needs to be studied in the budgeting process analysis. The limitation of the method is that if the independent variables are highly correlated, which makes the model non-linear, alternative options should be explored.

4.5 Implementation Strategy

ABC is applied to the cost price model using Microsoft Excel due to its accessibility and ease of use for employees at Company X. This choice ensures that refinements can be made with minimal training. The implementation process systematically utilises historical data, including production logs, monthly financial reports, and past quotations, to execute the cost accounting method step by step. After the model was finalised, it underwent a robustness assessment through sensitivity analysis. Key parameters are incrementally adjusted (first by 10%, then by 20%, for example) while others remain constant. The resulting variations in cost estimates highlight potential risk areas. Parameters causing large fluctuations indicate areas requiring more robust data collection or stricter process controls. This validation process ensures that the model remains adaptable to varying operational conditions.
Regression analysis begins with data preparation, forming the foundation for reliable analysis. Production order data is consolidated into a unified dataset, incorporating both independent and dependent variables, as outlined in Section 4.4. Data cleaning follows to address missing values. A robust validation strategy, as discussed in Section 2.4.4, is implemented to ensure the generalisability of the results. Cross-validation techniques, such as Leave-One-Out-Cross-Validation, further enhance the model's robustness by dividing the training set into multiple folds. This iterative process allows the model to be trained and validated on different subsets of data, reducing the risk of overfitting. The training set is used to build the model, while the test set evaluates its performance on unseen data.
Bringing together data preparation, appropriate tool selection, rigorous validation, and awareness of methodological constraints ensures a robust approach to studying the budgeting process. Once the final regression model was developed and validated, it was applied to the test data to identify systematic biases.

4.6 Summary

This chapter focuses on selecting the most appropriate cost accounting and regression analysis methods. The chapter begins by establishing key selection criteria, ensuring that the chosen methods align with the company's context. To determine the relative importance of these criteria, AHP was applied, allowing for a structured weighting process. ABC and TDABC emerged as the most suitable options. However, TDABC relies heavily on time tracking, making it less practical for Company Y's operations. Consequently, ABC was chosen as the most appropriate cost accounting method for this study. To enhance the budgeting process, a MLR model was selected to identify systematic inaccuracies in cost estimation. Multiple linear regression was considered appropriate as it allows for the analysis of multiple cost drivers influencing the total production cost. The model was designed to quantify how labour, material, subcontractor, indirect, and overhead costs contribute to deviations in cost estimations. Finally, an implementation strategy was outlined for integrating ABC into the cost price model and applying regression analysis. This includes testing the ABC model for robustness through multiple sensitivity analyses, cross-validating the regression model, and analysing performance metrics of the regression model to mitigate overfitting risks.

5 DEVELOPING TOOL & ANALYSING RESULTS

This chapter details the implementation of the selected cost accounting within Company Y's cost price model and regression methods. The primary objective is to enhance cost visibility and improve variance detection through the combination of an ABC model and an MLR analysis. By incorporating these methods, the study aims to provide a data-driven approach to cost allocation and variance identification, ultimately supporting strategic financial management.
The implementation process consists of the following steps. First, an ABC cost price model is developed to allocate direct and indirect costs more accurately. Second, a regression analysis using MLR is conducted to identify key cost drivers and quantify their impact on overall cost deviations. Afterwards, both models are assessed based on their performance and robustness through sensitivity analysis, cross-validation techniques, and error metrics to ensure reliability and applicability within Company Y's operational environment.

5.1 Data Preparation

A crucial step before implementing the ABC model and conducting the regression analysis is to ensure that the dataset is structured, realistic, and representative of actual production costs. Assessing the accuracy of the cost price model is preferable to determine its feasibility for implementation within Company Y's production system. However, there is not enough data available for a direct validation of the model's accuracy. Instead, a sensitivity analysis is conducted to evaluate the model's behaviour under varying conditions. This analysis requires a baseline derived from historical data to serve as a reference point, which is possible with the available data. By systematically applying relative changes to key parameters, the model's sensitivity can be examined using established sensitivity analysis techniques. This approach identifies the parameters that exercise the greatest influence on cost outcomes, highlighting the aspects that must be estimated precisely once sufficient data becomes available. Through this method, the robustness of the cost price model can be assessed, ensuring its reliability for future integration into Company Y's operational framework.
The dataset used for the regression analysis is less detailed than the one used for the ABC model. The dataset that is available for the regression analysis initially contained 71 data points for each cost component. However, upon reviewing the data, certain entries were identified where actual costs were recorded, but the corresponding budgeted values were missing. Given that the objective of this analysis is to identify inefficiencies within the budgeting process, such incomplete entries would introduce bias, distorting the outcomes. Consequently, these entries were excluded to maintain integrity. Following this, the dataset was reduced to 50 data points, ensuring that all retained observations contain both actual and budgeted values, thereby allowing for a reliable assessment of cost estimation accuracy. For the regression analysis, the use of dummy data is not feasible, as it would compromise the validity of the results. The analysis relies on real data to ensure meaningful insights into cost deviations and budgeting inefficiencies.

5.2 Implementing ABC

This section describes the implementation of ABC to improve cost allocation accuracy within Company Y. The process starts by identifying key activities and cost pools, including those directly related to production, such as stainless steel and electrical work, as well as supporting cost pools like quality management, logistics, and corporate overhead. Cost drivers are then assigned to each activity and cost pool based on resource consumption, such as labour hours or the number of production orders. The cost driver rates are calculated to distribute indirect costs proportionally (Arnaboldi & Lapsley, 2005). Finally, the ABC model is constructed by combining direct costs with allocated indirect costs using the calculated cost driver rates. This structured approach ensures precise cost attribution to projects.

5.2.1 Activities and Cost Drivers

First, we need to identify the activities that form the production process addressed in Section 3.1. The four activities that contribute directly to building renewable energy installations are the following. We have the *stainless steel*, *carbon steel*, *internal assembly* and *electrical* activities. Secondly, it is essential to identify the cost pools required for the entire operation that do not directly contribute to production. These include *quality management*, *production controlling*, *production coordination*, and *production management*. Additionally, there are *supply* costs (related to procurement), *warehousing*, and *logistics*, as well as *corporate overhead*. Corporate overhead covers expenses related to sales, office operations (such as rent and utilities), finance and accounting, administration and HR, and management. These cost pools are grouped based on their shared causal effects on costs, allowing for the assignment of appropriate cost drivers to each pool. This grouping ensures that each cost pool is traceable to the activities that genuinely consume the associated resources (Sarasanty & Asmorowati, 2023).
A specific cost driver is assigned to each activity and cost pool, selected to reflect how the activity consumes resources. Cost drivers are factors that influence cost fluctuations and directly impact expenditure levels (Gunasekaran & Sarhadi, 1998). The cost drivers corresponding to each activity or cost pool are presented in Table 5.1, where POs represent production orders.

Table 5.1: Cost Drivers per Activity/Cost pool

Activities	**Cost Driver**
Stainless steel	SS Labour hours
Carbon steel	CS Labour hours
Internal Assembly	Assembly Labour hours
Electrical	Electrical Labour hours
Cost Pools	**Cost Driver**
Quality Management	Number of inspections
Production Controlling	Number of POs
Production Coordination	Number of POs
Production Management	Number of POs
Supply	Weight
Warehousing	Number of POs
Logistics	Weight
Corporate Overhead	Labour hours

The cost pools contribute to the production of a single project to some extent. However, corporate overhead does not, as these costs remain fixed regardless of production volume. To allocate these costs to a single project, labour hours are used as a general but precise measure. Although sales costs could be attributed to a project, for example, based on the number of invoices, they are minimal and therefore negligible. Since Company X primarily manages the sales process rather than Company Y, these costs have a limited impact on production expenses. Consequently, sales costs are incorporated into the corporate overhead cost pool.
For each activity or cost pool, the cost driver rate is calculated (Tornberg et al., 2002). The cost driver rate is calculated in Equation (5.1).

$$\text{Cost Driver Rate} = \frac{\text{Total Cost in Pool}}{\text{Total Volume of Cost Driver}} \tag{5.1}$$

For instance, the total indirect costs for the stainless steel activity were €1,000,000 in one year, and the total hours of labour for that activity was 10,000. The cost driver rate would be €100 per hour. Likewise, the cost driver rates for each one are calculated. This is partly done with real data and partly with assumptions. Most of the financial data was real, and most of the production data was assumed. The assumptions were either made by experts in the company or estimated based on historical data. The assumptions based on historical data were checked with experts within the company to assess if they resembled the real situation.

5.2.2 ABC Model

With the activities, cost pools, and corresponding cost driver rates defined, the model can be constructed. The model's input consists of direct costs alongside variables required to ensure that all indirect costs are accurately allocated to the corresponding project. Direct costs include material costs, direct labour costs, and subcontractor costs. The direct labour costs are determined by multiplying the number of hours associated with each sub-activity by the corresponding salaries. Figure 5.1 illustrates the relationship between the inputs and cost driver rates. The light blue inputs represent the inputs that (partly) influence the direct costs of a project, while the white inputs correspond to the indirect costs. To enhance visibility, the lines originating from the number of POs are shown in blue.

