DEVELOPMENT AND VALIDATION OF AN EQUIPMENT COST EFFICIENCY FRAMEWORK (ECEF) FOR IMPROVING OPERATIONAL AND FINANCIAL PERFORMANCE OF PRODUCTION RESOURCES

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By

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ABSTRACT

DEVELOPMENT AND VALIDATION OF AN EQUIPMENT COST EFFICIENCY FRAMEWORK (ECEF) FOR IMPROVING OPERATIONAL AND FINANCIAL PERFORMANCE OF PRODUCTION RESOURCES

LIEW CHEN FUNG

This thesis investigates the limitations of relying solely on the overall equipment effectiveness (OEE) metric to evaluate equipment performance in manufacturing environments, emphasising the need for financial quantification. Current OEE assessments, while effective operationally, lack a comprehensive financial perspective, leaving high OEE devoid of meaningful significance to management without corresponding financial benefits. A systematic review of financial metrics reveals that equipment acquisition cost and maintenance cost are more relevant to OEE than profit, revenue, and operating cost. Notably, improvement cost, crucial for OEE enhancement, is often overlooked.

To address these gaps, the study proposes evaluating OEE's financial impact in terms of equipment acquisition cost, maintenance cost, and improvement cost. Additionally, it introduces the equipment cost efficiency (ECE) metric within a comprehensive framework, providing a systematic problem-solving approach. Real-world case studies in diverse manufacturing environments, including a medical device manufacturer, a tyre flap manufacturer, and a semiconductor manufacturer, showcase the effectiveness of the ECE framework. Implementation results in a 15.3% increase in OEE and 77.7% improvement in the ECE metric for the medical device manufacturer, a 20.2% increase in OEE and a 74.3% improvement in the ECE metric for the tyre flap manufacturer, and a 21.6% increase in OEE and a 56.4% improvement in the ECE metric for the semiconductor manufacturer.

The research broadens OEE to encompass both operational and financial performance, challenging traditional metrics like profit, revenue, and operating cost as relevant OEE indicators. Instead, the study advocates for ECE as a metric that quantifies equipment acquisition and maintenance cost wastage. This approach bridges the operational-financial gap, enhancing decision-making, cost optimisation, and resource allocation in manufacturing operations. The ECE framework emerges as a valuable tool for organisations seeking to improve equipment efficiency and financial outcomes.

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APPROVAL SHEET

This thesis entitled "**DEVELOPMENT AND VALIDATION OF AN EQUIPMENT COST EFFICIENCY FRAMEWORK (ECEF) FOR IMPROVING OPERATIONAL AND FINANCIAL PERFORMANCE OF PRODUCTION RESOURCES"** was prepared by LIEW CHEN FUNG and submitted as partial fulfilment of the requirements for the degree of Doctor of Philosophy (Engineering) at Universiti Tunku Abdul Rahman.

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SUBMISSION OF DISSERTATION

It is hereby certified that LIEW CHEN FUNG (ID No: 20AGD04659) has completed this thesis entitled "DEVELOPMENT AND VALIDATION OF AN EQUIPMENT COST EFFICIENCY FRAMEWORK (ECEF) FOR IMPROVING OPERATIONAL AND FINANCIAL PERFORMANCE OF PRODUCTION RESOURCES" under the supervision of **Assistant Professor Ir. Dr. Joshua Prakash** (Supervisor) from the Department of Industrial Engineering, Faculty of Engineering and Green Technology, and **Professor Ir. Dr. Ong Kok Seng** (Co-supervisor) from the Department of Industrial Engineering, Faculty of Engineering and Green Technology.

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Yours truly,

____

(Liew Chen Fung)

DECLARATION

I LIEW CHEN FUNG hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

Name ____________________________

(Liew Chen Fung)

Date 5 January 24

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LIST OF ABBREVIATIONS

A	Availability
Act_i	Actual resource input for item i
$COQL$	Cost of quality losses
D_i	Ideal resource input for item i
ECE_A	Equipment cost efficiency metric after improvement
ECE_B	Equipment cost efficiency metric before improvement
ECE_S	Equipment cost efficiency metric from simulation
$ECEF$	Equipment cost efficiency framework
$ECE\ metric$	Equipment cost efficiency metric
K_A	Tool cost
K_B	Material cost
K_D	Labour cost
K_E	Equipment earning capacity
K_P	Profit
K_R	Revenue
K_T	Total cost
K_{AC}	Average cost
K_{AL}	Availability monetary losses
K_{EC}	Equipment acquisition cost
K_{IC}	Improvement cost
K_{MC}	Maintenance cost
K_{OC}	Operating cost
K_{PL}	Performance monetary losses

K_{QL}	Quality monetary losses
K_{SC}	Setup cost
K_{SL}	Speed loss cost
K_{AFC}	Average fix cost
K_{AVC}	Average variable cost
K_{ECD}	Equipment acquisition cost during downtime
K_{ECO}	Equipment acquisition cost during operation
K_{PPU}	Price per unit
K_{Rwk}	Rework cost
K_{SUM}	Other additional cost
$K_{EC/M}$	Monthly equipment acquisition cost
$K_{MC/M}$	Monthly maintenance cost
$K_{OC/M}$	Monthly operating cost
K_{Prod}	Production cost
K_{Scrp}	Scrap cost
K_{total}	Total product cost
ΔK_E	Additional equipment earning capacity
ΔK_P	Additional profit
ΔK_{EC}	Saved equipment acquisition cost
ΔK_{MC}	Saved maintenance cost
ΔK_{OC}	Saved operating cost
ΔK_{Rwk}	Saved rework cost
ΔK_{Scrp}	Saved scrap cost
N_0	Nominal batch size

OCE	Overall cost efficiency
OEE	Overall equipment effectiveness
OIE	Overall input efficiency
$OECL$	Overall equipment cost loss
$OEQCL$	overall equipment and quality cost loss
P	Performance
PLI	Profit loss indicator
RPU	Revenue per utilization
Q	Quality
t_0	Nominal cycle time
t_p	Production time per part
TX	Taxes
TCO	Total cost of ownership
T_{CT}	Theoretical cycle time
T_{LT}	Loading time
T_{OT}	Operating time
t_{SU}	Setup time
t_{TSA}	Total setup and adjustment downtime
t_{life}	Equipment lifetime
t_{TRSL}	Total reduced speed loss
UTL	Utilization
w_i	Relative weight for resource input i
Y_{Rwk}	Rework quantity
Y_{Thr}	Throughput rate (parts per year or selected time)
Y_{Good}	Processed good quantity

ΔY_{Good}	Additional processed good quantity

CHAPTER ONE

INTRODUCTION

1.0 Overview

Chapter 1 is divided into five sections. Section 1.1 provides a detailed account of the research background. In Section 1.2, 1.3, and 1.4, the research problems, research objectives, and research scopes are presented, respectively. Finally, in Section 1.5, an outline of the thesis is provided.

1.1 Research Background

Manufacturing organisations are constantly experiencing high levels of competition from both customers and competitors in today's dynamic environment, which has been driven by globalisation (Ahuja and Khamba, 2008). To remain competitive in such a market, organisations must deliver high-quality products with lower costs and shorter delivery times. As a result of global competition, many organisations have invested in automated equipment to replace manual processes, which have been found to offer greater reliability, productivity, and lower unit costs compared to manual work. Industry 4.0 has been launched and emphasizes the importance of automation as a key factor for business excellence in future production (Landscheidt and Kans, 2016; Chopra et al., 2020). Industry 4.0 can help organisations manage and optimise their manufacturing processes and supply chains, leading to improved efficiency and profitability. However, for equipment to perform at the expected level, it must operate with high efficiency. To sustain or improve manufacturing productivity, a crucial performance metric is necessary to evaluate equipment performance, rather than relying on experience and intuition (Nelson Raja and Kannan, 2010; Zammori, 2015; Hasegan et al., 2018). Overall equipment effectiveness (OEE) is a commonly used metric for analysing the operational performance of one or more pieces of equipment in the manufacturing environment (Chikwendu et al., 2020).

OEE is a quantitative metric introduced by Nakajima in 1998 as a part of total preventive maintenance (TPM), and is used to measure the operational performance of equipment in the manufacturing environment by using a time loss structure (Mahfoud et al., 2017; Afy-Shararah and Rich, 2018). TPM is a widely used equipment maintenance method to optimise equipment operational performance (Azizi, 2015; Sharma, 2019) and is a change in philosophy that continuously improves equipment effectiveness by preventing equipment degradation (Wudhikarn, 2012; Gupta and Vardhan, 2016). OEE is the core performance metric used to measure the success of TPM initiatives (Wudhikarn, 2012; Tsarouhas, 2015). OEE has been highly utilized since its inception to measure equipment performance against perfect production (Al-Najjar et al., 2017; Gólcher-Barguil et al., 2019). As defined by the Japan Institute of Plant Maintenance (JIPM), the optimum production equipment operates at 85% world-class OEE, a composite metric comprising 90% availability, 95% performance, and 99% quality (Mail et al., 2021; Raju et al. 2022). OEE identifies downtime losses, speed losses, and defect losses based on equipment availability, performance, and quality, respectively (Zammori, 2015). The inherent strength of OEE lies in its ability to help organisations realize the hidden capacity of their existing equipment when losses are mitigated or minimised in the manufacturing environment.

1.2 Research Problems

The evaluation of equipment operational performance using the OEE metric has limitations when it comes to assessing its financial performance, potentially leading to unnecessary financial burden on organizations.

OEE is a commonly used metric for evaluating equipment operational performance. It serves as a sole performance metric that helps to identify production losses caused by various production disturbances. However, it should be noted that OEE has some limitations when it comes to assessing equipment financial performance. As some researchers have pointed out, OEE does not provide any information about the equipment's financial effectiveness (Chong and Ng, 2016; Kechaou et al., 2022). This could result in an unnecessary financial burden on the organisation if costly OEE improvement actions are implemented without evaluating the financial performance of the equipment. Although OEE provides cost reduction benefits, it does not give any information about the cost required to maintain the equipment's optimum performance. Furthermore, OEE does not take into account the impact of equipment downtime on the organisation's revenue, such as the loss of potential sales and the negative impact on customer satisfaction (Mamaghani and Yazdani, 2018). To make effective decisions regarding the organisation's operations, research is needed to explore the impact of the OEE metric’s shortcomings and to identify alternative approaches that can effectively evaluate the financial effectiveness of equipment (Novak and Vukasovic, 2016).

While operational performance determines financial performance, organisational management often evaluates operational effectiveness by financial performance (Esmaeel et al., 2018). Financial metrics are frequently employed to comprehend current and future financial performance and opportunities (Iuga et al., 2015). However, using only financial metrics to assess equipment performance can have limitations (Esmaeel et al., 2018). Financial metrics are backward-looking and may not provide enough information to make forward-looking decisions (Esmaeel et al., 2018). They can also fail to capture non-financial benefits such as customer satisfaction, quality improvements, or process improvement (Omran et al., 2021). Additionally, focusing solely on financial metrics can lead to suboptimal equipment performance if other important factors such as safety or environmental concerns are not considered (Mamaghani and Yazdani, 2018). Therefore, it is necessary to investigate the integration of financial and non-financial metrics to develop a more comprehensive financial metric that captures the holistic performance of equipment.

Both OEE and the existing financial metric are quantitative metrics. The lack of specific guidance in the OEE metric and financial metrics on how to optimise equipment operational and financial performance calls for research to develop a framework that provides actionable strategies for project team. The proficiency of project team can significantly influence the outcomes of equipment optimisation initiatives, necessitating the development of a systematic problem-solving framework that integrates the new financial metric with other methodologies. Standardization is also essential to ensure consistent evaluation and optimisation of equipment performance across different initiatives and regardless of project team's competencies. Research should focus on developing a standardised methodology that can be easily implemented and followed by project team. Lastly, continuous improvement is crucial in optimising equipment performance, and research should explore methods to monitor the effectiveness of improvement initiatives within the framework, enabling organisations to achieve sustainable improvements over time.

1.3 Research Objectives

The objectives of this research are stated as followings:

1. To review and classify existing OEE articles measuring financial performance to identify suitable metrics and approaches for assessing equipment financial performance in OEE initiatives.

2. To integrate the new financial metric into a framework with other problem-solving approaches, enhancing both operational and financial equipment performance.

3. To validate the new financial metric and the framework through three case studies in manufacturing environments.

1.4 Research Scopes

1. The scope of this research is focused on the industrial application of the new financial metric and framework, with the objective of validating their robustness and practicality through three case studies in manufacturing. Grounded in OEE, the financial metric and framework are deemed unsuitable for specific manufacturing types where OEE do not directly apply, such as batch and custom manufacturing, highly variable production processes, and non-physical equipment utilisation.