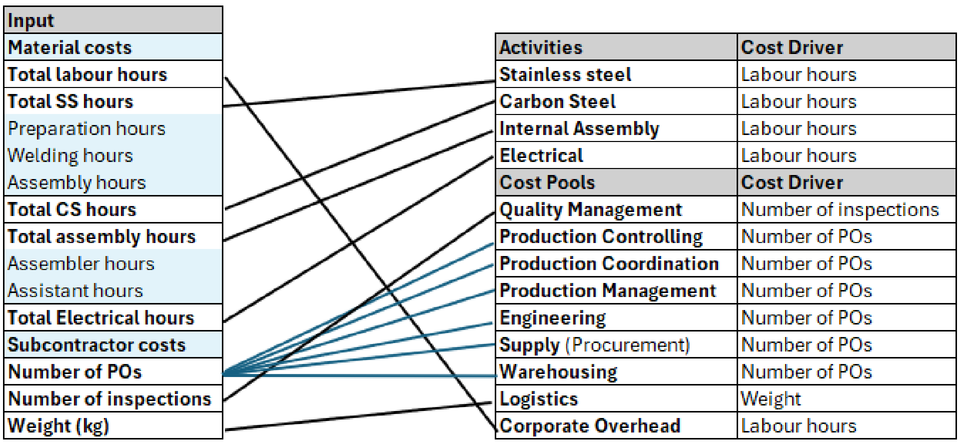

Figure 5.1: Relation between Inputs and Cost Driver Rates

The output of the model is presented in Appendix A.3.1, which is a summation of five main cost components mentioned in Section 4.4. It is important to note that the output makes a distinction between indirect costs and overhead costs. Typically, overhead costs are considered a subset of indirect costs. However, in this model, they are treated as separate cost pools due to the accounting structure used in Company Y.

5.3 Regression Analysis

In this section, the MLR model is used to conduct a regression analysis. This enables us to see which cost component of the quotation process is systemically wrong, leading to an inaccurate total cost. The goal is to identify which specific areas of the budgeting process are driving the differences between the budgeted and actual total costs.

5.3.1 Regression Model Setup

The formula of the MLR model is mathematically expressed in Equation (5.2).

$$\text{Cost Error} = \beta_0 + \beta_1 \times \text{Budgeted Material} + \beta_2 \times \text{Budgeted Labour} + \cdots + \epsilon \tag{5.2}$$

The dependent variable is the cost error made in the budgeting process. A positive error would indicate that the total budget is higher than the actual cost, and a negative error indicates an underestimate. Equation (5.3) determines the cost error.

$$\text{Cost Error} = \text{Total Budget} - \text{Total Cost Actual} \tag{5.3}$$

The independent variables in the model represent the budgeted costs across all cost components, including material costs, labour costs, subcontractor costs, indirect costs, and overhead costs. Additionally, the model includes an intercept term β_0 The ideal value of the intercept is zero. The intercept reflects the baseline cost error when all budgeted components are zero (Montgomery et al., 2012), though this scenario is not realistic because budgets typically are not zero. A non-zero intercept suggests a systematic discrepancy between budgeted and actual costs that is not accounted for by individual components.
Each coefficient $\beta_1, \beta_2, \ldots, \beta_5$ represents the expected change in the overall cost error for a one-unit increase in that specific budget component while holding all other components constant (Chatterjee & Hadi, 2006). If a coefficient is positive, it indicates that as the corresponding budget component increases, the estimation error increases. This means that higher values in that budget component are associated with a greater overestimation if the error is positive or reduced underestimation. If a coefficient is negative, it indicates that as the corresponding budget component increases, the estimation error decreases. In other words, increasing that component's budget is associated with a lower error or a shift towards underestimation.
Since cost error is defined as the difference between budgeted and actual costs, a positive error indicates overestimation (budget exceeds actual costs), whereas a negative error indicates underestimation. The model is, therefore, designed to isolate the individual impact of each cost component, identifying which elements contribute most to budget deviations while controlling for overall budget magnitude.

5.3.2 Multicollinearity

Multicollinearity occurs in MLR when two or more independent variables are highly correlated. This means that one variable can be predicted from the others, making it difficult to determine their individual impact on the dependent variable. As a result, the regression coefficients become unstable, meaning small changes in the data can lead to large differences in the results. Additionally, the p-values become unreliable, making it harder to identify which variables are truly important (Chatterjee & Hadi, 2006). In this case, multicollinearity might be a problem of a more theoretical nature. The predictors included in this regression analysis are naturally interdependent, meaning that multiple predictors partially capture the same underlying patterns in the data. As a result, interpreting the individual effects of each predictor becomes more complex, as their contributions to the dependent variable cannot be entirely separated. While multicollinearity does not necessarily undermine the model's predictive power, it can lead to misleading conclusions regarding the significance and relative importance of individual cost components. Therefore, this limitation should be acknowledged when drawing insights from the regression results, ensuring that any conclusions regarding cost drivers and budgeting inefficiencies are made with caution.

To check for multicollinearity, a correlation matrix heatmap was created, as shown in Appendix A.3.2. This heatmap shows how strongly the independent variables are related to each other. In this case, the predictors show a high correlation, which is expected given the nature of the data. To further address the issue, the Variance Inflation Factors (VIF) are calculated for each cost component. As mentioned in Section 2.4.3, VIF is one of the key measures to detect multicollinearity (Kim, 2019). The results of this calculation are shown in Table 5.2. When the VIF is 1, there is no multicollinearity present. a VIF between 1 and 5 is considered low, above 5 is considered high, and above 10 is considered severe (Kim, 2019). However, since addressing multicollinearity in detail is beyond the scope of this research, no further steps were taken to correct it. Still, this should be kept in mind when interpreting the final results of this study.

Table 5.2: VIF values

Feature	**VIF**
Constant	1.94
Material Budget	11.27
Labour Budget	28.98
Subcontractor Budget	3.30
Indirect Budget	5.78
Overhead Budget	3.18

5.3.3 Cross-Validation Approach

As mentioned in Section 2.4.4, leave-one-out cross-validation (LOOCV) is particularly useful for small datasets (Martens & Dardenne, 1998). According to the rule of thumb, at least 10 data points are needed for each predictor present in the model (Stevens, 1996). As there are 50 data points available for 5 predictors, this would be the bare minimum. Considering this makes LOOCV a good cross-validation method to implement in the MLR model in this study. LOOCV maximises the use of training data and provides a nearly unbiased estimate of the out-of-sample error compared to other cross-validation methods. This is because each validation set closely represents the full data distribution (Auddy et al., 2024). A limitation of LOOCV is that it is computationally expensive with larger datasets, but, in this case, that is not an issue.

5.4 Performance Evaluation of the Models

In this section, the results from both model evaluations are presented. Firstly, the sensitivity analysis of the ABC model is shown using One-Factor-at-a-Time (OFAT) analysis, followed by Morris analysis. Secondly, the statistical analysis of the MLR model coefficients is explained. The significance of the coefficients is assessed, followed by an evaluation of the model's fit.

5.4.1 ABC Model Sensitivity Analyses

The ABC model's robustness is tested through sensitivity analysis by varying input variables and observing total cost price fluctuations. This can be done through various techniques. The context of this sensitivity analysis can be described as follows. There is little real-world data available, and the goal is to identify which inputs (budgeting amounts) and which cost driver rates should carefully be calculated if data becomes completely available. Based on this situation, the sensitivity analysis is conducted through the OFAT technique. Multiple sensitivity analyses create a more robust understanding of the cost price model. Therefore, the Morris method is implemented to investigate combinations between parameters.

OFAT is used to measure the impact of an individual parameter on systems outputs while keeping other variables fixed (Koushik, 2022). It helps identify critical factors affecting the cost price total in this case. It is simpler to implement and interpret compared to other global methods like Monte Carlo simulation (Delgarm et al., 2018). This is why it is a convenient method for an initial screening. By screening influential parameters, the model can be adjusted before applying advanced methods. Furthermore, it is a beneficial method when computational power or time is limited, which is the case for this study. However, there are limitations. OFAT is often criticised for its inability to handle complex, non-linear situations, which could lead to misleading conclusions if used solely (Ferretti et al., 2016). Furthermore, it ignores the effect of combinational changes in parameters. It also depends heavily on the chosen baseline, potentially missing non-linear behaviour (Koushik, 2022).

The OFAT method is applied in the following steps (Ferretti et al., 2016). This approach operates through parameter variation, where a single input parameter (both the input variables as well as the cost driver rates) is systematically varied across its range. The baseline for this analysis is derived from real project data from the previous year. Each parameter is adjusted within a range of 5%, 10%, and 20%, both increasing and decreasing relative to the baseline value, while all other parameters remain unchanged. The corresponding changes in the output are recorded, and the relative impact on the total cost price (TCP) is calculated using Equation (5.4). This process is repeated for each parameter to isolate its individual effect on the TCP while maintaining all other variables at their baseline values.

$$\text{Relative Deviation (\%)} = \frac{\text{Modified TCP} - \text{Baseline TCP}}{\text{Baseline TCP}} \times 100 \tag{5.4}$$

By conducting this analysis, we can create a Tornado diagram. A Tornado diagram is a visual tool used in sensitivity analysis to rank input factors by their impact on the model's output. This helps identify key drivers (Borgonovo & Plischke, 2016). This is closely integrated with the objective of OFAT. The diagram displays horizontal bars representing the sensitivity of the model output to changes in individual inputs. The bars are sorted by magnitude, with the largest effects at the top, creating a "tornado" shape.

In Figure A.4 located in Appendix A.3.3, we can see the relative impact of the changes in input variables. In this diagram, material costs and direct labour hours stand out by having the largest percentage range (range between the highest and lowest deviation) in the total cost price, 13.13% and 9.13%, respectively. By contrast, inputs such as the assembly labour in the stainless steel phase, as well as the preparation labour, have a much smaller effect, under 1%. In practical terms, that means the overall costing model is most sensitive to changes in material costs and direct labour hours. If Company Y were to improve cost estimates, they would want to pay particular attention to accurately budgeting these two drivers since a small error in either could lead to a change in the total cost that is larger than expected. Conversely, the model is less sensitive to some other inputs, such as the assembly labour for the stainless steel activity, so errors in estimating those have a relatively smaller impact on the bottom line.

Looking at the Tornado diagram in Figure A.4, it is easy to interpret that the diagram is symmetric. This indicates that the model behaves linearly in each input variable. Note that the deviations shown in the diagram are the highest and the lowest deviations. If we look at the detailed results, we can conclude that for each input variable, the highest and lowest deviation stems from a parameter change of 20% and -20%, which makes sense since the model behaves linearly. Zooming into a particular input variable, we can see the linear behaviour in the changes between the incremental steps. This can be seen in Figure A.5.

However, in the previous OFAT analysis, dependency between input variables was not taken into account. This is a limitation of the OFAT analysis. For example, increasing the value of the welding hours in the stainless steel activity also increases the costs related to the direct labour hours. Taking this into account for all input variables gives us the following Tornado diagram in Figure A.6. In this figure, we see that material costs still have the largest impact on the total cost price, which makes sense as it does not depend on other input variables. The impact from other input variables is now illustrated more realistically. Note that the direct labour hours did not change. They consist of carbon steel, stainless steel, internal assembly and electrical labour. However, it is difficult to say if direct labour hours increase, what part of them increases, affecting indirect costs of these activities, which ultimately influences the total cost price. This effect is not incorporated into the analysis. Conducting the same analysis for the cost driver rates, gives us the diagram shown in Figure A.7. Again, in practical terms, these outcomes highlight corporate overhead cost driver as the main rate to watch if the total cost price has to be accurately calculated. While it is still important to monitor the smaller drivers, they are less likely to cause a major swing in overall costs unless they change by a very large amount.

The Morris method, also known as the Elementary Effect (EE) method, is an efficient approach for high-dimensional models with limited computational resources. This is relevant to this study as 24 parameters are part of the costing model. The method identifies non-linear effects and interactions between parameters, providing qualitative rankings to prioritise parameters requiring tighter control (Nguyen & Reiter, 2015). Although originally developed for screening, the Morris method can also rank inputs by importance (Saltelli, 2002).

The costing model in this study contains dependent inputs. For example, preparation, welding, and assembly hours together form the total number of stainless steel labour hours. A limitation of the Morris method is that it does not account for input dependence (Ge & Menendez, 2017). Based on assumptions validated by company experts, a distribution is made when calculating a joint rate for both direct and indirect costs per activity. For instance, the stainless steel activity consists of 31.28% preparation labour, 26.13% assembly labour, and 42.60% welding labour. The direct cost rates are multiplied by these percentages to form a single direct cost rate for the stainless steel activity. Subsequently, the indirect cost rate is added to establish a unified stainless steel cost driver rate. This makes the analysis less granular but allows for investigating relationships between parameters in the costing model. We now have nine input variables and 13 cost driver rates, totalling 22 parameters.

First, the input space must be defined. The input space consists of five discrete steps per variable, centred around the baseline value. The steps are incremented by 10%, both positively and negatively, resulting in the following values for each parameter: (-20%, -10%, 0, 10%, 20%).

Next, the number of trajectories (r) must be determined. A trajectory represents a structured sequence through the input space, where parameters are systematically perturbed one at a time (Paleari et al., 2021). This process begins at a randomly selected point within the input space. Perturbation refers to the adjustment of a parameter's value to examine its impact on the total cost price. For k parameters, each trajectory consists of $k + 1$ points, as each input is changed once (Menberg et al., 2016).

For this analysis, 50 trajectories are performed. For each trajectory, the elementary effects (EE) are computed (Menberg et al., 2016), quantifying the impact of individual parameter perturbations on the model output. Equation (5.5) calculates the elementary effects.

$$EE_i = \frac{f(X_1, \ldots, X_i + \Delta, \ldots, X_k) - f(\mathbf{X})}{\Delta} = \frac{\text{New Output - Original Output}}{\text{Step size (10\%)}} \tag{5.5}$$

Where delta (Δ) is the perturbation or step each of the variables experiences, a 10% change in this case. This process repeats itself. Eventually, we can compute the mean of absolute elementary effects (μ^*) and the standard deviation of elementary effects (σ). Equation (5.6) and Equation (5.7) determine these values (Menberg et al., 2016).

$$\mu_i^* = 0.5 \sum_{t=1}^{r} |EE_{it}| \tag{5.6}$$

and;

$$\sigma = \sqrt{\frac{1}{(r-1)} \sum_{t=1}^{r} (EE_{it} - \mu_i)^2} \tag{5.7}$$

With 50 trajectories in the Morris analysis, there are 50 elementary effects per parameter. Through bootstrapping, 50 numbers are randomly picked with replacements. 'With replacement' refers to the possibility of picking a number that has already been picked in that sample. Bootstrapping is a statistical resampling method used to estimate the uncertainty of a sample statistic (Wood, 2005), in this case, μ^*. For every sample, the average is calculated. This is repeated a thousand times. So now we have a thousand different means of μ^*. This spread gives us the confidence interval of μ^*, by taking the 2.5% and 97.5% percentiles.

The outcomes are shown in Appendix A.3.4. The mean of absolute elementary effects and the sigma are normalised because they should be interpreted relative to the rest of the parameters, as shown in Table A.3. The confidence interval is normalised by dividing the width of the confidence interval of μ^* by μ^* times 100%. This relative confidence interval is more straightforward for interpretability.

The mean of absolute elementary effects is the main indicator of how influential a parameter is on the model output. The bigger it is, the more it changes the outcome overall. The table is sorted according to this value. This measure is more robust for ranking inputs than the mean elementary effect (μ) (Campolongo et al., 2007). The standard deviation of elementary effects captures how inconsistent or non-linear a parameter's effect is across the input space. A high value suggests that it could behave differently at different points or interact strongly with other parameters (Menberg et al., 2016). The confidence interval around the mean of absolute elementary effects, the third column, indicates that if the interval is small, there is high certainty in that parameter's estimated influence (Campolongo et al., 2007).

Analysing the outcomes, it can be concluded that material costs and subcontractor costs have the most significant impact on the total cost price. This is evident from their high mean values and near-zero standard deviations, indicating a consistently strong influence across different scenarios. Furthermore, the confidence interval is so small that there is essentially no ambiguity about their importance. Additionally, the corporate overhead cost driver and internal assembly labour also show a substantial impact. However, these parameters show a higher standard deviation, suggesting that their effect varies significantly depending on interactions with other input variables. This variability indicates the presence of non-linearities or dependencies within the model. Other parameters that demonstrate substantial but less dominant effects include carbon steel labour, stainless steel labour, the internal assembly rate, the number of production orders, and electrical labour. Comparatively smaller influences are observed for the production controlling cost driver rate and the production coordination cost driver rate, which have a more limited effect on the final cost estimate. Essentially, all of the confidence intervals are relatively small, showing the estimates are reasonably robust.

5.4.2 Analysing the Coefficients

The outcome of the regression analysis is stated in this section. Furthermore, a few statistical techniques are applied to measure the accuracy and significance of the coefficients $\beta_1, \beta_2, \ldots, \beta_5$. This is done through several statistical measures. First of all, the standard error (SE) is measured, which is the variability of the coefficient estimate. Additionally, the t-value and the p-value are calculated.
The coefficients are calculated in the MLR model. Additionally, the measures to evaluate the coefficients are also calculated. How this is done is explained earlier in Section 2.4.7. The outcomes of these can be found in Table 5.3.

Table 5.3: Statistical Values of MLR

	Coefficient	**Std. Error**	**t-Value**	**p-Value**
Constant	5422.306	3717.307	1.458665	0.151759
Material Budget	0.326227	0.263071	1.240072	0.221521
Labour Budget	-3.41929	0.629942	-5.42795	2.32 E-06
Subcontractor Budget	0.082989	0.186015	0.446143	0.657682
Indirect Budget	0.745235	0.225261	3.308322	0.001877
Overhead Budget	1.441165	0.399824	3.604496	0.000793

First, we see that the coefficient for the constant is large. This means that when all predictor variables are set to zero, the model's predicted cost error is around 5422. This could be caused by several phenomena. The most feasible reason is that the dataset is not centered (Nimon & Oswald, 2013). Centering is the action of subtracting the means from the values in the dataset. The dataset consists of POs which vary greatly in size. Some POs have a total budgeted cost amount of a few thousand, others exceed three hundred thousand. Another reason could be the multicollinearity. High correlations between predictors can destabilise coefficient estimates, indirectly affecting the intercept (Nimon & Oswald, 2013). As we concluded in Section 5.3.2, we are dealing with a high level of multicollinearity, so this is feasible as well.
The other coefficients reflect the contribution of the budgeted amount to the cost error. So, for instance, if the coefficient of the material budget is 0.326227, it means that when the material budget increases by 1, and the other budgets are held constant, the cost error will increase by 0.326227 on average. This suggests that there is an underestimation in material budgets. For labour budgets, it suggests that there is a large overestimation. The subcontractor budget has a small underestimation. Furthermore, the indirect cost has a large underestimation and especially the overhead budget is greatly underestimated.
After looking at the results, we also need to explore if the coefficients are precise and significant. According to Montgomery (2012), an absolute t-value exceeding 2.015, in this case, is considered to be suggesting significance. Looking at the table, we can conclude that this is the case for the labour budget, indirect budget, and overhead budget. The p-value is considered to be significant if it is lower than 0.05 (Siegel, 2016). This is, as well, the case for the labour budget, indirect budget, and overhead budget. This essentially indicated that these three cost components significantly influence the cost error in the budgeting process. Considering the nature of these three components, and comparing them to the nature of material and subcontractor costs, this makes sense. However, it should be noted that the p-values are also sensitive to sample size and multicollinearity, which inflate the standard errors (Nimon & Oswald, 2013).