2. It is important to note that the new financial metric and its integrated framework were developed specifically for optimising the operational and financial performance of existing equipment. Therefore, it is not appropriate to use them for assessing or acquiring new equipment.

3. The case studies are limited to the manufacturing section of the company, as the new financial metric and framework are intended to enhance the operational and financial performance of existing equipment in this specific area. As a result, the supply chain and facilities of the organisation were excluded from this research.

4. The new financial metric and framework are established based on OEE. OEE should avoid implementing on the batch and custom manufacturing, highly variable production processes, and non-physical equipment utilisation.

1.5 Structure of the Thesis

The structure of this thesis comprises seven chapters. Chapter 1 introduces the research and outlines the background, problem statement, objectives, and scopes of the study. This chapter also provides a brief overview of the entire thesis.

Chapter 2 is dedicated to reviewing various relevant articles on financial metrics that aim to quantify the equipment financial performance in OEE initiatives. The insights gained from these articles are essential for establishing the new financial metric and its framework.

In Chapter 3, the methodology for developing the new financial metric and constructing the integrated framework that incorporates the new financial metric with other practical methodologies is presented. Furthermore, the method used to validate the new financial metric and its framework is outlined in this chapter.

In Chapter 4, the new financial metric and its framework are deduced and presented. The framework is integrated with other methods that provide step-by-step guidelines to improve the new financial metric.

In Chapter 5, the validation process of the new financial metric and its framework is presented through three different case studies. Relevant data were collected throughout the validation of the new financial metric and its framework.

In Chapter 6, the validity of the new financial metric was first examined based on the findings obtained from the three case studies. Subsequently, the significant achievements gained were used to demonstrate the practicality of the new framework.

Chapter 7, the final chapter, provides a summary of the entire research, including the conclusions of the new financial metric and its framework. Additionally, this chapter offers recommendations for future research in this area.

CHAPTER TWO

LITERATURE REVIEW

2.0 Overview

This chapter builds a solid theoretical foundation by thoroughly reviewing the literature on financial metrics in OEE initiatives to ascertain the key elements that will be deployed in the new financial metric and its framework. The chapter is organised into five sections. Section 2.1 reviews OEE, while Section 2.2 details the methodology used in the literature review. Section 2.3 reviews the articles that measured financial metrics in OEE. In Section 2.4, the reviewed articles are classified, and a comparative analysis of the reviewed financial metrics in OEE is presented, along with opportunities to expand the OEE literature in relation to financial metrics. Finally, Section 2.5 summarises Chapter 2.

2.1 Overall Equipment Effectiveness

OEE is a quantitative metric to measure equipment operational performance in the manufacturing environment by using the time loss structure (Mjimer et al., 2022). As expressed in Equation (1), OEE is the product of three different equipment performance aspects, which are availability, performance, and quality (Ghafoorpoor et al., 2018; Cheah et al., 2020a).

$$OEE = A \cdot P \cdot Q \tag{1}$$

Where

A availability

P performance

Q quality

Availability is the ratio of the operating time to loading time, as expressed in Equation (2). The loading time of an equipment is the available time to operate. The operating time is the loading time less the equipment downtime, which includes breakdown, setup and adjustment. (Kwon and Lee, 2004; Wudhikarn, 2016).

$$A = \frac{T_{OT}}{T_{LT}} \tag{2}$$

where,

T_{LT} the loading time

T_{OT} the operating time

Performance is the ratio of the net operating time to operating time, as expressed in Equation (3). The net operating time is the product of the processed quantity and the theoretical cycle time (T_{CT}). (Kwon and Lee, 2004; Wudhikarn, 2016). The T_{CT}, specified in design, represents the ideal duration for a single cycle under optimal conditions, serving as a benchmark for the shortest achievable cycle time and providing a reference for evaluating efficiency in processes or manufacturing systems (Kwo and Lee, 2004).

$$P = \frac{T_{NOT}}{T_{OT}} \tag{3}$$

where,

T_{NOT} the net operating time

Quality is defined as the ratio of the good quantity to processed quantity, as expressed in Equation (4). Quality is also defined as the ratio of the valuable operating time to net operating time. (Kwon and Lee, 2004; Wudhikarn, 2016).

$$Q = \frac{Q_G}{Q_P} \tag{4}$$

where,

Q_G the good quantity

Q_P the processed quantity

Note that the OEE in Equation (1) can be formulated as Equation (5) (Kwon and Lee, 2004).

$$OEE = \frac{T_{OT}}{T_{LT}} \cdot \frac{T_{CT} \cdot Q_P}{T_{OT}} \cdot \frac{Q_G}{Q_P}$$

$$OEE = \frac{Q_G \cdot T_{CT}}{T_{LT}} \tag{5}$$

where,

T_{CT} the theoretical cycle time

To attain 85% world-class OEE, the six major losses that affect OEE and need to mitigate or minimise include (Wudhikarn, 2012; Gandhi and Deshpande, 2018): (1) equipment failure losses - the time consumed to correct equipment failures, (2) setup and adjustment losses - the time required for equipment adjustments after the production of one product ends and the subsequent product specifications are met, (3) idling and minor stoppage losses - losses incurred when production is interrupted by minor malfunctions or when equipment goes idle, (4) reduced speed losses - the difference between the equipment designed speed and actual operating speed, (5) reduced yield losses - losses that occur during equipment stabilisation, and (6) defect and rework losses - the result of manufacturing products that do not conform to product specifications. Losses (1) and (2) are downtime losses and are linked to availability. Losses (3) and (4) are speed losses and are linked to performance, while losses (5) and (6) are defect losses that affect the quality. Figure 2.1 illustrates the relationship between the six big OEE losses and OEE factors.

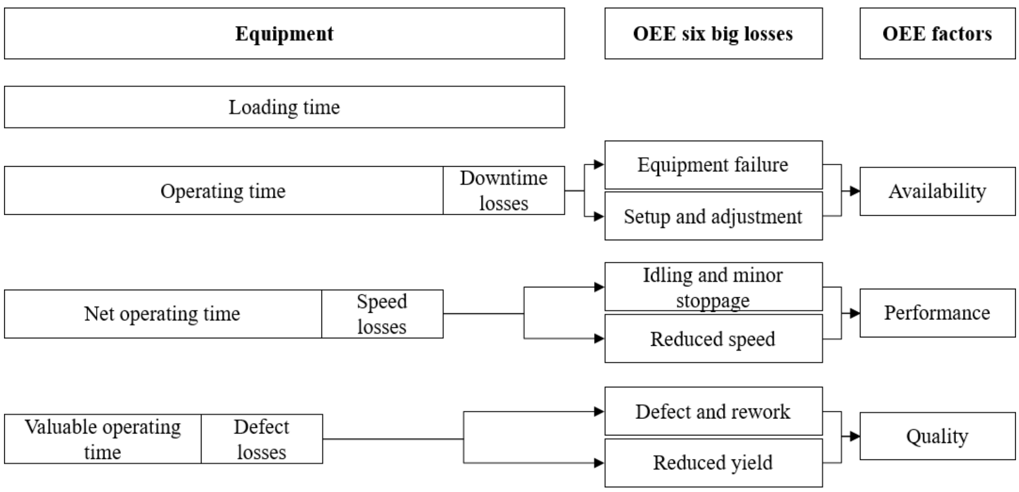

Figure 2.1. The relationship between OEE six big losses and OEE factors (Singh and Narwal, 2017)

2.2 The Methodology of Literature Review

The literature review integrates journals and conference proceedings spanning from 2004 to 2022, sourced from reputable platforms such as Google Scholar, Science Direct, Emerald Insight, IEEE Xplore Digital Library, and Taylor & Francis Online. The decision to exclude articles predating 2004 is rooted in their prior citation in subsequent research, steering the review towards recent studies to prevent redundancy and emphasize contemporary insights. Additionally, this choice acknowledges the dynamic nature of academic discourse, ensuring the review captures the latest perspectives and advancements from 2004 to 2022, fostering a nuanced understanding of the field. Moreover, narrowing the scope to post-2004 research facilitates a more efficient and targeted examination of the most relevant and current contributions in the field.

The review focuses on keywords of OEE and its combination with financial metrics such as ‘profit’, ‘revenue’, and ‘cost’. Every organisation intends to earn high profit (Prasad and Jayswal, 2018), and profit (K_P) is the difference between revenue and cost. Revenue (K_R) is the product of price per unit and quantity sold. Cost is the value of money devoted to buying equipment, materials, utility, and facility for manufacturing goods. In simple terms, cost refers to the expenses incurred in the process of production. Based on the life cycle cost distribution (Bengtsson and Kurdve, 2016; Kianian et al., 2019), these expenses can be broken down into three main categories: (1) equipment acquisition cost (K_{EC}), which includes initial capital cost, equipment cost, installation cost, tool cost, spare part cost, equipment operating and maintenance training cost, and equipment reconditioning cost; (2) operating cost (K_{OC}), which includes labour cost, raw material cost, material handling cost, rent cost, energy cost, downtime cost, setup cost, and yield loss cost; and (3) maintenance cost (K_{MC}), which includes preventive maintenance cost, corrective maintenance cost, repair cost, equipment servicing contract cost, maintenance activity documentation cost, and inspection cost. Figure 2.2 illustrates the relationship between K_P, K_R, K_{EC}, K_{OC}, and K_{MC}. The relationship between OEE and K_P, K_R, K_{EC}, K_{OC}, and K_{MC} undergoes detailed analysis.

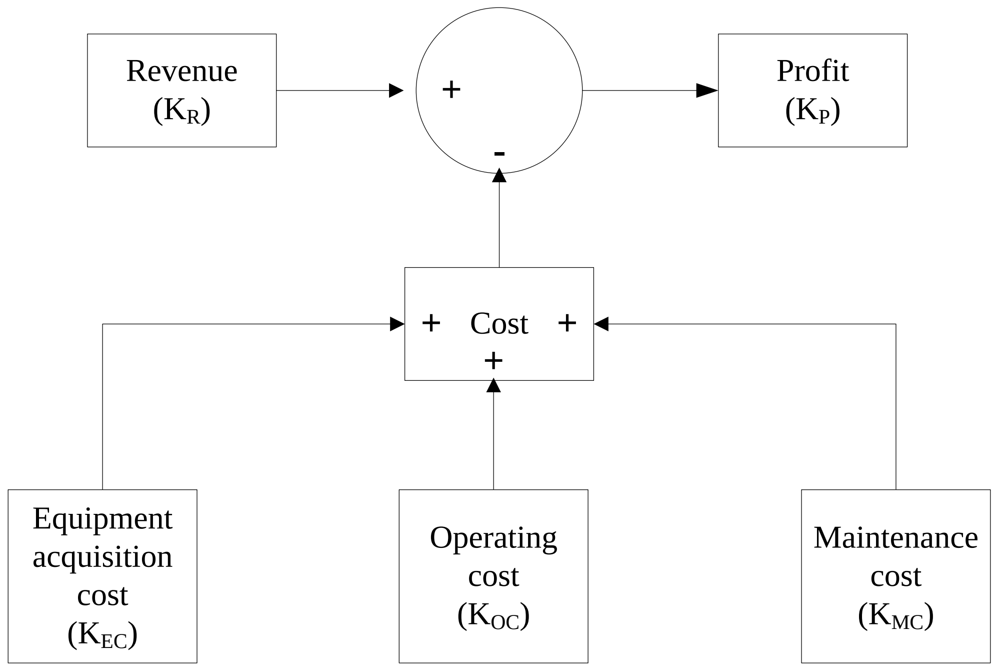

Figure 2.2. The relationship between K_P, K_R, K_{EC}, K_{OC}, and K_{MC} (Bengtsson and Kurdve, 2016; Kianian et al., 2019)

Based on the chosen keywords and an initial review of titles and abstracts, 75 articles were collected. After reviewing the full text of each article for eligibility and relevance, 46 articles were excluded because the relationship between OEE and financial metrics could not be examined. These articles mentioned that OEE could influence financial metrics without providing evidence of the application of financial metrics in OEE initiatives. The remaining 47 articles that applied financial metrics in OEE were retained. From these 47 articles, 18 financial metrics were proposed. The following section will discuss the details of each proposed financial metric.