5.4.3 Model's fit

In MLR, the goal is to explain the variation in a dependent variable by using several independent variables. Two closely related metrics for evaluating how well the regression model fits the data are R^2 (the coefficient of determination) and adjusted R^2. However, with using multiple predictors like in this model, adjusted R^2 is preferred (Jianlong et al., 2015) as it, among other things, takes the number of predictors into account by penalising overfitting. Both of the metrics are calculated as explained in Section 2.4.6. They are both calculated because comparing one to the other also gives us insights about the number of predictors. Additionally, the Leave-One-Out Cross-Validation (LOOCV) method is implemented to assess the model's generalisation performance by testing one data point at a time. This approach provides a more realistic estimate of real-world performance, as it evaluates the model's ability to predict unseen data. Cross-validation measures how well the model explains out-of-sample data, meaning data not included in the training set. This process helps identify and mitigate overfitting, where the model becomes too closely adapted to the training data and struggles to generalise effectively (Cheng et al., 2017). By applying LOOCV, the model is not overly tailored to the specific dataset but instead captures broader underlying trends. The resulting values of R^2 and adjusted R^2 obtained through LOOCV are calculated as well.

The R^2 and adjusted R^2 values of the full dataset are 0.82 and 0.80, respectively. The metrics are relatively high, which is positive. This means that 80% of the variance in the cost error is explained by the model. However, the R^2 metrics are more biased in small samples compared to the number of predictors or when explanatory power is low (Akossou & Palm, 2013). A small sample was used for this study. According to Akossou and Palm (2013), a large difference between these values signals overfitting due to irrelevant predictors or a small sample size compared to the number of predictors. In our case, the R^2 and adjusted R^2 differ little from each other, which is a positive sign. A large gap between the two indicates that there are redundant variables, which is not the case (Jianlong et al., 2015).

The values of R^2 and adjusted R^2 obtained through LOOCV are 0.75 and 0.72, respectively. The metrics are lower than those calculated from the full dataset. If the opposite were true, it would indicate that the model is overly optimistic, which is not the case. The difference between the R^2 values from the full dataset and LOOCV provides insight into the model's fit. A significant decline in R^2 suggests poor robustness, particularly in small datasets, as it indicates the model memorises noise rather than learning general patterns (Martens & Dardenne, 1998). In this case, the gap between the R^2 values is 0.076, while the difference in adjusted R^2 is 0.085. These values indicate that the drop in performance is relatively small, suggesting the model maintains a reasonable level of generalisation and does not suffer from severe overfitting.

To assess the fit of the regression model beyond R^2 and adjusted R^2 values, we compare these values with the Root Mean Squared Error (RMSE). While R^2 is useful for understanding how well the model explains variance, RMSE gives a direct measure of the model error. Combining them helps identify issues such as high bias, high variance, or non-linear relationships (Chakraborty & Elzarka, 2017). The goal of this study is not to predict cost error but to identify systematic estimation errors. Although RMSE indicates predictive ability, combining it with R^2 can tell something about the model's fit, confirming whether the relationships between cost components and budget deviations are well captured. Conclusions drawn from a well-fitted model are much more reliable as they are based on statistically significant patterns rather than random noise. The RMSE is calculated with Equation (2.7). Normalising the RMSE by range gives a better understanding of how high or low the RMSE is. The normalised RMSE is 7.10% for the training set and 8.48% for the LOOCV, both below the 10% threshold considered low (Chakraborty & Elzarka, 2017). A high R^2 with a low RMSE indicates that the model captures patterns in cost estimation well and, therefore, provides meaningful insights. However, a slightly higher LOOCV's normalised RMSE indicates that there is a moderate degree of overfitting. Since the difference is relatively small, the model still maintains a reasonable level of generalisability.

5.5 Summary

This chapter outlines the development and evaluation of the cost price model, incorporating an ABC approach and multiple linear regression (MLR) analysis. The ABC model enhances cost allocation by associating indirect costs with relevant cost drivers, while the regression analysis identifies systematic errors in budget estimations. To assess the accuracy and reliability of both models, sensitivity analysis and cross-validation techniques were applied. The findings highlight key cost components contributing to overall cost deviations and provide insights into areas requiring improvement in cost estimation accuracy.

The ABC model analysis identified material costs, carbon steel labour, and the corporate overhead cost rate as the most influential factors in determining the total cost price. Sensitivity analysis demonstrated that deviations in these components had a significant impact, with material costs causing fluctuations of up to 13.13% and carbon steel labour leading to deviations of 13.1% in the total cost price. Corporate overhead cost driver rate and the internal assembly labour emerged as highly influential factors due to their effect on other parameters, highlighting the need for a more precise allocation procedure.

The regression analysis revealed systematic biases in cost estimations. Labour costs were found to be consistently overestimated, with a coefficient of -3.42 and a statistically significant p-value below 0.001. Conversely, indirect and overhead costs were significantly underestimated, with coefficients of 0.75 and 1.44, respectively. Material and subcontractor costs exhibited minimal impact on cost deviations, with coefficients of 0.33 and 0.08, and were not statistically significant. The model achieved an R^2 value of 0.80, indicating strong explanatory power. The adjusted R^2 remained close to R^2, suggesting minimal overfitting. Additionally, leave-one-out cross-validation (LOOCV) produced slightly lower R^2 values, confirming that the model generalises well beyond the training dataset. A relatively low normalised RMSE also shows that the model fits the data reasonably well.

These findings underscore the importance of refining cost estimation for labour, indirect and overhead costs, given their strong influence on total cost deviations. Addressing multicollinearity in labour and indirect cost components further enhances the model's accuracy and predictive reliability, ensuring more robust budgeting processes and improved financial planning.

6 CONCLUSIONS & RECOMMENDATIONS

This chapter presents the key conclusions derived from the research, addressing the central research question of how a structured cost accounting method, combined with regression analysis, can enhance cost insights at Company X. As the production of Company X is carried out by Company Y, the study mainly focused on this company. Following the conclusions, the discussion section reflects on the implications of these findings, acknowledging the study's limitations and practical constraints. Based on the research findings, specific recommendations are formulated to support Company Y in refining its cost accounting and budgeting practices. Finally, suggestions for future research are outlined.

6.1 Conclusions

This research addresses expenses that frequently deviate from initial estimates, leading to financial discrepancies due to unforeseen production costs. The study examined how implementing a structured cost accounting method, combined with regression analytics, could enhance cost visibility and improve financial decision-making. Therefore, the research question was formulated as follows:

How can implementing a new cost accounting method and regression analytics improve Company X's insight into production costs?

The results of the literature review and AHP indicate that activity-based costing (ABC) is the most suitable cost accounting method for Company Y, as it provides a more accurate allocation of indirect costs than the currently used standard costing method. ABC allows for the allocation of costs based on actual resource consumption, making it particularly beneficial in the company's dynamic project-based environment. Although time-driven activity-based costing (TDABC) was considered as an alternative, its reliance on precise time-tracking data was identified as a limitation. Furthermore, ABC is more accurate when it is easy to track which activities contribute to specific products, even if it is difficult to see exactly how resources are used in those activities. A cost price model was made while applying ABC to the production environment of Company Y. A key finding of the OFAT (One-Factor-at-a-Time) sensitivity analysis done on the cost price model. This analysis measures the impact of one variable by incrementally changing the input while holding all other variables constant. It showed that material costs (13.13%), carbon steel labour (13.1%), and the corporate overhead cost driver rate (9.12%) are the most significant influence on total cost estimations. The Morris sensitivity analysis, used to investigate relationships between variables, showed that the corporate overhead cost driver rate and internal assembly labour had a substantial impact on the cost price due to their interaction with other factors influencing the cost price. Variations in these cost components result in substantial fluctuations in the overall cost price, highlighting the need for more precise budgeting and monitoring of these factors. The study also demonstrated that the company's current standard costing approach does not sufficiently reflect these cost dynamics, further supporting the need to shift towards a more granular cost allocation method.

The regression analysis provided further insights into the underlying inefficiencies in the company's cost estimation process. The study found that labour costs are systematically overestimated, while indirect and overhead costs are consistently underestimated. This imbalance in cost estimation contributes to deviations between budgeted and actual costs, reducing the reliability of financial planning. The analysis also showed that material costs and subcontractor costs do not play a big role in financial discrepancies. The multiple linear regression (MLR) model developed in this study accounted for approximately 80% of the variance in cost deviations. However, the presence of multicollinearity among certain cost components suggests that further refinement of the regression model is necessary to improve the interpretability of individual cost drivers described in the model.
To answer the research question, the study confirms that the implementation of a more structured cost accounting method, coupled with regression-based budget analysis, significantly enhances insight into production costs at Company Y. ABC broke down the production and operational processes into specific activities and assigns cost based on the consumption of resources. It identifies the true cost drivers. Furthermore, indirect costs are allocated more accurately. The regression analysis provides more insight into production costs by analysing the budgeting process. The transition towards ABC, combined with a refined budgeting process supported by regression analysis, represents a critical step towards achieving greater transparency and control over production costs. While further refinements and validations are necessary, this research demonstrates that structured cost accounting and data-driven budgeting methodologies are essential for improving financial oversight and strategic decision-making in a complex manufacturing environment.