2.3 The Financial Metric in OEE

Kwon and Lee (2004) estimated that equipment earning capacity (ΔK_E) can be gained by upraising OEE by 1%. As expressed in Equation (6), ΔK_E is calculated by adding the additional profit gained from selling additional processed good quantity (ΔY_{Good}), saved equipment acquisition cost (ΔK_{EC}), saved operating cost (ΔK_{OC}) and saved maintenance cost (ΔK_{MC}). The additional profit is the product of ΔY_{Good} and price per unit (K_{PPU}).

$$\Delta K_E = (\Delta Y_{Good} \cdot K_{PPU}) + \Delta K_{EC} + \Delta K_{OC} + \Delta K_{MC} \tag{6}$$

Heilala et al. (2006), Heilala et al. (2007), Jimenez (2009), Roda et al. (2020), Wibowo et al. (2019), and Sharma et al. (2022) applied total cost of ownership (TCO) to assess all costs incurred throughout the entire life cycle of a piece of equipment. TCO quantifies equipment effectiveness operationally and financially. TCO is derived by dividing the sum of equipment acquisition cost (K_{EC}), operating cost (K_{OC}) and maintenance cost (K_{MC}) incurred during the equipment life cycle with the product of equipment lifetime ($t_{lif'}$), throughput rate (Y_{Thr}), processed good quantity (Y_{Good}) and utilisation (UTL), as expressed in Equation (7). Despite TCO having no direct relationship with OEE, OEE has an indirect impact on TCO. Higher OEE generates better t_{life}, Y_{Thr} and UTL, which eventually leads to lower TCO.

$$TCO = \frac{\sum(K_{EC}+K_{OC}+K_{MC})}{(t_{life} \cdot Y_{Thr} \cdot Y_{Good} \cdot UTL)} \tag{7}$$

Identical equipment may operate at the same OEE, but with different K_{EC}, K_{OC}, K_{MC}, labour cost (K_D), material cost (K_B) and/or other consumable costs. Sheu (2006) proposed the overall input efficiency (OIE) to assess the input consumption efficiency. The OIE includes the K_{EC}, K_{OC}, K_{MC}, K_D, K_B, and other consumable costs. Assuming several categories of inputs, Equation (8) is used to calculate the OIE. The input efficiency compares the actual resource input (D_i) to the theoretical ideal resource input (Act_i). The sum of the relative weights (W_i) for all the categories is 1. Organisations can utilise the OIE to show which equipment has the highest wastage.

$$OIE = \sum_{i=1}^{I} w_i \cdot \frac{D_i}{Act_i} \tag{8}$$

Siong and Ahmed (2007), Dogra et al. (2011), Desai and Khare (2017), Singh and Ahuja (2017), Er-Ratby and Mabrouki (2018), Chikwendu et al., (2020), Gallesi-Torres et al. (2020), and Mizgan and Genea (2022) measured the saved maintenance cost (ΔK_{MC}). The ΔK_{MC} is calculated by comparing the K_{MC} before and after the OEE initiative. ΔK_{MC} and OEE have an inverse proportional relationship. Equipment with higher OEE results in lower ΔK_{MC}. Besides OEE, saved ΔK_{MC} assesses the effectiveness of implemented corrective actions, as expressed in Equation (9).

$$\Delta K_{MC} = K_{MC}(After) - K_{MC}(Before) \tag{9}$$

Badiger and Grandhinathan (2008) used the equipment earning capacity (K_E) to estimate the equipment earning capacity when OEE is increased by 1%.

The K_E is estimated by multiplying the expected theoretical output when OEE is increased by 1% by the sum of K_{MC} and K_{OC}, as expressed in Equation (10). The expected theoretical output is calculated by dividing the operating time (T_{OT}) by the theoretical cycle time (T_{CT}). Higher OEE results in higher operating time, which leads to higher K_E.

$$K_E = \frac{T_{OT}}{T_{CT}} \cdot (K_{MC} + K_{OC}) \tag{10}$$

Overall equipment cost loss (OECL) quantifies monetary losses that result from OEE losses (Wudhikarn et al., 2009; Wudhikarn, 2016; Mahmoud et al., 2019; Dewi et al., 2020). OECL is the sum of the availability monetary losses (K_{AL}), performance monetary losses (K_{PL}), and quality monetary losses (K_{QL}), as expressed in Equation (11). The K_{AL} is the sum of opportunity loss of availability and other production cost loss of availability. The K_{PL} adds the opportunity loss of performance and production cost loss of performance. The K_{QL} is the sum of reject cost loss and rework cost loss. OEE measures different OEE losses equally; thus, all OEE losses have the same impact in OEE. Unlike OEE, OECL weights OEE losses differently depending on resource consumption. OECL further identifies what type of OEE losses should be focused on.

$$OECL = K_{AL} + K_{PL} + K_{QL} \tag{11}$$

Wudhikarn (2012) proposed the overall equipment and quality cost loss (OEQCL) by adding the cost of quality losses (COQL) in OECL, as expressed in Equation (12). The COQL is the sum of conformance cost (paid for prevention of poor quality) and non-conformance cost (paid for poor product quality) (Schiffauerova and Thomson, 2006; Khaled and Murgan, 2014). OEQCL determines a more refined priority than OEE and OECL, because COQL is a hidden cost that consumes more resources in organisations.

$$OEQCL = OECL + COQL \tag{12}$$

Profit loss indicator (PLI) measures financial losses due to OEE losses and waste in production (Rødseth et al., 2015; Sandengen et al., 2016). Waste in production does not create any value to customers. Such waste includes overproduction, inventory, motion, over-processing, defects, transportation and waiting (Jasti and Kodali, 2015). The PLI is calculated by adding turnover loss and extra costs. The K_{AL}, K_{PL}, and K_{QL} result in turnover loss, whereas extra cost is the sum of the additional K_{EC}, K_{OC}, and K_{MC}. As illustrated in Figure 2.3, the PLI is divided into three dimensions. The first dimension is about the physical asset. The second dimension is about accounting, which is meant to distinguish between turnover loss and extra cost. The third dimension is meant to analyse time losses and waste separately.

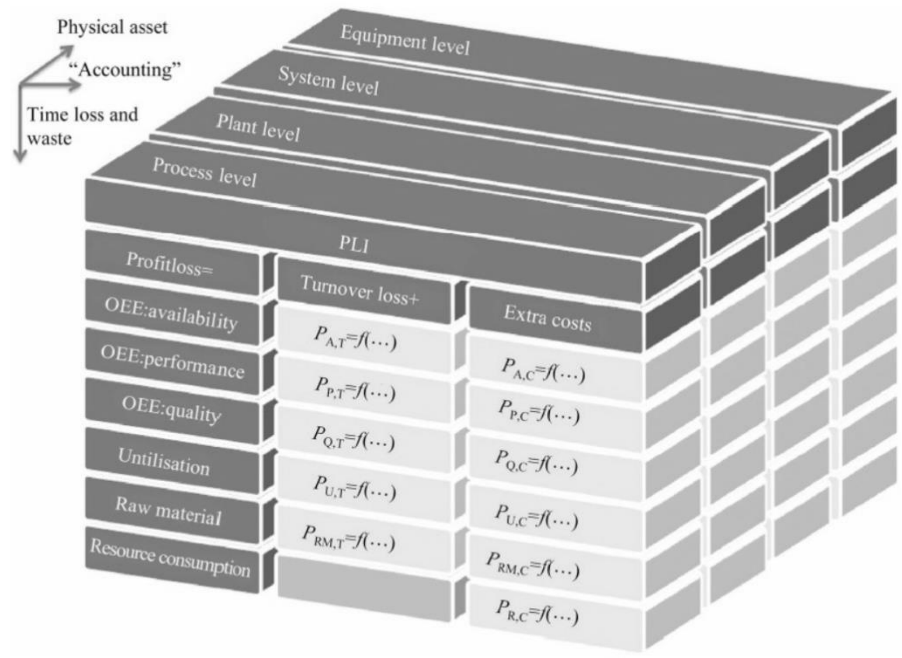

Figure 2.3: PLI (Rødseth et al., 2015; Sandengen et al., 2016)

Benjamin et al. (2015) quantified reduced speed loss (t_{TRSL}) in monetary terms using speed loss cost (K_{SL}). Reduced speed loss occurs because of inefficiency. As expressed in Equation (13), the K_{SL} is the product of t_{TRSL} and labour cost (K_D). K_D is the cost that is used to pay workers working on a product, and it includes salary, taxes and other benefits (Lima and Castilho, 2015; Maralcan and Ilhan, 2017).

$$K_{SL} = t_{TRSL} \cdot K_D \tag{13}$$

Raj and Gupta (2016), Rimawan and Irawan (2017), Rodrigues and Cabral (2017), Knop (2018), Muñoz-Villamizar et al. (2018), Mardono et al. (2019) and Cheah et al. (2020b) measured additional profit (ΔK_P) in an OEE initiative. The Δk_P is the difference between additional revenue and ΔK_{EC}, ΔK_{OC}, and ΔK_{MC} as expressed in Equation (14). Additional revenue is the product of ΔY_{Good} and price per unit (K_{PPU}). Equipment with high OEE produces a high quantity of good-quality products with lower cost, which subsequently leads to high profit when a high quantity of such products is sold.

$$\Delta K_P = (\Delta Y_{Good} \cdot K_{PPU}) - (\Delta K_{EC} + \Delta K_{OC} + \Delta K_{MC}) \quad (14)$$

Chong and Ng (2016), Gupta and Vardhan (2016), Rimawan et al. (2018), Zahoor et al. (2018), Hooda and Gupta (2019) and Haddad et al. (2021) quantified financial achievement in OEE using production cost (K_{Prod}). The K_{Prod} is the cost required to operate a process for producing a specific amount of good quantity. As expressed in Equation (15), the K_{Prod} is calculated by dividing the sum of K_{EC}, K_{OC}, and K_{MC} with the total of the Y_{Good} and rework quantity (Y_{Rwk}). The availability losses, performance losses, and quality losses in OEE have significant impact on K_{Prod}. Higher OEE leads to lower K_{Prod}.

$$K_{Prod} = \frac{(K_{EC} + K_{OC} + K_{MC})}{(Y_{Good} + Y_{Rwk})} \quad (15)$$

Posteuca and Zapciu (2016) estimated setup cost (K_{SC}) in an improvement initiative. The K_{SC} is the associated cost of switching a machine, work centre, or assembly line from a current product to a subsequent product (Vijayashree and Uthayakumar, 2016). The K_{SC} is estimated by multiplying the total setup and adjustment time (t_{TSA}) by the sum of monthly equipment acquisition cost ($K_{EC/M}$), monthly operating cost ($K_{OC/M}$), and monthly maintenance cost ($K_{MC/M}$), as expressed in Equation (16). A reduction in t_{TSA} leads to higher OEE and a corresponding decrease in K_{SC}.

$$K_{SC} = t_{TSA} \cdot (K_{EC/M} + K_{OC/M} + K_{MC/M}) \quad (16)$$

Overall cost efficiency (OCE) shows how inefficient equipment operates in terms of OEE and cost (Novak and Vukasovic, 2016). As expressed in Equation (17), OCE relates OEE, average fixed cost (K_{AFC}), average variable cost (K_{AVC}) and average cost (K_{AC}). The K_{AVC} (operating cost and maintenance cost) is the sum of expenditures that varies depending on production volume, whereas the K_{AFC} (equipment acquisition cost) is the other cost incurred by organisations (Tosarkani and Amin, 2018). The K_{AC} is the sum of K_{AFC} and K_{AVC}. OCE predicts how much cost efficiency can be gained by enhancing OEE.

$$OCE = \frac{1}{OEE} \cdot \left(\frac{K_{AFC}}{K_{AVC}}\right) + \frac{K_{AVC}}{K_{AC}} \qquad (17)$$

As shown in Equation (18), besides OEE, K_{OC}, K_{EC}, K_{PPU}, and Y_{Good}, Rodrigues and Cabral (2017) related the profit (K_P) to taxes (TX). TX has an inverse proportional relationship to the K_P; thus, higher TX leads to lower performance. Although the K_{OC}, K_{EC}, OEE, K_{PPU}, Y_{Good} and TX remain constant, the K_P and OEE present a linear correlation.

$$K_P = \left[\frac{Y_{Good} \cdot (S - \sum K_{OC})}{(1+TX)}\right] \cdot OEE - \left[\frac{\sum K_{EC}}{(1+TX)}\right] \qquad (18)$$

Venkateswaran (2017) and Ungern-Stemberg et al. (2021) measured the saved scrap cost (ΔK_{Scrp}), while Nallusamy and Majumdar (2017) measured the saved rework cost (ΔK_{Rwk}) in separate OEE initiative. The scrap cost (K_{Scrp}) is incurred by scrapping a product that is not meeting requirements (Omachonu et al., 2004). Rework cost (K_{Rwk}) is incurred from redoing a process more than once to correct errors in the original requirements (Liew et al., 2018) and K_{Rwk} is the associated cost from rework. The ΔK_{Scrp} and ΔK_{Rwk} are calculated by comparing the K_{Scrp} and K_{Rwk} before and after the OEE initiative, as expressed in Equation (19) and (20). The ΔK_{Scrp} and ΔK_{Rwk} are used to assess the effectiveness of the implemented correction action in financial terms.

$$\Delta K_{Scrp} = K_{Scrp}(After) - K_{Scrp}(Before) \tag{19}$$

$$\Delta K_{Rwk} = K_{Rwk}(After) - K_{Rwk}(Before) \tag{20}$$

Jönsson et al. (2008) and Kianian and Andersson (2018) used total product cost (K_{total}) to relate operational performance parameters, such as nominal cycle time (t_0), setup time (t_{su}), production time (t_p), nominal batch size (N_0), UTL, availability (A), performance (P) and quality (Q) with tool cost (K_A), equipment acquisition cost during operation (K_{ECO}), equipment acquisition cost during downtime (K_{ECD}), material cost (K_B), K_D, maintenance cost (K_{MC}) and other additional costs (K_{SUM}). As expressed in Equation (21), K_{total} is calculated in a cumulative method where the cost of each process is added as the input cost to the next. K_{total} has an inverse proportional relationship to A, P, and Q in OEE; thus, higher A, P, and Q lead to lower K_{total}.

$$K_{total} = K_A + \frac{K_B}{Q} + \frac{K_{ECO} \cdot t_0}{Q \cdot P \cdot 60} + \frac{K_{ECD}}{60}\left[\frac{(1-A) \cdot t_0}{Q \cdot P \cdot A} + \frac{t_{SU}}{N_0} + \frac{t_p}{N_0} \cdot \frac{1-UTL}{UTL}\right] + \frac{K_D}{60}\left[\frac{t_0}{Q \cdot P \cdot A} + \frac{t_{SU}}{N_0} + \frac{t_p}{N_0} \cdot \frac{1-UTL}{UTL}\right] + \frac{K_{MC}}{60} + \frac{K_{SUM}}{N_0} \tag{21}$$

Bataineh et al. (2019) applied revenue per utilisation (RPU) to identify which equipment has high revenue but low effectiveness for improvement. RPU is derived by dividing revenue (K_R) by UTL, as shown in Equation (22). UTL is calculated by dividing the actual quantity produced by the targeted quantity produced. Although RPU has no direct relationship with OEE, equipment with high OEE produces more actual quantity, which subsequently results in higher UTL and lower RPU.

$$RPU = \frac{Revenue}{Utilization} \tag{22}$$

2.4 Discussion

This section is divided into three parts. Section 2.4.1 classifies all the reviewed financial metrics in OEE according to a classification scheme, which will be detailed later. In Section 2.4.2, the advantages and disadvantages of the reviewed OEE financial metrics are analysed. Finally, Section 2.4.3 explores gaps in the research and opportunities that can be further developed to enhance financial metrics in OEE literature.

2.4.1 Classification Scheme

The reviewed articles are classified into two main categories, as per the proposed classification scheme. The first category focuses on two aspects: (1) the approach used to apply the financial metric in OEE, which can either measure the same financial metric before and after the improvement or integrate the financial metric with OEE through mathematical modelling; and (2) the aim of the financial metric, which is to examine its relationship with OEE and various financial metrics, such as K_P, K_R, K_{EC}, K_{OC}, and K_{MC}. This classification scheme allows for a comparison of the strengths and weaknesses of each financial metric and provides a more accurate and in-depth understanding of their respective categories. Additionally, the financial metrics were further categorized into K_P, K_R, K_{EC}, K_{OC}, and K_{MC}, as these metrics are interrelated and may relate to more than one category.

The second category focuses on whether the financial metric is integrated with a problem-solving methodology into a framework to improve both the OEE and financial metrics. Each collected methodology is assessed, and the most suitable one is identified to be used along with OEE and financial metrics. Furthermore, this classification may lead to the discovery of new problem-solving methodologies that are not currently deployed in the existing literature. Overall, these classification schemes aim to provide an accurate, in-depth, and intuitive understanding of the different categories of financial metrics that quantify the most relevant financial performance in OEE. Tables 2.1 and 2.2 summarise the first and second categories, respectively.

Table 2.1: Classification of OEE with financial metric

Reference	Financial metric	A	K_P	K_R	K_{EC}	K_{OC}	K_{MC}
Kwon and Lee (2004)	Equipment earning capacity	R	✓				
Rødseth et al. (2015), Sandengen et al. (2016)	Profit loss indicator	R	✓				
Bataineh et al. (2019)	Revenue per utilization	R		✓			
Heilala et al. (2006), Heilala et al. (2007), Jimenez (2009), Wibowo et al. (2019), Roda et al. (2020), Sharma et al. (2022)	Total cost of ownership	R			✓	✓	✓
Sheu (2006)	Overall input efficiency	R			✓	✓	
Siong and Ahmed (2007), Dogra et al. (2011), Desai and Khare (2017), Singh and Ahuja (2017), Er-Ratby and Mabrouki (2018), Chikwendu et al., (2020), Gallesi-Torres et al. (2020), Mizgan and Genea (2022)	Saved maintenance cost	R					✓
Badiger and Gandhinathan (2008)	Equipment earning capacity	R				✓	
Wudhikarn (2009), Wudhikarn (2016), Mahmoud et al. (2019), Dewi et al. (2020)	Overall equipment cost loss	R			✓	✓	✓
Wudhikarn (2012)	Overall equipment and quality cost loss	R			✓	✓	✓
Benjamin et al. (2015)	Speed loss cost	R				✓	
Novak and Vukasovic (2016)	Overall cost efficiency	R			✓	✓	✓
Posteuca and Zapciu (2016)	Setup cost	R				✓	
Chong and Ng, (2016), Gupta and Vardhan (2016), Rimawan et al. (2018), Zahoor et al. (2018), Hooda and Gupta (2019), Haddad et al. (2021)	Production cost	R			✓	✓	✓
Jönsson et al. (2018), Kianian and Andersson (2018)	Total product cost	R			✓	✓	✓
Raj and Gupta, (2016), Rimawan and Irawan (2017), Rodrigues and Cabral (2017), Knop (2018), Muñoz-Villamizar et al. (2018), Mardono et al. (2019), Cheah et al. (2020b)	Additional profit	M	✓				
Nallusamy and Majumdar (2017)	Rework cost	M				✓	
Venkateswaran (2017), Ungern-Stemberg et al. (2021)	Scrap cost	M				✓	

Notes: ✓ - applicable; A – approach; R – relate the financial to OEE; M – measure the financial metric in OEE initiative; K_P: profit; K_R: revenue; K_{EC}: equipment acquisition cost; K_{OC}: operation cost; K_{MC}: maintenance cost

Table 2.2: Methodology to enhance the equipment operational and financial performance

Reference	5-why analysis	6S	Brainstorming	Cause-and-effect diagram	Failure mode effect analysis	Histogram	Kaizen	Pareto analysis	Simulation	Single minute exchange die	Value stream map	Process flowchart
Bataineh et al. (2019)				✓	✓			✓				
Heilala et al. (2006)									✓			
Heilala et al. (2007)									✓			
Dogra et al. (2011)							✓					
Benjamin et al. (2015)	✓											
Rimawan et al. (2018)										✓		
Zahoor et al. (2018)											✓	
Hooda and Gupta (2019)							✓					
Venkateswaran (2017)	✓			✓		✓		✓				
Nallusamy and Majumdar (2017)				✓								
Posteuca and Zapciu (2016)										✓		
Mahmoud et al. (2019)								✓				
Dewi et al. (2020)				✓				✓				
Chikwendu et al. (2020)												✓
Gallesi-Torres et al. (2020)		✓										✓
Rimawan and Irawan (2017)										✓		
Cheah et al. (2020b)			✓	✓				✓				

Note: ✓- applicable

2.4.2 Comparative Analysis of The Reviewed Financial Metric in OEE

With the exception of additional profit (ΔK_P) and scrap cost (K_{Scrp}), all other financial metrics that were reviewed are mathematically linked to OEE. In practice, most organisations find it easy to comprehend and implement the approach of measuring financial metrics in improvement initiatives. By comparing financial metrics before and after an improvement initiative, it is possible to assess the effectiveness of the improvement actions. However, one drawback of this approach is that project team cannot predict the impact of the improvement actions on the financial metrics until after the improvement actions have been implemented. Therefore, the effectiveness of the improvement actions should be verified before implementation to avoid costly rework. Measured financial metrics may not necessarily apply to the implemented improvement actions. For example, a measured K_{Scrp} may also be induced by other factors that are irrelevant to the equipment, such as immature product design, incorrect order, or impurity of raw materials. An inaccurately measured financial metric will result in incorrect assessments, which could subsequently overestimate or underestimate the effectiveness of the improvement actions.

Integrating OEE with financial metrics is a more complex approach than measuring financial metrics alone. However, the established mathematical relationship between OEE and financial metrics can help project team estimate the financial metric while planning OEE improvement actions. OEE is a practical metric that comprehensively evaluates equipment performance by considering availability, performance, and quality, providing a holistic understanding of operational efficiency through its accessible calculation method (Ahire and Relkar, 2012; Relkar and Nandurkar, 2012). To sustain the simplicity and practicability of OEE, the mathematical relationship between OEE and financial metrics should be simple to understand and easy to implement in real-world manufacturing environment. A widely recognized process improvement method should not involve complex mathematical methods (Vergidis et al., 2008). Among all reviewed financial metrics, the profit loss indicator (PLI) and total product cost (K_{total}) are amongst the most complex.

PLI and K_{total} are too wide, as they consider the financial impact of OEE in many aspects. OEE aims to quantify the operational performance of equipment. Besides the various OEE losses, the PLI also includes extra costs that are caused by various wastes in production. The PLI also analyses the loss induced by the process, plant, and system. By definition, OEE already considers the impact of the nominal cycle time (t_0), setup time (t_{SU}), and production time (t_p). However, besides OEE, the K_{total} relates the t_0, t_{SU}, and t_p individually; hence, K_{total} estimates the impact of the t_0, t_{SU}, and t_p redundantly. By comparison, the approach of relating OEE to financial metrics is more suitable. OEE itself is a metric to quantify equipment operational performance. Therefore, integrating OEE with financial metrics expands the scope of OEE to examine equipment performance operationally and financially. The mathematical equation that links OEE and financial metrics should be expressed in a simple and practical manner.

Various studies have established a direct or indirect linear relationship between OEE and K_P (Kwon and Lee, 2004; Rødseth et al., 2015; Sandengen et al., 2016; Rodrigues and Cabral, 2017) and K_R (Bataineh et al., 2019). However, while K_P or K_R is commonly used as a financial metric, it may not be suitable for quantifying the financial achievement in OEE improvement initiatives. This is because K_P and K_R are the result of the quantity sold and price per unit (K_{PPU}) and are influenced by various non-equipment operational factors besides OEE. One such factor is customer demand, where additional capacity resulting from improved equipment OEE may lead to an increase in K_P or K_R if the goods produced are traded. However, if market demand does not increase, the surplus produced goods will be stored as inventory, ultimately eroding the organisation's K_P (Nagare and Dutta, 2012; Panigrahi, 2013). On the other hand, an abrupt increase in customer demand beyond the equipment's maximum capacity operating at 85% world-class OEE does not necessarily relate to equipment operational performance. The second factor is K_{PPU}, which is determined by supply and demand (Azevedo and Leshno, 2016). Organisations set the K_{PPU} irrespective of the equipment's OEE, which implies that a product manufactured using equipment with 65% or 85% OEE may have the same K_{PPU}. In cases where a product has a low-profit margin, the impact of K_P could be negligible despite the increased OEE of the equipment. The third factor is product design, where products with immature or complex designs incur higher defects and longer cycle times (Bogue, 2012; Conner et al., 2014). Under these circumstances, equipment operational performance should not be solely accountable for achieving low K_P or K_R. When many factors influence K_P or K_R, which are not related to equipment operational performance, these metrics should not be used to assess the financial effectiveness of the equipment.