6.2 Discussion

This section critically reflects on the research findings, considering their broader implications and potential limitations. It assesses the validity and reliability of the results while acknowledging constraints that may have influenced the outcomes. Additionally, it discusses the practical and theoretical relevance of the study. By doing so, this section provides a foundation for interpreting the conclusions and formulating recommendations.
The findings of this study highlight several key insights regarding the budgeting process and cost estimation methods within the company. While the regression analysis provides a structured approach to identifying cost drivers, it does not account for external factors that may influence budget deviations. External factors that could have possibly influenced the budget deviations are inflation, interest rates, market volatility, supplier issues, etcetera. This limitation emphasises the challenge of relying solely on historical financial data to measure budgeting inefficiencies.
Integrating a refined cost-tracking system within the existing enterprise resource planning (ERP) framework introduces both technical and organisational challenges. The implementation requires reconfiguring ERP functionalities to support real-time cost data collection, integrating automated alerts for budget deviations, and developing custom reporting dashboards for financial analysts. These modifications ask for targeted training for project managers, financial analysts, and production supervisors, ensuring accurate data collection and effective cost interpretation. Collaboration between departments will intensify. Moving from an end-of-quarter financial reconciliation to continuous cost monitoring imposes additional responsibilities on financial analysts, requiring frequent variance analysis and proactive budget adjustments. Furthermore, real-time access to cost data enhances decision-making efficiency by enabling immediate responses to cost overruns. For instance, if labour costs exceed the estimated budget by a predetermined threshold, automated notifications will prompt project managers to investigate and mitigate discrepancies. To maximise the system's effectiveness, structured training programmes should be established, ensuring that employees develop the necessary expertise

to integrate cost insights into their daily operational decision-making.
The study also has limitations that influence the generalisability of its conclusions. One major constraint is the availability of data. Due to the limited dataset, the accuracy of the cost price model incorporating ABC could not be validated. While the study provides insights into the application of ABC and the factors that must be considered when calculating cost prices, the effectiveness of the model remains unproven. The reliance on assumptions further adds an element of subjectivity to the findings. Despite validation through expert consultation within the company, assumptions introduce potential biases that may affect the findings of this matter. Additionally, ABC is an internal management tool. Despite external reporting not being a focus of this research, it should be remembered that ABC alone is not enough for financial reporting. Another important limitation concerns the presence of multicollinearity within the regression analysis. The model includes predictors that exhibit high intercorrelation, which can distort coefficient estimates and reduce the reliability of the findings. This issue complicates the interpretation of individual cost drivers, as it becomes difficult to isolate the impact of specific variables. Addressing multicollinearity would require either the removal of redundant predictors or the application of advanced statistical techniques such as principal component regression or ridge regression.
Despite these limitations, the study contributes valuable insights into cost estimation challenges within project-based manufacturing environments. It emphasises the necessity of a dynamic approach to cost forecasting, integrating both quantitative modelling techniques and qualitative expert judgement.

6.3 Recommendations

This section addresses recommendations to the company based on the conclusion provided in Section 6.1. Actionable steps are provided to tackle existing issues identified in this research. These steps focus on improving data gathering, accurately allocating indirect costs and mitigating labour overestimation.
To improve cost estimation and financial forecasting, Company Y must enhance its data gathering and collection procedures. The research indicates that cost-tracking inconsistencies or lack of insight arise due to limitations in data availability, outdated cost allocations, and insufficient real-time monitoring. Therefore, the most potential lies in structuring their data architecture. The IT department will lead the integration of computer panels on the production floor to automate data collection, reducing human errors and ensuring consistency. Production supervisors will oversee data accuracy and real-time monitoring, while finance will analyse and report the collected data. The implementation process takes about 18 months for a business such as Company Y (Sarker, 2024; Katuri, 2025; Mabert et al., 2003). Initially, a comprehensive assessment of the current system's capabilities will be conducted over two months, followed by a selection of ERP software and system design in months two to six. The system integration with data migration in months six to eight, and the testing phase takes from months nine to ten. Training takes another month, after which the system goes live for deployment. Post-implementation support and evaluation take up the rest of the time. According to Mabert, Soni, and Venkataramanan (2003), medium-sized manufacturing companies, such as Company Y, spent 3.08% on average on an ERP implementation. Besides size, factors that influence total costs are the extent of customisation and implementation strategy. Costs mainly consist of software costs, hardware costs, consulting costs, training costs, implementation team costs and maintenance costs. Annual maintenance costs around 20% of the initial investment (Katuri, 2025).
A more precise cost accounting method, such as ABC, should be adopted to refine cost price estimation. Implementing ABC would allow for a more accurate allocation of indirect and overhead costs, which, as demonstrated in the regression analysis, are currently not systematically assigned to production orders. The finance department will be responsible for identifying key

activities and cost pools, determining cost drivers, and calculating accurate cost driver rates as demonstrated in the study. The IT department will integrate ABC into the existing ERP system, while production management will validate the accuracy of identified activities and cost drivers. The implementation process lasts about 12 months and begins with a detailed analysis and identification of relevant cost components in the first two months. Cost driver selection will follow in month three, with rate calculations and validation occurring in month four. ERP system integration and preliminary ABC implementation will take place in months five and six. Training for financial and production staff is scheduled for month seven, and full ABC implementation will be completed in month eight. Evaluation afterwards is important to refine the method until the twelfth month. Some factors influencing the cost of implementation are the size of the company, the complexity of operations, and the fixed-to-variable cost ratio (Needy et al., 2003). Costs consist of components such as software licensing, consulting, training, data integration with the ERP system, and maintenance (Cokins, 2006; Wegmann, 2008).
By improving cost allocation in Company Y, Company X can establish a stronger foundation for project pricing, reducing the risk of underestimating costs and, consequently, setting prices too low. This refinement in cost estimation would not only enhance profitability but also strengthen the company's competitive position in the renewable energy sector.
To mitigate the overestimation of labour in production orders, a more dynamic approach should be implemented. Instead of relying on fixed labour standards, the actual labour spent on parts within the production should continuously be monitored to adjust estimations. Production supervisors will monitor real-time data and investigate any alerts triggered by deviations, while production planners will regularly assess estimation accuracy and adjust labour standards based on historical data. The IT department will establish a centralised database connected to the computer panels and integrate it into the ERP system. Thresholds for deviations in labour time will be set to trigger alerts. Initial database setup and ERP integration will take place in month one, with alert mechanisms developed in month two. Testing of the monitoring and alert systems will occur in month three, followed by training sessions for supervisors and planners in month four. By month five, the transition to estimation based on historical averages will be finalised. Full implementation and ongoing monitoring will be in place by month six. Statistical analysis, such as the regression analysis in the study, can be used to detect recurring deviations for long-term data trends. If deviations often occur due to worker inefficiency, training programmes can be introduced. If the tasks require less or more labour than estimated, the standard work procedures can be updated.

6.4 Future Research

This research has provided valuable insights into cost estimation and forecasting within Company Y. However, several areas require further investigation to refine and extend these findings. Future research should focus on improving the robustness of regression analysis, validating cost models over the long term, and exploring alternative cost accounting methodologies.
An area for further research is addressing the multicollinearity identified in the regression analysis. While this study identified potential issues with predictor correlations, future research could apply Principal Component Analysis (PCA) to mitigate theoretical multicollinearity by transforming correlated variables into uncorrelated components. Alternatively, regularisation techniques such as ridge regression could be employed to stabilise coefficient estimates and improve predictive reliability in the presence of practical multicollinearity. A more refined regression model, with reduced collinearity, would enhance the accuracy of cost error predictions and strengthen the reliability of cost drivers identified in this study.

Another subject for future research is the long-term validation of costing models on accuracy. Due to data constraints, the applied cost models could not be tested on accuracy but only on robustness and see what areas need precise consideration. Future studies should evaluate these models' accuracy against real-world data when it becomes available. Furthermore, long-term validation would improve the reliability of these models. This would allow for assessing their accuracy in predicting actual costs and provide insights into how well the ABC approach and regression models function in dynamic production environments. A longitudinal analysis, in which cost forecasting models are tested over multiple projects and across different time periods, would provide a more definitive validation of their effectiveness.

If time-based cost data becomes more readily available in a centralised database, future research could also explore the feasibility of TDABC. TDABC offers a dynamic and scalable approach by linking cost allocations directly to time estimates rather than fixed activity cost drivers. By comparing TDABC with the ABC model currently proposed, further insights could be gained into the suitability of each method for different project types and production environments. A comparative analysis between these cost accounting methods would help determine which approach, or a combination of them, provides the most precise and flexible cost estimation.

Extending the regression analysis by incorporating additional predictors could further improve the accuracy of the cost error forecasting. Future studies should explore (qualitative) factors that contribute to cost deviations, such as complexity metrics (e.g., number of components, number of sum-assemblies, degree of customisation), project size indicators, or external market factors such as inflation rates and material cost fluctuations. These additional predictors could help identify recurring cost patterns and improve the accuracy of budget planning. Furthermore, the application of time-series regression models could allow for the tracking of cost build-up over different project phases. If repeated observations are collected across multiple projects or costs are tracked continuously over time, advanced regression methods could reveal trends, project-specific effects, and efficiency improvements that result from experience and process refinements over time.