Increasing the OEE has shown improvement in various cost elements of K_{OC}. Nallusamy and Majumdar (2017) reported reduced rework costs, while Venkateswaran (2017) and Ungern-Stemberg et al. (2021) noted a decrease in scrap costs. Benjamin et al. (2015) reported enhancements in setup costs, and Posteuca and Zapciu (2016) reported enhancements in setup costs. However, each analysis focuses on specific cost elements of K_{OC}. In Kianian et al.'s study (2019), an increase in equipment OEE led to decreased raw material costs and yield loss costs, but increased labour costs. K_{OC} represents the sum of all cost elements, making it challenging to determine if the overall K_{OC} increases or decreases when not all elements exhibit a proportional or reverse relationship with OEE. Additionally, not all K_{OC} reductions are solely attributed to OEE improvements, as highlighted by Garza-Reyes (2015). For instance, labour costs could be reduced by balancing the production line and optimising operator efficiency. Similarly, cost savings in raw materials could result from using lower-cost substitute materials. Thus, linking OEE with K_{OC} to assess the financial effectiveness of OEE improvement initiatives yield inaccurate conclusions due to the complex and multifaceted impact of OEE on K_{OC} estimation. Therefore, it is essential not to use the K_{OC} to quantify the financial effectiveness of equipment.

In hindsight, K_{EC} and K_{MC} can be considered more comprehensive measures of equipment financial performance in conjunction with OEE. K_{EC} typically represents the largest proportion of capital investment in an organisation, with K_{MC} accounting for a significant portion of this amount as it covers equipment maintenance activities. Studies have reported that K_{MC} constitutes 20% to 50% of K_{EC} (Parida and Kumar, 2006; Jha and Singh, 2016). The impact of OEE and its losses on K_{EC} and K_{MC} is noteworthy. For instance, higher equipment failure, idling, and minor stoppage losses result in increased spare part, preventive and maintenance, and repair costs. A decrease in speed losses and defect and rework losses reduces the lost capacity, thereby minimising the need to acquire additional equipment, which reduces K_{EC}. Therefore, higher OEE leads to lower equipment acquisition and maintenance costs. The inverse proportional relationship between OEE and K_{EC} and K_{MC} makes them suitable for quantifying the financial performance of equipment in improvement initiatives. Table 2.3 summarises the observations regarding the approach of applying financial metric in OEE and their relationship with K_P,

K_R, K_{EC}, K_{OC}, and K_{MC}.

Table 2.3: Summary of financial metric application in OEE and their relationship

	Findings	Observations
Approach of applying the financial metric in OEE	• Financial metric comparison can assess effectiveness, but impact is uncertain until implementation. • Integrating OEE with financial metrics is complex, but mathematical equation can help estimate during planning.	• Integrating OEE with financial metrics is a suitable approach that expands the scope of OEE to evaluate equipment performance operationally and financially. • The mathematical equation linking OEE and financial metrics should be expressed simply and practically.
K_P and K_R	• Influenced by various non-equipment factors.	• When unrelated factors influence K_P or K_R, these metrics should not assess equipment's financial effectiveness.
K_{OC}	• Not all elements of K_{OC} exhibit a proportional or reverse relationship with OEE.	• The OEE-K_{OC} relationship is complex and multifaceted, making K_{OC} unsuitable for measuring financial impact in OEE initiatives.
K_{EC} and K_{MC}	• Higher OEE losses lead to increased maintenance cost, lost capacity, and the need for additional equipment, resulting in higher K_{EC} and K_{MC}.	• The inverse OEE-K_{EC} and K_{MC} relationship makes them suitable for quantifying equipment financial performance in OEE initiatives

Note: OEE: overall equipment effectiveness; K_P: profit; K_R: revenue; K_{OC}: operating cost; K_{EC}: equipment acquisition cost; K_{MC}: maintenance cost

All of the financial metrics reviewed, with the exception of Cheah et al. (2020b), fail to provide guidelines for improving equipment OEE and financial performance. Without such guidance, initiatives are typically left to the discretion of project team, whose varying competencies may result in inconsistent outcomes across projects (McMeekin et al., 2020). To enhance the practicability of these metrics, they should be integrated into a comprehensive and systematic framework alongside other methodologies. This approach can provide problem-solving steps to help project team achieve their objectives for the initiative. While the reviewed literature generally lacks such an integrated approach, a number of methodologies, such as 5-why analysis, 6S, brainstorming, cause-and-effect diagrams, failure mode effect analysis, histograms, kaizen, Pareto analysis, simulation, single-minute exchange of dies, value stream mapping, and process flow chart, have been used to improve equipment operational and financial performance.

The two visualisation techniques, value stream map and process flowchart, demonstrate sequential steps in a task (Andreadis et al., 2017; Adhikari et al., 2017). Although both techniques serve similar purposes, value stream map includes multiple factors like cycle time, wait-time between processes, work-in-progress, customer order to delivery, which may not be directly relevant to OEE initiatives. On the other hand, the process flowchart emphasizes the manufacturing process and equipment operation while simplifying decision points, feedback loops, and parallel or hierarchical flows (Vergidis et al., 2008). Thus, process flowchart is more applicable to OEE initiatives compared to the value stream map.

The definition of a histogram is that it displays the occurrence of an event using the bar's height in a bar graph, while Pareto analysis prioritises and analyses which problem should be dealt with first based on the Pareto's 80-20 principle (Adhikari et al., 2017). The principle suggests that 20% of the factors cause 80% of the problems. Compared to histograms, most of the reviewed literature deploys Pareto analysis in the OEE initiative. In the actual manufacturing environment, OEE is often affected by more than one factor, and the initiative project team are limited by time and resources. Thus, instead of working on all factors, Pareto analysis prioritises the most significant factors to focus on.

The 5-why analysis is a questioning technique used to identify the underlying cause-and-effect relationship of a problem (Gangidi, 2019). In this method, the answer to each "why" forms the basis of the subsequent question (Rahmana, 2021). On the other hand, the cause-and-effect diagram is a systematic tool used to identify, sort, and display the potential causes of a problem in a fishbone structure (Ratnasari et al., 2020). In this method, the problem or effect to be analysed is displayed on the head of the fish, while the causes of the problem or effect are shown as the bones of the main fishbone (Ratnasari et al., 2020). Although both 5-why analysis and cause-and-effect diagram are used to identify the root causes that result in low OEE of the equipment, the cause-and-effect diagram is more commonly used. This is because the graphical representation of the cause-and-effect diagram provides better visualization and understanding of the potential causes of the problem.

The failure mode effect analysis (FMEA) is a technique used to evaluate potential failures of a product, process, or system and develop strategies to reduce the risk and improve control (Sulaman et al., 2019). FMEA utilizes a risk priority number (RPN) which is determined by multiplying the severity, occurrence, and detection scores. However, since RPN is not directly related to OEE, FMEA is not an ideal approach for prioritising and evaluating the success of OEE initiatives.

Various methodologies are used to develop improvement actions that minimise or mitigate OEE losses, including 6S, brainstorming, kaizen, and single minute exchange die. 6S is a methodology that integrates 5S with security to optimise the workplace and improve occupational safety and health (Gallesi-Torres et al., 2020). Kaizen is a methodology that involves continuous improvement through small, incremental process improvements by all members of the organisation (Carnerud et al., 2018; Kumar et al., 2018). The single minute exchange die methodology focuses on reducing setup time by identifying opportunities to reprocess internal setup to external setup as much as possible (Posteuca and Zapciu, 2016). Brainstorming is a group technique that generates solutions for a problem by collecting ideas based on the knowledge of team members (Cheah et al., 2020a). Although 6S focuses on housekeeping and safety, and single minute exchange die aims to address setup and adjustment losses only, both methodologies are not appropriate for planning OEE improvement actions because their scopes are too specific. Kaizen may result in faster and cheaper incremental improvements, but may not provide the necessary insight to develop comprehensive and longer-term improvement plans for a problem. In contrast, the collective brainstorming methodology plans relevant improvement actions by understanding the problem and its root causes.

Heilala et al. (2006) and Heilala et al. (2007) utilised simulation to pre-evaluate improvement actions prior to their implementation. The simulation not only assesses the effectiveness of the intended improvements but also identifies any unintended negative consequences that may result (Liew et al., 2018). This approach can mitigate the possibility of costly rework due to potential issues arising from the improvement actions. Table 2.4 summarises the findings and observations of the analysed methodologies that used to enhance equipment operational and financial performance.

Table 2.4: Summary of methodology to enhance the equipment operational and financial performance

	Findings	Observations
Value stream map	Include multiple factors not relevant to OEE	Not suitable for framework deployment
Process flowchart	Emphasise manufacturing process and equipment, simplifies decision points and feedback loops	Suitable for framework deployment
Histogram	Does not prioritise which problems to address first	Not suitable for framework deployment
Pareto analysis	Prioritise the most significant factors to focus on	Suitable for framework deployment
5-why analysis	Less effective in visualising potential problem causes	Not suitable for framework deployment
Root cause analysis	Graphical representation	Suitable for framework deployment
FMEA	Risk priority number is not ideal for prioritising OEE initiatives	Not suitable for framework deployment
Simulation	Mitigate the possibility of costly rework	Suitable for framework deployment
6S	Focus on housekeeping and safety	Not suitable for framework deployment
Kaizen	Inadequate insight for long-term improvement planning	Not suitable for framework deployment
Single minute exchange die	Aim to reduce the setup and adjustment losses only	Not suitable for framework deployment
Solution brainstorming	Generate relevant improvement plans	Suitable for framework deployment

2.4.3 Opportunities to Expand OEE Literature in Relation to Financial Metrics

The financial metrics reviewed in this study establish a connection between OEE and K_P, K_R, K_{EC}, K_{OC}, and K_{MC}. However, research suggests that organisations prioritize K_P and K_R over cost considerations (Anderson et al., 2007). K_P is influenced by K_R, K_{OC}, and K_{MC}, while K_R is a function of the quantity of goods sold and the K_{PPU}. Improving OEE has the potential to increase production output, but the quantity sold and K_{PPU}, which determine K_P and K_R, are more dependent on market demand. Therefore, the insignificant effect of OEE on K_P and K_R renders these financial metrics unsuitable for assessing equipment financial success in OEE initiatives.

The financial metrics reviewed in relation to OEE predominantly focus on K_{OC} rather than K_{EC} and K_{MC}. K_{OC} has a proportional and inverse relationship with OEE, which can lead to both lower and higher K_{OC}. This ambiguous relationship between OEE and K_{OC} makes K_{OC} an unsuitable indicator for accurately measuring the financial impact of improvement actions in OEE initiatives. On the other hand, K_{EC} and K_{MC} are more relevant to OEE, as they consistently have an inverse relationship with OEE. Therefore, not only can they quantify equipment financial performance, but they can also assess the effectiveness of OEE improvement actions.

Based on the analysis presented in Section 2.3, it was found that none of the financial metrics reviewed included the cost of improvement actions in their analysis. Improvement cost (K_{IC}) refers to the cost associated with implementing improvement actions to enhance OEE. While costly improvement actions may improve OEE, they may also increase the financial burden on an organisation in other areas, resulting in no net financial gain. Therefore, organisations should avoid implementing expensive improvement actions if possible, and if necessary, assess the return on investment before implementation.

In manufacturing settings, K_{EC} and K_{MC} are inescapable costs, especially since equipment maintenance is crucial in maintaining operational performance to meet customers' high expectations (Eti et al., 2006; Thun, 2008). However, it is important to ensure that these costs are not wasted on OEE losses. K_{IC} refers to the expenses incurred in enhancing OEE, and considering it in conjunction with K_{EC} and K_{MC} ensures that the improvement actions taken are cost-effective. To evaluate the extent of wastage in K_{EC}, K_{MC}, and K_{IC} due to OEE losses, a new financial metric is proposed, which compares the cost per good quantity for an 85% world-class OEE with the current OEE, as shown in Equation (23). The new financial metric is expected to decline to zero wastage in K_{EC}, K_{MC}, and K_{IC} when the OEE is improved to 85% world-class OEE.

$$F_{OEE} = f(K_T, Q_{85\%}, Q_{OEE}) \tag{23}$$

where,

F_{OEE} the wastage of K_{EC}, K_{MC}, and K_{IC} for OEE losses

K_T the sum of K_{EC}, K_{MC}, and K_{IC}

$Q_{85\%}$ the good quantity that produced by equipment at 85% world-class OEE

Q_{OEE} the good quantity that produced by equipment at current OEE

A comprehensive framework for equipment performance improvement should include the current situation evaluation, improvement planning, improvement implementation, and improvement effectiveness measurement phases (Rahman et al., 2011; Kabaale & Kituyi, 2015). Various tools and techniques, such as process flowcharts, Pareto analysis, cause-and-effect diagrams, brainstorming, and simulation, should be employed to ensure that the framework is successful. At the current situation evaluation phase, the process flowchart helps to identify the equipment that requires improvement, while the new financial metric prioritises the equipment for improvement. The project team then use Pareto analysis, cause-and-effect diagrams, and brainstorming to identify the root causes and relevant improvement actions at the improvement planning phase, which is driven by the new financial metric. The new financial metric simulates the effectiveness of the improvement actions before the implementation phase. Finally, the success of the initiative can be determined by comparing the new financial metric before and after the improvement at the improvement effectiveness measurement phase.