Finally, a direction for future research is, if the dataset is sufficiently large, the exploration of AI-driven cost forecasting models. Machine learning techniques could enhance cost estimation by identifying complex relationships in data that traditional regression models may not capture. Supervised learning models, such as Random Forests, Gradient Boosting models or Artificial Neural Networks, could predict cost overruns with greater accuracy and minimise human error. Random Forests improves accuracy by reducing variance, Gradient Boosting models improve predictions by correcting errors from previous iterations. Artificial Neural Networks need a large dataset and are harder to interpret compared to the previous two, but can capture hidden patterns in cost fluctuations. This data-driven approach would provide a more adaptive and scalable methodology for cost estimation, enabling Company Y to optimise its budgeting strategies.

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A APPENDIX

A.1 Introduction

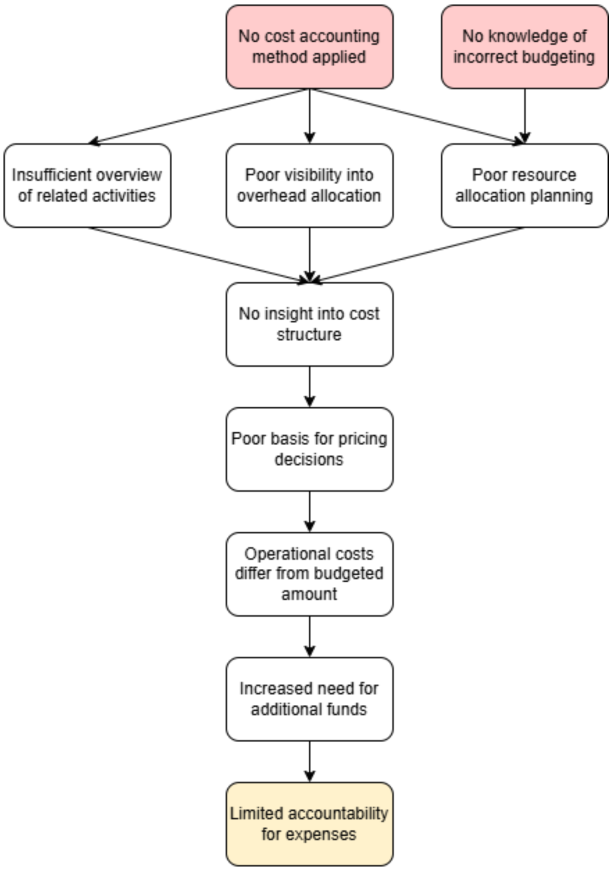

Figure A.1: Problem Cluster

A.2 Selecting Costing & Regression Methods

Table A.1: Step 1 and 2 of consistency check

Criteria

Weight vector		Consistency vector			
0.380		1.976			5.195802775
0.058		0.290	Consistency vector		5.035731187
0.135	x Matrix =	0.687	——————-	=	5.092370948
0.342		1.756	Weight vector		5.138547793
0.085		0.429			5.029358064

Sub-criteria

Weight vector		Consistency vector			
0.106		0.31965812	Consistency vector		3.011201867
0.633	x Matrix =	1.945621206	——————-	=	3.071973401
0.260		0.790082167	Weight vector		3.032968775

Table A.2: Step 3 and 4 of consistency check

Criteria

Lambda max =	5.098362154
CI =	0.024590538
RI =	1.12
CR =	0.021955838

Sub-criteria

Lambda max =	3.038714681
CI =	0.01935734
RI =	0.58
CR =	0.033374725

A.3 Developing Tool & Analysing Results

A.3.1 ABC Model

Direct Material Costs
Direct Labour Costs
Subcontractor Costs
Stainless Steel
Carbon Steel
Internal Assembly
Electrical
Quality Management
Production Controlling
Production Coordination
Production Management
Engineering
Supply (Procurement)
Warehousing
Logistics
______________________ +
Indirect costs
Overhead costs
Cost Price