To ensure that the most relevant improvement actions are selected, the gap analysis provides a platform to present the list of proposed improvement actions to enhance the equipment's operational and financial performance and understand the management's expectations (Rahman et al., 2011). Brainstorming is used to collect a series of improvement actions proposed by project team. However, not all improvement actions are accepted if the management is dissatisfied with the consequential effects from the improvement actions. Therefore, understanding the management's expectations is crucial in determining the best improvement actions. The cause-and-effect diagram, brainstorming, and gap analysis at the improvement planning phase facilitate the initiative with less back-and-forth movements by helping to determine the most relevant improvement actions.

2.5 Summary

Equipment is a costly investment that must be a productive asset throughout its life cycle to produce excellent-quality products for an organisation. However, various losses impede the optimum performance of equipment, and OEE, which displays equipment operational performance, may be viewed by the management of organisations simply as an ordinary technical improvement without considering equipment financial performance. Financial metrics that attempt to quantify equipment financial performance in OEE initiatives are categorised into K_P, K_R, K_{EC}, K_{OC}, and K_{MC}. However, metrics linked with K_P and K_R may inappropriately measure the impact of OEE on equipment financial performance, while OEE has an insignificant impact on either K_P or K_R. OEE has a proportional and inverse relationship with K_{OC}, making the impact of OEE in K_{OC} estimation complicated and inaccurate. K_{EC} and K_{MC}, the largest portion of capital investment in an organisation, have an inverse relationship with OEE. None of the reviewed financial metrics assesses the impact of K_{IC}, which is the associated cost from OEE improvement actions. Therefore, a new financial metric is proposed to assess the financial impact on OEE initiatives in terms of K_{EC}, K_{MC}, and K_{IC}. The new financial metric is integrated into a framework that provides systematic problem-solving steps to increase the equipment operational and financial performance. Chapter 3 will discuss the details of how the new financial metric and its framework are developed.

CHAPTER THREE

METHODOLOGY

3.0 Overview

This chapter details the methodology employed to fulfil the research objectives outlined in Chapter 1 (as outlined in Section 1.3, page 5). It is structured into two sections. Section 3.1 outlines the step-by-step framework development methodology utilized for creating the novel financial metric and its corresponding framework. The final section of this chapter, Section 3.2, provides a summary of the content covered in Chapter 3.

3.1 Methodology of New Financial Metric Framework Development

The methodology for developing the new financial metric framework is presented in Section 3.1 of this chapter and is depicted in Figure 3.1. The framework development methodology is a set of techniques and methods utilised in a specific field and its purpose is to establish a robust and sustainable framework. The methodology consists of four steps, which are described in greater detail in the subsequent sections. McMeekin et al. (2020) define a framework as a set of guidelines or rules that structure the approach to a given problem or task.

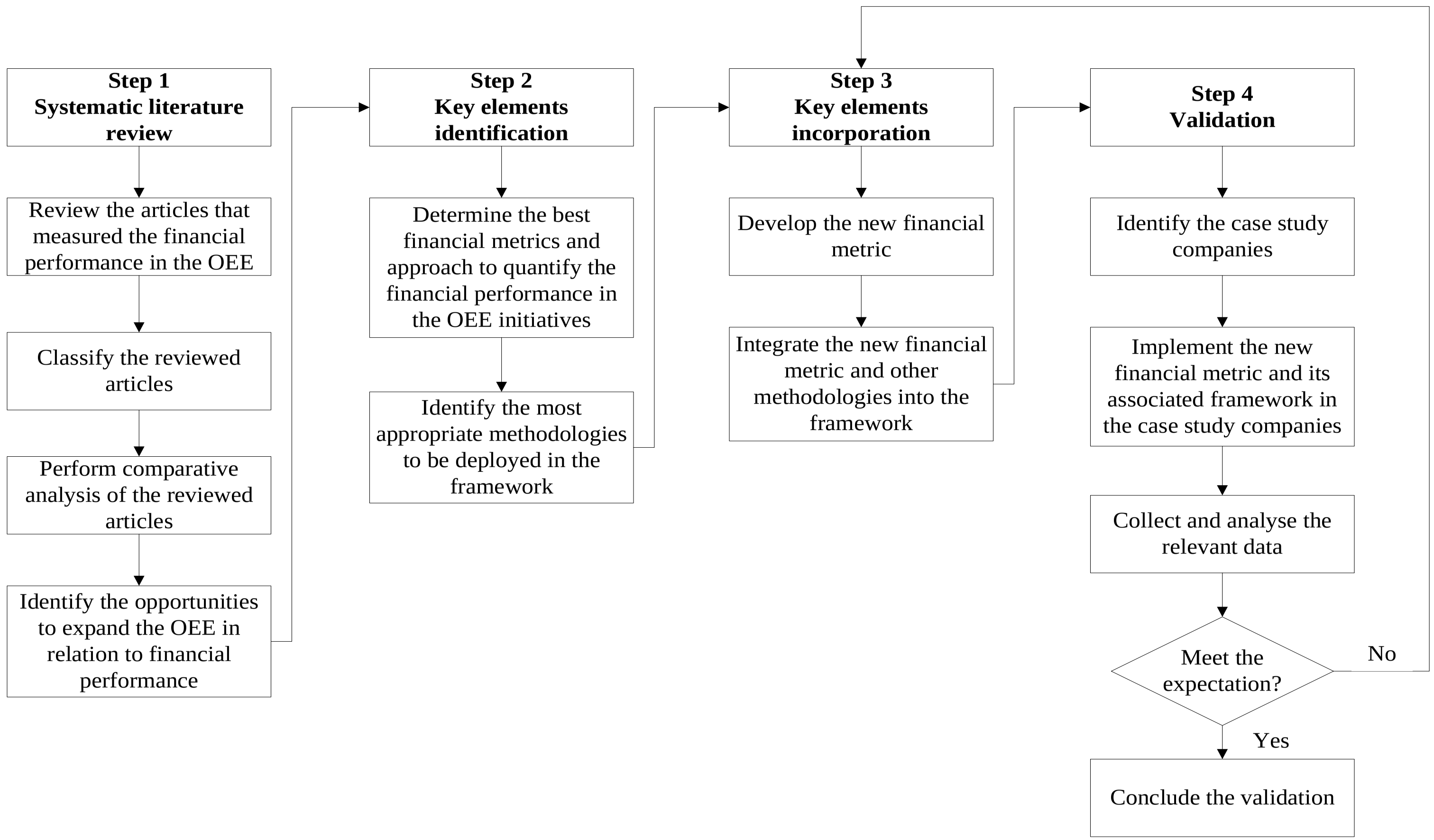

Figure 3.1: Four steps framework development methodology

3.1.1 Step 1 – Systematic Literature Review

A comprehensive literature review is deemed crucial in the development of a new financial metric framework, as it lays a robust foundation for advancing knowledge and fostering new theory development through the collection and synthesis of existing research (Snyder, 2019; Xiao and Watson, 2019). The objectives of the literature review include: (1) to review and comprehend the current state-of-the-art research that is diverse and interdisciplinary, (2) to integrate and synthesize research findings from multiple sources to address research questions, and (3) to identify crucial theoretical concepts and uncover areas for developing new theoretical concepts or frameworks (Palmatier et al., 2018; Snyder, 2019). Although all relevant literature should be included in the review, collecting literature is a challenging and costly endeavour. As discussed in Chapter 2, the literature that applied financial metrics in the OEE initiative and provided evidence was sequentially reviewed to identify the key elements that would be deployed in the new financial metric framework. Additionally, methodologies used to enhance the financial metrics in the OEE initiative were also reviewed. The results of the key elements identification from the literature review will be discussed in the following subsection.

3.1.2 Step 2 – Key Elements Identification

The primary goal of the second step in the framework development methodology is to identify the key elements that significantly contribute to the development of the new financial metric framework. In conjunction with the literature review, the key elements that have the potential to contribute to the development of the new financial metric framework are collected. The key elements obtained from the literature review are crucial to the success of the development of the new financial metric framework. The details of the key elements identified will be presented in Chapter 4. The subsequent step will illustrate the approach to incorporate the key elements into the new financial metric framework.

3.1.3 Step 3 – Key Elements Incorporation

After identifying the key elements in the previous step, the subsequent step involves two stages: (1) developing a new financial metric that overcomes the limitations of existing metrics in terms of measuring equipment performance operationally and financially, and (2) integrating the newly developed financial metric with other methodologies into a framework to increase its practicality in the actual manufacturing environment. The framework aims to provide project team with a systematic and practical problem-solving approach to enhance equipment operational and financial performance. The key elements identified from the literature review, which were absent in the existing literature, were integrated into the new financial metric framework. Based on the functionality of each key element, all the identified key elements were sequentially grouped into different phases within the framework. An activity-tree-diagram was used to map the key elements in a sequence, showing the process activities in which one box connects to others (Mohammadi et al., 2021). The final step in the framework development was refining the framework to meet its design requirements, making it practical and simple to implement. The validation of the framework will be discussed in the following subsection.

3.1.4 Step 4 –Validation

The case study aims to assess the feasibility and validity of a new financial metric and its accompanying framework. Case study research, as defined by Gerring (2004) and Flyvbjerg (2007), involves an empirical examination of a contemporary, real-world phenomenon through the contextual analysis of a singular unit of events, with the goal of understanding a larger class of similar units. Compared to alternative research methods such as surveys, experiments, and historical research, case study research provides more robust and reliable data, reflecting real-world applications. This method captures an in-depth understanding of the phenomenon under investigation, and replicates real-world scenarios, thereby ensuring the applicability and reliability of the new financial metric and framework.

The case study can be executed through either a single-case or multiple-case design. The latter design, which involves the analysis and synthesis of similarities and differences across two or more cases, provides stronger validation of the results through the demonstration of multiple sources of replicated evidence. In the present study, a multiple-case design was employed, evaluating the robustness and versatility of the new framework through its implementation in diverse manufacturing environments, such as medical devices, tire flaps, and semiconductors.

The success of the new financial metric and its accompanying framework validation is measured by whether the results align with expectations. In the event that the results from any case study do not meet expectations, it is necessary to revisit the third step of the process.

3.2 Summary

This chapter presents the research methodology employed in the creation of a new financial metric and its associated framework. The process of framework development commences with an exhaustive examination of literature pertinent to financial metrics within the context of the OEE initiative. This review process serves to identify key elements that could contribute to the development of the new financial metric and its framework. The subsequent step involves the utilisation of a systematic mapping method to integrate all identified key elements into the framework. Finally, the validation process is described to ensure the thoroughness and comprehensiveness of the newly developed framework.

CHAPTER FOUR

NEW FINANCIAL METRIC AND FRAMEWORK DEVELOPMENT

4.0 Overview

This chapter focuses on the development of a new financial metric and its accompanying framework. It is organised into four sections. The first section, Section 4.1, summarises the results of the framework development methodology outlined in Chapter 3. The next two sections, Section 4.2 and 4.3 detail the development of the new financial metric and its associated framework. Finally, Section 4.4 provides a summary of the entire chapter.

4.1 New Financial Metric and Framework Development

As outlined in Section 3.1, the methodology for developing the new financial metric and its framework was deployed, as described on page 42. The framework development methodology consists of four steps: Step 1 - Literature Review, Step 2 - Key Element Identification, Step 3 - Key Element Incorporation, and Step 4 - Validation. The Literature Review conducted in Chapter 2 provides a comprehensive examination of relevant literature from diverse sources. The subsequent subsections elaborate on Steps 2 to 4 of the framework development methodology.