Figure A.2: Output

A.3.2 Correlation Matrix Heatmap

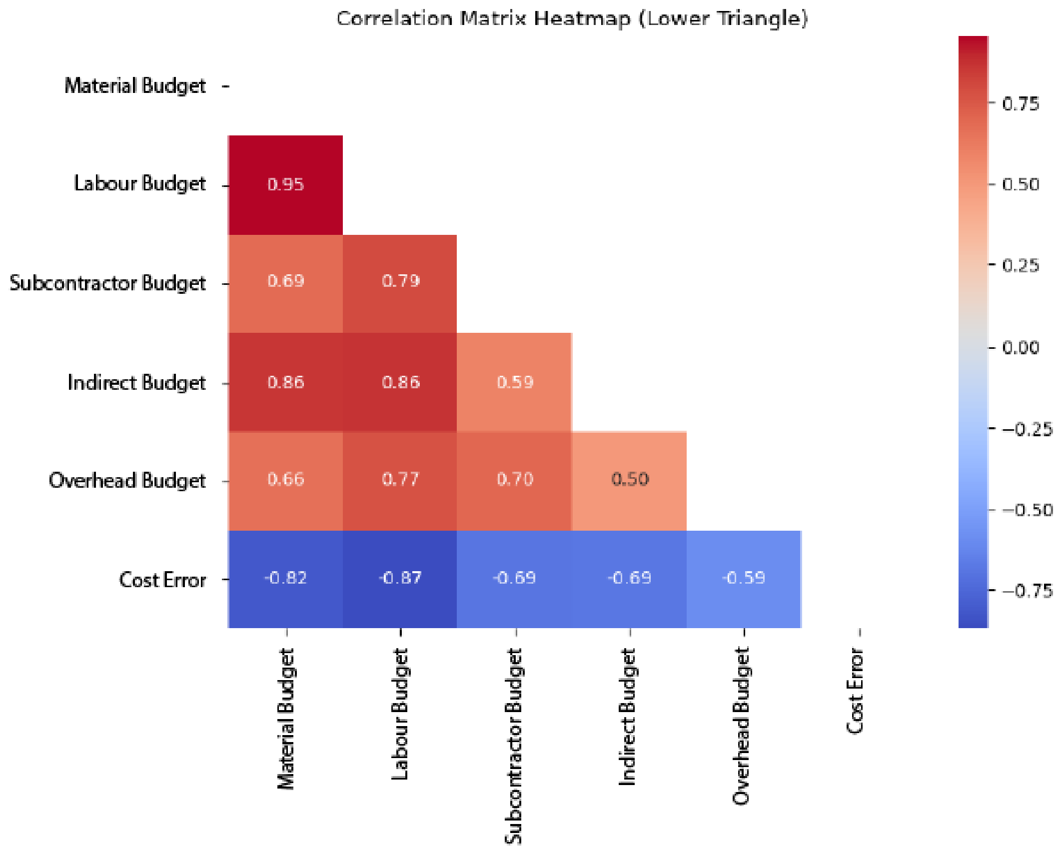

Figure A.3: Correlation Matrix Heatmap

A.3.3 OFAT Analysis

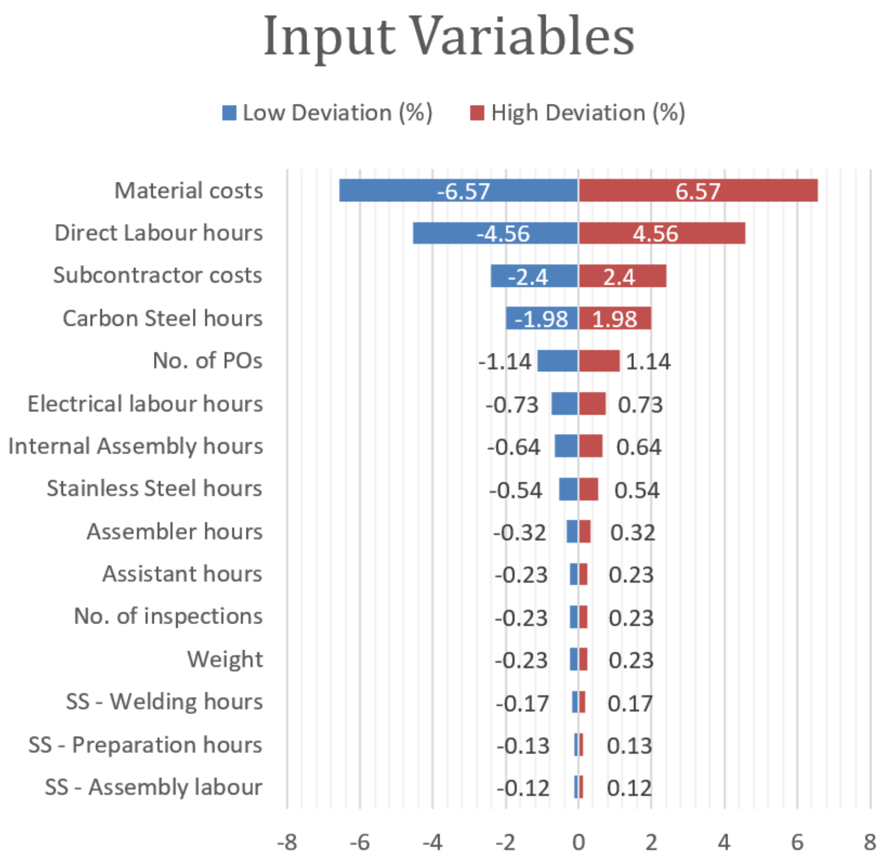

Figure A.4: Tornado Diagram of Input Variables

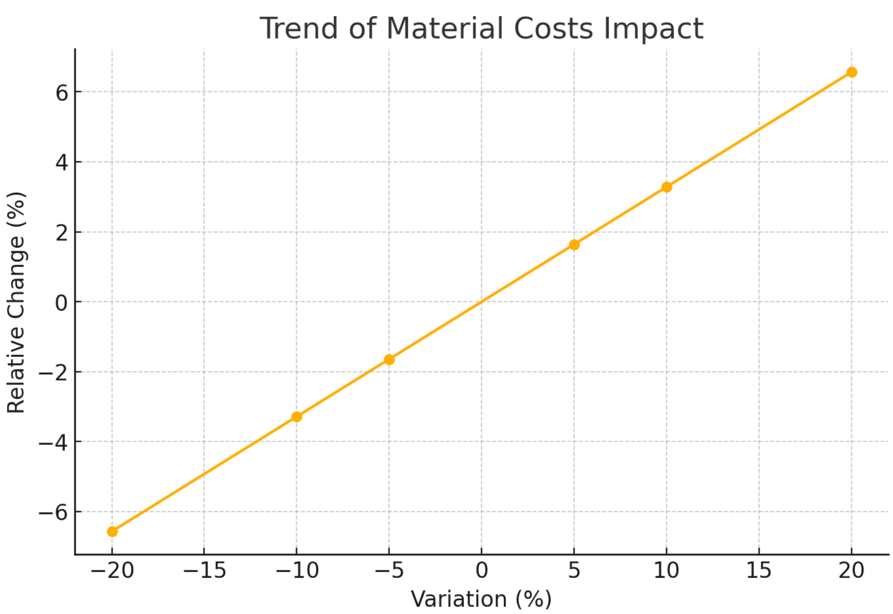

Figure A.5: Material Costs Impact

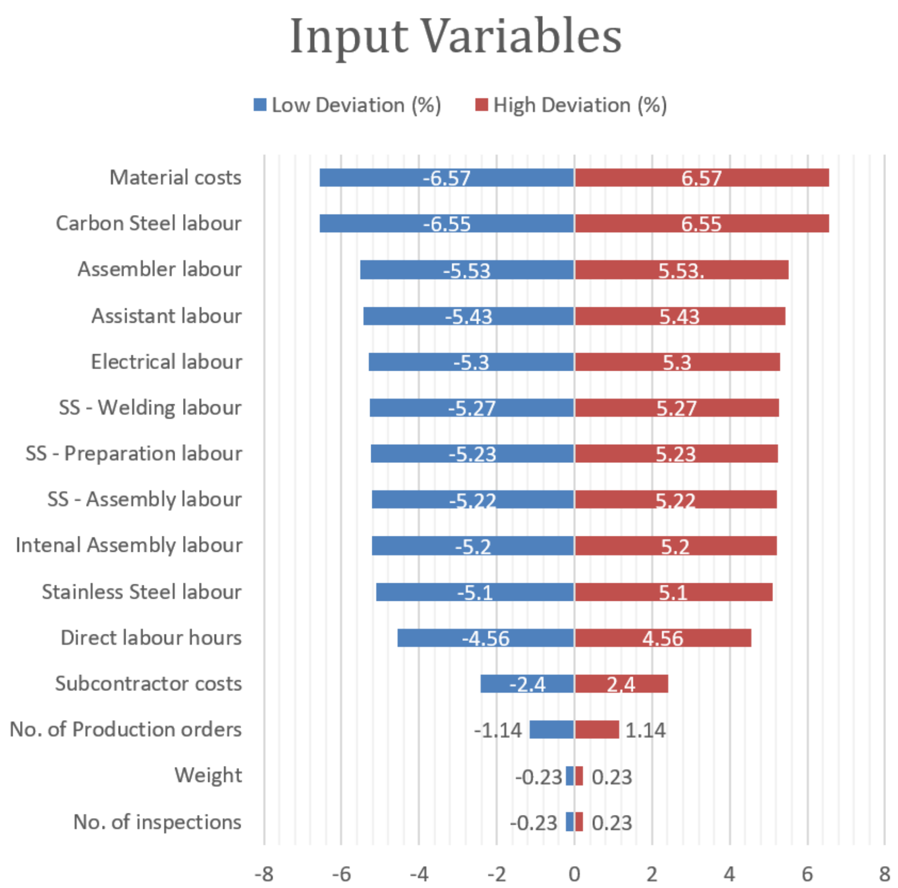

Figure A.6: Tornado Diagram of Input Variables with dependency

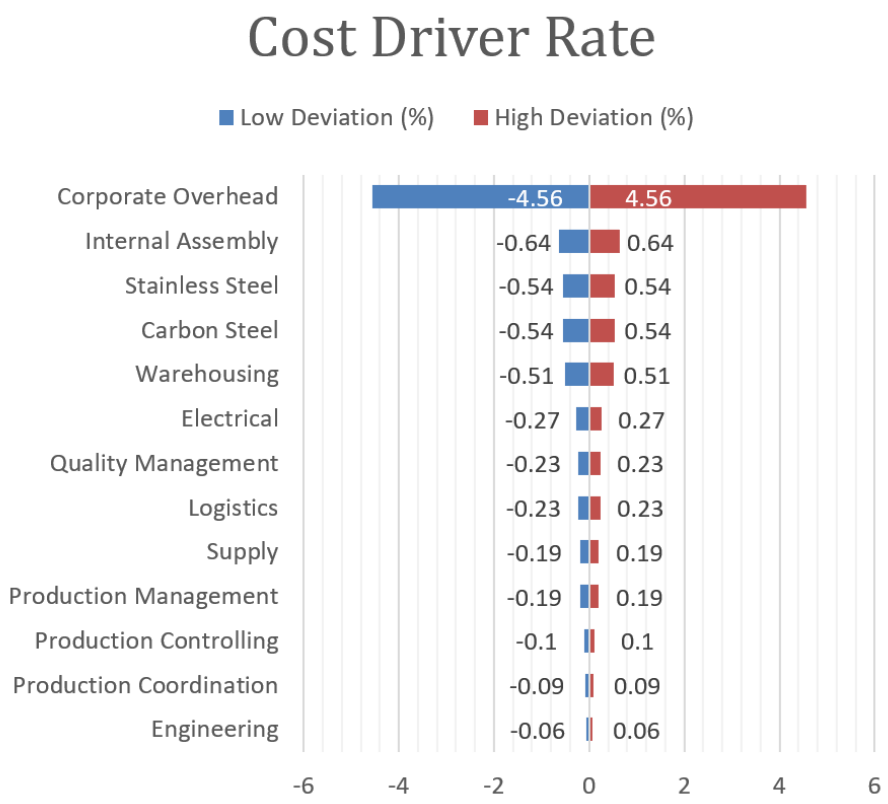

Figure A.7: Tornado Diagram of Cost Driver Rates

A.3.4 Morris Method

Table A.3: Outcomes Morris method

Parameter	μ^*	σ	$\mu^*\ conf.$
Corporate overhead rate	100.00%	572551.1	2.27%
Material costs	95.95%	0.00e+00	7.46E-16%
Subcontractor costs	79.43%	0.0	8.11E-14%
Internal assembly labour	78.68%	1000000.0	3.23%
Carbon steel labour	63.40%	789842.0	3.13%
Stainless steel labour	48.93%	589200.0	3.09%
Number of production orders	41.90%	365352.7	2.19%
Internal assembly rate	41.73%	741705.3	4.28%
Carbon steel rate	28.76%	503839.5	4.10%
Stainless steel rate	27.45%	456140.7	3.92%
Electricity labour	26.24%	280428.8	2.87%
Engineering rate	13.62%	267173.5	3.80%
Electricity rate	13.11%	275022.1	4.21%
Warehousing rate	13.07%	231992.9	3.28%
Logistics rate	5.64%	53698.2	3.22%
Quality management rate	5.62%	112887.8	4.44%
Number of inspection	5.30%	96772.2	4.65%
Weight	5.11%	86028.5	4.02%
Supply rate	4.56%	97179.6	4.73%
Production management rate	4.15%	95152.7	4.04%
Production coordination rate	1.98%	46358.2	4.54%
Production controlling rate	1.95%	50435.1	5.00%

A.4 Systematic Literature Review

Table A.4: Inclusion criteria

Inclusion criteria	Argumentation
Similar company	If the article is related to the costs of a company or sector comparable to the one in which this research is conducted, it will be included.
Cost accounting methods	The article will be included if it analyses one or multiple cost accounting methods.

Table A.5: Exclusion criteria

Exclusion criteria	Argumentation
Language	This literature review will exclude studies that are not written in English. English is the primary research language, so more people will review these studies, making them more reliable.
Focus	Studies unrelated to cost accounting, cost estimation or cost management will be excluded.
Peer-reviewed	The article will not be included if it isn't peer-reviewed. This ensures the credibility of the sources as they are checked by other experts.
Publication date	Articles published before 2000 will be excluded to ensure they are still relevant.
Area	Studies related to the production environment will be included to ensure the articles are relevant enough. If not, the article will be excluded.

Table A.6: Search strings

Key concepts	Related terms	Narrower terms	Broader terms
Cost accounting	Costing, cost analysis, cost development, cost allocation, costing techniques	Activity-based costing, job costing, cost drivers, product costing, traditional costing	Cost management, financial analysis, financial management, cost control
Production	Manufacturing, assembly	make-to-order, customization, unique product, complex product	Supply chain, production processes
Project	Project-based, project-oriented, project-specific	Process, job	Project management

Table A.7: Search log

Date	Source	Search Query	Hits	Remarks
21/10/2024	Scopus	(”cost accounting methods” OR ”costing methods” OR ”cost accounting”) AND (”project-based business*” OR ”project-based compan*” OR ”project-based organization*” OR ”per project”) AND (”job costing” OR ”project costing” OR ”activity-based costing” OR ”cost allocation”) AND (”product*” OR ”material*” OR ”project requirement*”)	3	Too specific, documents were not useful.

Continued on next page

Table A.7: Search log (Continued)

Date	Source	Search Query	Hits	Remarks
21/10	Scopus	(”project accounting” OR ”project-based accounting”) AND (”costing methods” OR ”cost management”) AND (”job order costing” OR ”activity-based costing” OR ”process costing”) AND (”unique product*” OR ”custom product*” OR ”project-specific material*”)	0	Too specific
24/10	Scopus	(“cost accounting” OR costing) AND compar* AND method*	629	Too many sources, difficult to screen. 2 included
24/10	Scopus	(“cost accounting” OR costing) AND compar* AND method* AND production AND NOT “life cycle”	80	3 included
27/10	Web of Science	(”Cost Accounting” OR costing OR Cost analysis) AND Method AND NOT(”Life cycle” OR ”life-cycle”) AND production AND (analy* OR compar*) AND (assembl* OR manufactur*) AND NOT ”lot-size”	6259	Too broad
27/10	Web of Science	(”Cost Accounting” OR costing OR Cost analysis) AND Method AND NOT(”Life cycle” OR ”life-cycle”) AND production AND (analy* OR compar*) AND (assembl* OR manufactur*) AND NOT ”lot-size” AND “cost of production”	89	The term ‘cost of production’ did not attract the right documents.
27/10	Web of Science	(”Cost Accounting” OR ”Cost analysis”) AND method* AND NOT (life-cycle OR ”life cycle”) AND NOT ”lot-size”AND compar* AND Production	297	Too broad
27/10	Web of Science	(”Cost Accounting” OR ”Cost analysis”) AND (“unique product” OR “custom* product”)	2	Not useful.
27/10	Web of Science	(“cost accounting” AND production AND assembl* AND process*)	6	4 duplicates.
27/10	Business Source Complete	Cost accounting methods AND NOT life cycle	441	Too broad
27/10	Business Source Complete	Cost accounting methods AND production AND NOT life cycle	83	Useful ones also available on Scopus
28/10	Scopus	(”costing methods” OR ”cost management” OR ”cost accounting” OR ”Cost accounting methods”) AND (project* OR ”project management”)	18,246	Too broad

Continued on next page

Table A.7: Search log (Continued)

Date	Source	Search Query	Hits	Remarks
28/10	Scopus	(”cost accounting methods” OR ”costing techniques” OR ”management accounting”) AND (project* OR ”project management”))	353	Too broad
28/10	Scopus	(”cost accounting” OR ”costing estimation” OR ”cost estimation”) AND costing AND (project* OR ”project management”) AND NOT “life cycle” OR “life-cycle”)	219	Not related
29/10	Scopus	”cost accounting” AND production AND estimat* AND compar* AND NOT environment*	137	1 included
29/10	Scopus	”cost development” AND estimat* AND compar*	34	Not relevant
29/10	Scopus	(”cost accounting” AND ”complex product*”)	16	1 included
29/10	Scopus	(”cost accounting” AND ”custom* manufactur*”)	3	
29/10	Scopus	(”cost accounting” AND make-to-order)	25	no good combination of the two search terms available.
29/10	Scopus	(”cost estimat*” AND make-to-order)	9	2 duplicates. Interesting papers for later on in this research.
29/10	Scopus	”cost accounting” AND assembl* AND production AND process*	97	Useful, 1 included.
2/12	Scopus	“Job costing”	96	Narrow down
2/12	Scopus	“Job costing” AND (production OR assembl*)	27	2 incl, 2 duplicates.
2/12	Scopus	“Process costing”	92	Narrow down
2/12	Scopus	“Process costing” AND (production OR assembl*)	24	
2/12	Scopus	“Direct costing”	95	Narrow down
2/12	Scopus	“direct costing” AND (production OR assembl*)	24	
2/12	Scopus	(“Full costing” OR absorption) AND (production OR assembl*)	29	Not relevant
2/12	Scopus	“Costing techniques” AND (production OR assembl*)	56	Too specific
2/12	Scopus	costing AND (production OR assembl*) AND (method OR technique*) AND compar*	460	Too broad

Table A.8: Included articles

Source	**Author**	**Year**	**Title**
Journal of Industrial Ecology	Walz, Matthias; Guenther, Edeltraud	2021	What effects does material flow cost accounting have for companies?: Evidence from a case studies analysis
Custos e Agronegocio	Corrêa, R.G.F.; Kliemann Neto, F.J.; Denicol, J.; Kahmann, A.	2015	Proposal and implementation of a costing system for beef production
Gestao e Producao	Da Silva Medeiros, H.; Santana, A.F.B.; Da Silva Guimarães, L.	2017	The use of costing methods in Lean Manufacturing industries: A literature review
Engineering Economics	Stonciuviene, N.; Usaite-Duonieliene, R.; Zinkeviciene, D.	2020	Integration of activity-based costing modifications and LEAN accounting into full cost calculation
Australasian Accounting, Business and Finance Journal	Vedernikova, O.; Siguenza-Guzman, L.; Pesantez, J.; Arcentales-Carrion, R.	2020	Time-driven activity-based costing in the assembly industry
Cost Engineering	Fayek, A.R.	2001	Activity-based job costing for integrating estimating, scheduling, and cost control
Procedia CIRP	Alami, D., El-Maraghy, W.	2020	Traditional and activity based aggregate job costing model
Lecture Notes in Mechanical Engineering	Zamrud, N.F. Abu, M.Y. Kamil, N.N.N.M.,Safeiee, F.L.M.	2020	A comparative study of product costing by using activity-based costing (Abc) and time-driven activity-based costing (td-abc) method

Table A.9: Conceptual matrix

Title	Concepts	Key Findings
What effects does material flow cost accounting have for companies?: Evidence from a case studies analysis	• Material Flow Cost Accounting (MFCA); • Material Flow Analysis (FCA); • Environmental cost accounting;	MFCA provided a better basis for the calculation of costs and material flows. It reveals hidden costs and inefficiencies. MFCA enabled financial analysis of material losses that were impossible with traditional cost accounting.

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Table A.9: Conceptual matrix (Continued)

Title	Concepts	Key Findings
Proposal and implementation of a costing system for beef production	• ABC; • Standard costing	The costing system combined Activity-Based Costing (ABC) for indirect costs and Standard Costing for direct costs. The system provides more accurate cost information to identify opportunities for cost reduction. The challenges mentioned were defining accurate cost drivers and needing more detailed data collection on the farm.
The use of costing methods in Lean Manufacturing industries: A literature review	• Activity-based costing; • Lean Manufacturing; • Time-driven activity-based costing; • Value stream costing	Activity-Based Costing (ABC): • It takes time to develop and implement Time-Driven Activity-Based Costing (TDABC): • Easy to apply • Provides better visibility of cost items • Depends on time equations for effectiveness Value Stream Costing (VSC): • Measures cost through value stream based on a lean model A few documents were recommended for deepening the literature.
Integration of activity-based costing modifications and LEAN accounting into full cost calculation	• Activity-Based Costing; • Time Driven Activity Based Costing; • Service-Based Costing; • Duration Based Costing; • LEAN accounting; • Full Cost Calculation	ABC provides accurate product costing but is labour-intensive and difficult to implement in complex organizations. Time-Driven ABC simplifies ABC by using time as the primary cost driver, but it may be limited to manufacturing applications. Service-Based Costing and Duration-Based Costing offer useful elements for allocating costs based on customer complexity and production duration. LEAN accounting focuses on value streams but lacks methodology for allocating indirect costs.

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Table A.9: Conceptual matrix (Continued)

Title	Concepts	Key Findings
Time-driven activity-based costing in the assembly industry	• Time-driven Activity-based costing (TDABC); • Traditional costing; • Assembly industry	TDABC identified inefficiencies in resource usage that traditional costing could not detect. Manual assembly processes showed fewer differences between TDABC and traditional costing than semi-automated processes. Implementing TDABC was challenging for strategic and support processes due to low standardisation.
Traditional and activity based aggregate job costing model	• Activity-based costing; • Direct cost; • Job shop	The paper introduces MILP models for both traditional and ABC costing methods. It addresses the differences in cost allocation and the mathematical formulation. The results show that the ABC method offers a competitive advantage by reducing operating costs
Activity-Based Job Costing for Integrating Estimating, Scheduling, and Cost Control	• Accounting; Budget; • Cost control; • Data collection; • Estimating; • Job costing; • Scheduling	Unlike traditional job costing methods, this alignment allows for more precise tracking of costs. The paper presents a comprehensive framework for enhancing job costing practices in construction through an activity-based approach. This method aims to improve accuracy in cost tracking, facilitate better decision-making, and ultimately lead to more successful project outcomes.
A comparative study of product costing by using activity-based costing (Abc) and time-driven activity-based costing (tdabc) method	• Activity-Based Costing; • Comparative study; • Time-Driven Activity-Based Costing	This paper presents a comparative study of Activity-Based Costing (ABC) and Time-Driven Activity-Based Costing (TDABC) methods for product costing in a manufacturing company. The paper shows that TDABC has greater accuracy, is more structured, and has more detail in activity breakdowns.