4.1.1 Step 2 – Key Element Identification

Step 2 of the framework development process focuses on the identification of the critical components that contribute to the development of the new financial metric and its associated framework. The following are the key elements that have been identified.

a) Although the methodology of comparing pre- and post-improvement financial metric is straightforward and easily implemented, the effect of improvement actions on financial metrics cannot be accurately predicted until they have been carried out.

b) The approach of integrating OEE with financial metrics is more complex compared to measuring financial metrics alone. However, the mathematical relationship established between OEE and financial metrics provides project team with a means to estimate the financial performance when planning OEE improvement actions.

c) Integrating OEE with financial metrics enhances the capabilities of the OEE, allowing for a comprehensive evaluation of equipment performance, encompassing both operational and financial aspects.

d) The mathematical relationship between OEE and financial metrics must be simple in nature and easy to comprehend in order to maintain the simplicity and practicality of OEE.

e) K_P and K_R exhibit a direct or indirect linear relationship with OEE. However, K_P or K_R alone should not be relied upon to determine the financial effectiveness of equipment, as these metrics are influenced by various factors unrelated to the operational performance of the equipment.

f) The relationship between OEE and K_{OC} may be proportional or inversely proportional, leading to potential overestimation or underestimation of the impact of OEE improvement actions. As such, K_{OC} should not be relied upon as a sole indicator of the financial effectiveness of equipment.

g) K_{EC} and K_{MC} are better suited to reflect the financial performance of equipment in conjunction with OEE, as there exists a significant inverse proportional relationship between OEE and its losses and K_{EC} and K_{MC}.

h) The implementation of costly improvement actions may result in an increased financial burden for the organisation, even if they are effective in enhancing OEE. To avoid this potential outcome, the impact of K_{IC} should be thoroughly evaluated prior to implementation.

i) The process flowchart visually represents the sequence of steps involved in the manufacture of a product or operation of equipment

j) The Pareto analysis is a method used to prioritise issues and allocate resources by identifying the 20% of contributing factors that account for 80% of the problems.

k) The cause-and-effect diagram provides a graphical representation of the relationship between the root causes and the problem, thus facilitating the visualization and understanding of the root causes.

l) Solution brainstorming is a team-based approach that generates a list of potential solutions by gathering and synthesizing the collective knowledge and ideas of the team members.

m) Gap analysis serves as a platform not only to compile a list of proposed improvement actions, but also to comprehend the expectations of the organisation's management.
n) The efficacy of improvement actions must be assessed before their implementation to prevent the possibility of costly rework.
o) A framework provides systematic and clear connection between problem-solving steps by offering a methodology that is both easy to understand and implement.

The key elements labelled from a to h contribute to new financial metric development, while elements labelled from i to o are used in the framework development.

4.1.2 Step 3 – Key Element Incorporation

After the incorporation of all the key elements, the number of phases in the newly developed framework must be determined. A successful framework should encompass, at a minimum, the phases of assessment, improvement planning, simulation, and implementation and monitoring, as demonstrated in previous studies by Rahman et al. (2011) and Kabaale and Kituyi (2015). The mapping of each key element into the respective phases of the framework is achieved through the use of an activity-tree-diagram, as depicted in Figure 4.1. To enhance the success of the new financial metric and its framework, both should be evaluated and reorganised, if necessary, to ensure that they effectively drive both operational and financial equipment performance through practical and straightforward steps.

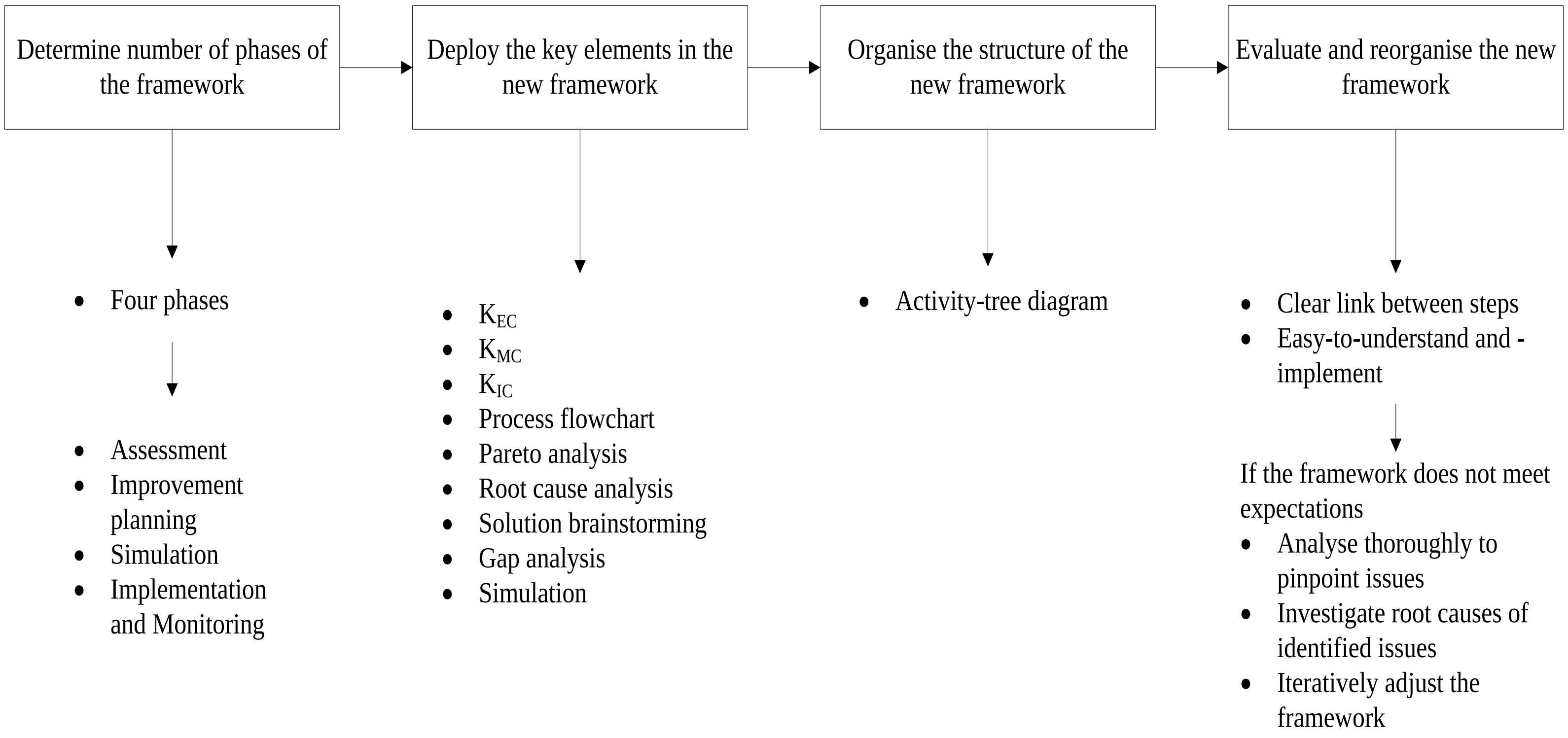

Figure 4.1: The activity-tree diagram

4.2 Equipment Cost Efficient (ECE) Metric Development

This subsection aims to demonstrate the development of the equipment cost efficiency (ECE) metric. ECE metric evaluates the cost per unit difference by comparing equipment performance at the current OEE to the benchmark 85% world-class OEE, as outlined in Equation (24). The ECE metric involves a comprehensive cost analysis, incorporating the sum of K_{EC}, K_{MC}, and K_{IC} (referred to as K_T) at current OEE and 85% world class OEE. A more significant disparity indicates heightened operational and financial inefficiency. The relationship between K_{EC} and K_{MC} with OEE is noteworthy; they demonstrate an inverse correlation, leading to K_T being higher at the current OEE than it is at the benchmark 85% world-class OEE. Importantly, ECE metric considers the worst-case scenario, assessing equipment K_T when operated at the current OEE.

The 85% world-class OEE is defined by Japan Institute of Plant Maintenance (JIPM) and is widely acknowledged in the manufacturing industry (Mail et al., 2021; Raju et al. 2022) The selection of 85% is rooted in the belief that attaining higher OEE levels can pose challenges for diverse manufacturing processes, making it a practical target for many facilities (Muñoz-Villamizar et al., 2018). Continuous improvement initiatives and technological advancements may empower modern production line to surpass the 85% benchmark. As technologies progress and best practices are honed, the definition of world-class OEE could shift to mirror the evolving landscape of manufacturing capabilities. However, considering that the ECE metric are tailored for distinct manufacturing environments, the general target of 85% world-class OEE in the manufacturing industry serves as the benchmark.

However, it is crucial to acknowledge that the actual K_T at 85% world-class OEE is only attainable after enhancing the equipment to achieve 85% world-class OEE. Consequently, ECE metric cannot assess the operational and financial performance of the equipment before these improvements. As a result, quantifying the ECE metric of the equipment necessitates estimating the K_T at 85% world-class OEE. Although advanced mathematical modelling techniques can predict this value, practical implementation in real-life manufacturing environments can be challenging due to the complexity of these models. Manufacturing settings are dynamic, and equipment performance can evolve over time, potentially rendering estimation data less effective at accounting for these changes. Therefore, it is advisable for ECE metric to account for the same K_T at both the current OEE and the 85% world-class OEE to provide a conservative assessment.

$$ECE_i = \left(\frac{K_{T_i}}{Q_{85\%_i}} - \frac{K_{T_i}}{Q_{OEE_i}}\right) \tag{24}$$

where,

ECE_i	the equipment cost efficiency metric for equipment i
K_{T_i}	the sum of $\mathrm{K_{EC}}$, $\mathrm{K_{MC}}$, and $\mathrm{K_{IC}}$ for equipment i, represent the equipment's total cost at current OEE.
$Q_{85\%_i}$	the good quantity that produced by equipment i at 85% OEE
Q_{OEE_i}	the good quantity that produced by equipment i at current OEE

Comparing the current OEE to world-class OEE enables manufacturers to establish a stringent standard for equipment performance and identify areas for enhancement. World-class OEE is typically considered the optimal level of performance achievable for a given process or manufacturing line. By comparing the current OEE to world-class OEE, manufacturers can see how far they are from optimal performance and identify areas for improvement. Conversely, evaluating OEE in comparison to the equipment with the highest OEE within the manufacturing line might not yield an accurate performance measure, as this equipment might not be operating at 85% world-class OEE. Moreover, utilizing world-class OEE as a benchmark facilitates cross-comparison across various manufacturing lines and facilities, streamlining the assessment and improvement processes. Ideally, equipment should fully leverage its K_T to attain 85% world-class OEE. However, when the equipment operates at 81% OEE, there is a 4% waste of K_T due to OEE losses (85% - 81%).

According to Kwon and Lee (2002), the OEE equation can be further simplified into Equation (25).

$$OEE_i = \frac{T_{OT_i}}{T_{LT_i}} \cdot \frac{T_{CT_i} \cdot Q_{P_i}}{T_{OT_i}} \cdot \frac{Q_{G_i}}{Q_{P_i}}$$

$$OEE_i = \frac{Q_{G_i} \cdot T_{CT_i}}{T_{LT_i}} \tag{25}$$

where,

T_{LT_i}	the loading time for equipment i
T_{OT_i}	the operating time for equipment i
T_{CT_i}	the theoretical cycle time for equipment i
Q_{P_i}	the processed quantity for equipment i
Q_{G_i}	the good quantity for equipment i

By substituting Equation (25) into Equation (24), the ECE metric can be expressed in terms of T_{LT}, T_{CT}, K_T, current OEE, and 85% world-class OEE, as expressed in Equation (26).

$$ECE_i = K_{T_i} \cdot \left(\frac{1}{Q_{85\%_i}} - \frac{1}{Q_{OEE_i}}\right)$$

$$ECE_i = K_{T_i} \cdot \left(\frac{1}{\frac{0.85 \cdot T_{LT_i}}{T_{CT_i}}} - \frac{1}{\frac{OEE_i \cdot T_{LT_i}}{T_{CT_i}}}\right)$$

$$ECE_i = K_{T_i} \cdot \left(\frac{T_{CT_i}}{0.85 \cdot T_{LT_i}} - \frac{T_{CT_i}}{OEE_i \cdot T_{LT_i}}\right)$$

$$ECE_i = K_{T_i} \cdot \left(\frac{T_{CT_i}}{T_{LT_i}}\right)\left(\frac{1}{0.85} - \frac{1}{OEE_i}\right)$$

$$ECE_i = \frac{K_{T_i} \cdot T_{CT_i}}{T_{LT_i}} \cdot \left(\frac{OEE_i - 0.85}{0.85 \cdot OEE_i}\right) \tag{26}$$

The ECE metric, designed to complement the widely accepted OEE in manufacturing, introduces a nonlinear relationship with OEE, as demonstrated in Equation (26). Departing from the conventional linearity associated with manufacturing metrics, this nonlinearity challenges traditional linear modelling approaches. While nonlinear relationships often suggest heightened mathematical complexity, the ECE metric has been meticulously crafted to reconcile this complexity with simplicity for practical implementation on the manufacturing floor. Despite its nonlinear foundation, the ECE metric remains accessible to the project team, enabling straightforward implementation without the need for advanced mathematical expertise. This equilibrium between complexity and practicality positions the ECE metric as a valuable tool for assessing both equipment performance and financial impact in manufacturing environments, providing nuanced insights into operational efficiency and resource allocation.

The ECE metric does not consider K_{OC} as OEE has a complex and variable relationship with it. Higher OEE may lead to either lower or higher K_{OC}, making it challenging to determine the actual financial impact of OEE initiatives using K_{OC} as an indicator. K_{OC} involves expenses on input resources, including materials, labour, and utilities. However, K_{EC} and K_{MC} are used to obtain and maintain the equipment, which are more related to the equipment's operational performance. Therefore, it is important to focus on K_{EC} and K_{MC} to evaluate the equipment's financial performance and effectiveness.

By referring to Equation (26), ECE metric comprises two factors, namely, the cost per unit and OEE losses, as expressed in Equation (27).

$$ECE_i = (cost\ per\ unit) \cdot (OEE\ losses) \tag{27}$$

where,

$$cost\ per\ unit = \frac{K_{T_i} \cdot T_{CT_i}}{T_{LT_i}}$$

$$OEE\ losses = \left(\frac{OEE_i - 0.85}{0.85 \cdot OEE_i}\right)$$

The cost per unit provides a way to connect the operational performance of equipment with its financial performance, assuming that the equipment operates at 100% OEE. However, in the reality, equipment usually operates at less than world-class OEE of 85%, resulting in OEE losses. By considering these losses, the ECE metric, which is the product of cost per unit and OEE losses, quantifies how much of the K_T was wasted by OEE losses. Depending on the OEE level, the ECE metric can be negative, zero, or positive. A negative ECE metric indicates that a certain portion of the T_{LT} and K_T of the equipment is wasted by OEE losses. The only way to achieve zero or positive ECE metric is to improve OEE to at least 85% world-class OEE. When the ECE metric is zero or positive, it implies that the T_{LT} and K_T are being effectively utilised to produce high-quality goods within the expected cycle time. Another avenue to reach zero ECE metric is a T_{CT} of zero, though such a scenario is unattainable in real-world manufacturing environments. T_{CT}, which denotes the minimal time needed for a manufacturing process to complete, inherently reflects the practical limitations and constraints that define the physical reality of production.

The theoretical validation is further supported by validation. By plotting various combinations of K_T, T_{CT}, T_{LT}, and OEE, the OEE and ECE metric relationship (Figure 4.2) validated that ECE metric equals zero at 85% world-class OEE, negative below, and positive above this benchmark. Figures 4.3 to 4.5 consistently showed negative ECE metric values, irrespective of K_T, T_{CT}, and T_{LT}, confirming OEE as the key variable in minimising K_T wastage. Both validations instilled confidence in ECE metric for real data analysis.

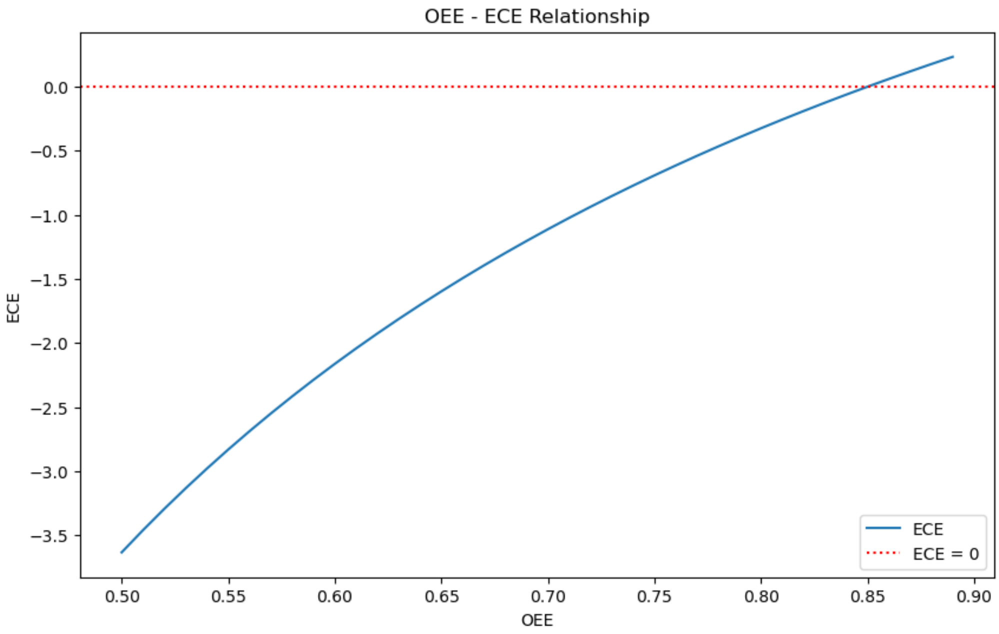

Figure 4.2: Relationship of OEE and ECE metric

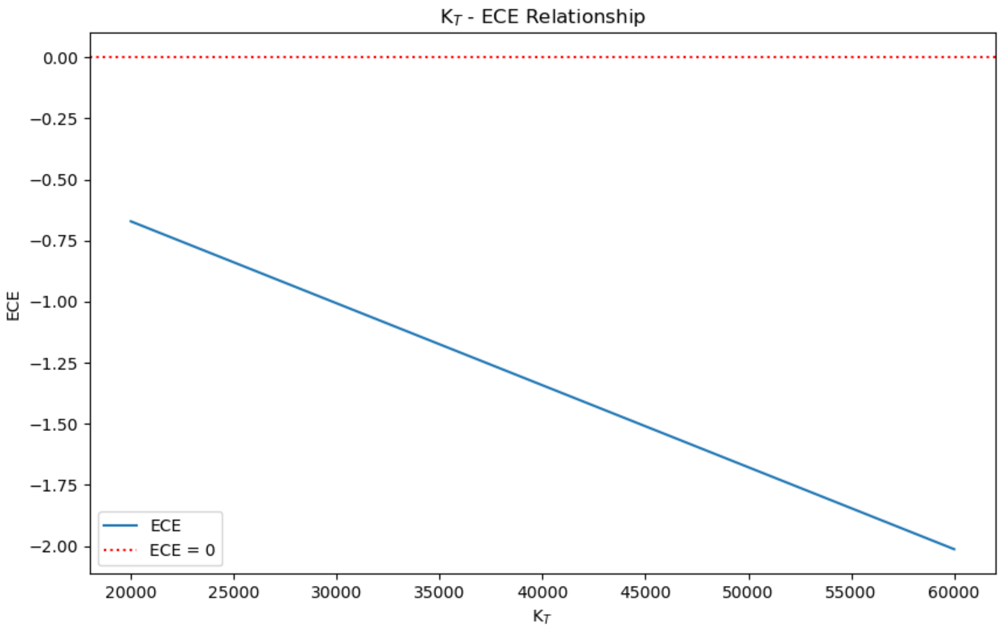

Figure 4.3: Relationship of K_T and ECE metric

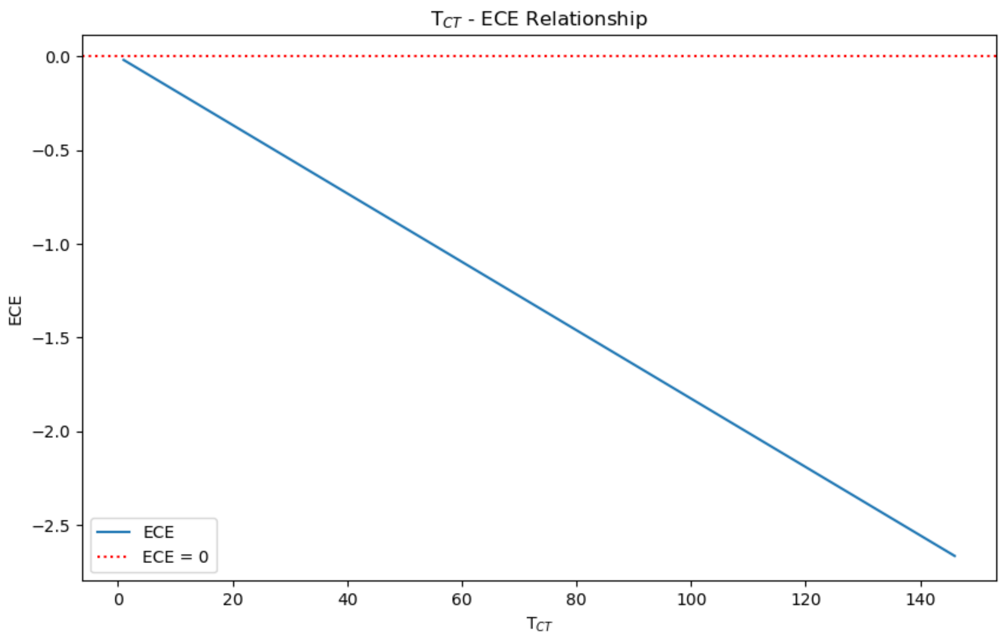

Figure 4.4: Relationship of T_{CT} and ECE metric

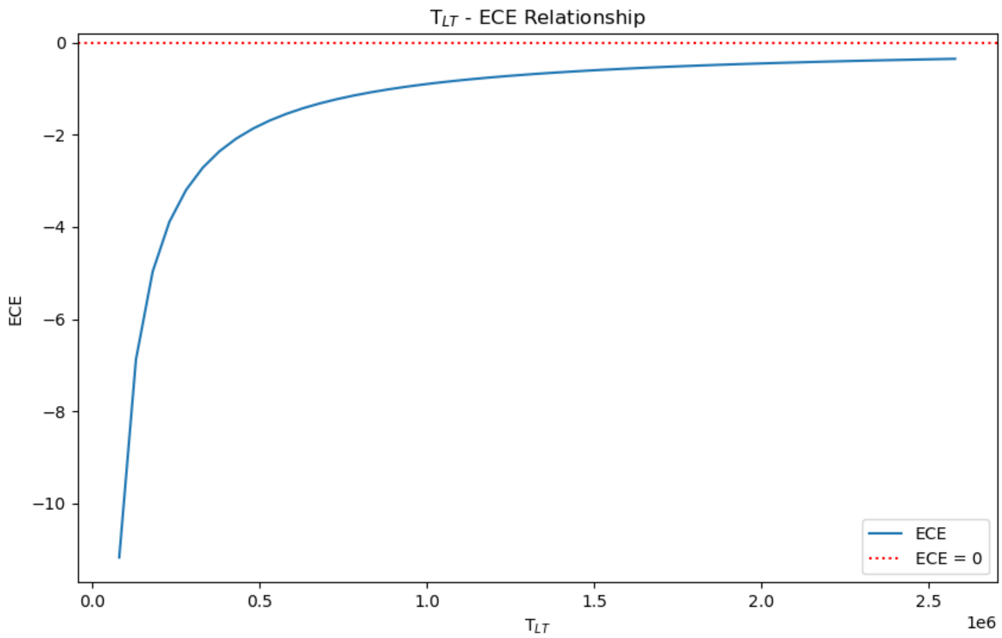

Figure 4.5: Relationship of T_{LT} and ECE metric

The K_{IC} represents the expenses related to the improvement actions that aim to enhance the ECE metric. The magnitude of K_{IC} may vary depending on the chosen approach for the improvement actions, which can range from low to high. The costs may be one-time or recurring, depending on the amount of K_{IC}. For instance, if a costly improvement action is implemented, such as an equipment upgrade, manufacturers may depreciate the K_{IC}, which reoccurs over the defined depreciation period of the asset. Conversely, if the amount of K_{IC} is not significant, manufacturers may choose to pay it off outright.

The ECE metric is a useful tool for evaluating the financial impact of OEE losses on the equipment's overall performance. By multiplying the cost per unit with the OEE losses, the ECE metric provides a quantitative measurement of how much of the equipment's overall capacity has been lost due to OEE losses. This enables manufacturers to identify the cost of inefficiencies caused by equipment downtime, quality defects, or low performance rates. By monitoring and analysing the ECE metric, manufacturers can determine the actual cost of OEE losses and identify opportunities for improvement to increase equipment effectiveness, which results in a positive ECE metric. The ECE metric can be used as a key performance indicator for equipment performance and can be used to benchmark performance across different equipment or production lines.

4.3 Equipment Cost Efficiency Framework (ECEF) Development

The ECE metric, a novel metric that quantifies the wastage of K_{EC}, K_{MC}, and K_{IC} due to OEE losses, while useful in determining the financial impact of OEE, does not offer practical guidance on how to improve the ECE metric of equipment. To increase its practicality, the ECE metric has been integrated into a comprehensive framework, the ECEF, which includes various elements such as a process flowchart, Pareto analysis, root cause analysis, solution brainstorming, gap analysis, and simulation. The ECEF provides a systematic approach to problem-solving by offering a method that is easy to implement. The nine steps of the ECEF, structured into assessment, improvement planning, simulation, and implementation and monitoring phases, are illustrated in Figure 4.6. These steps will be further detailed in subsequent subsections.

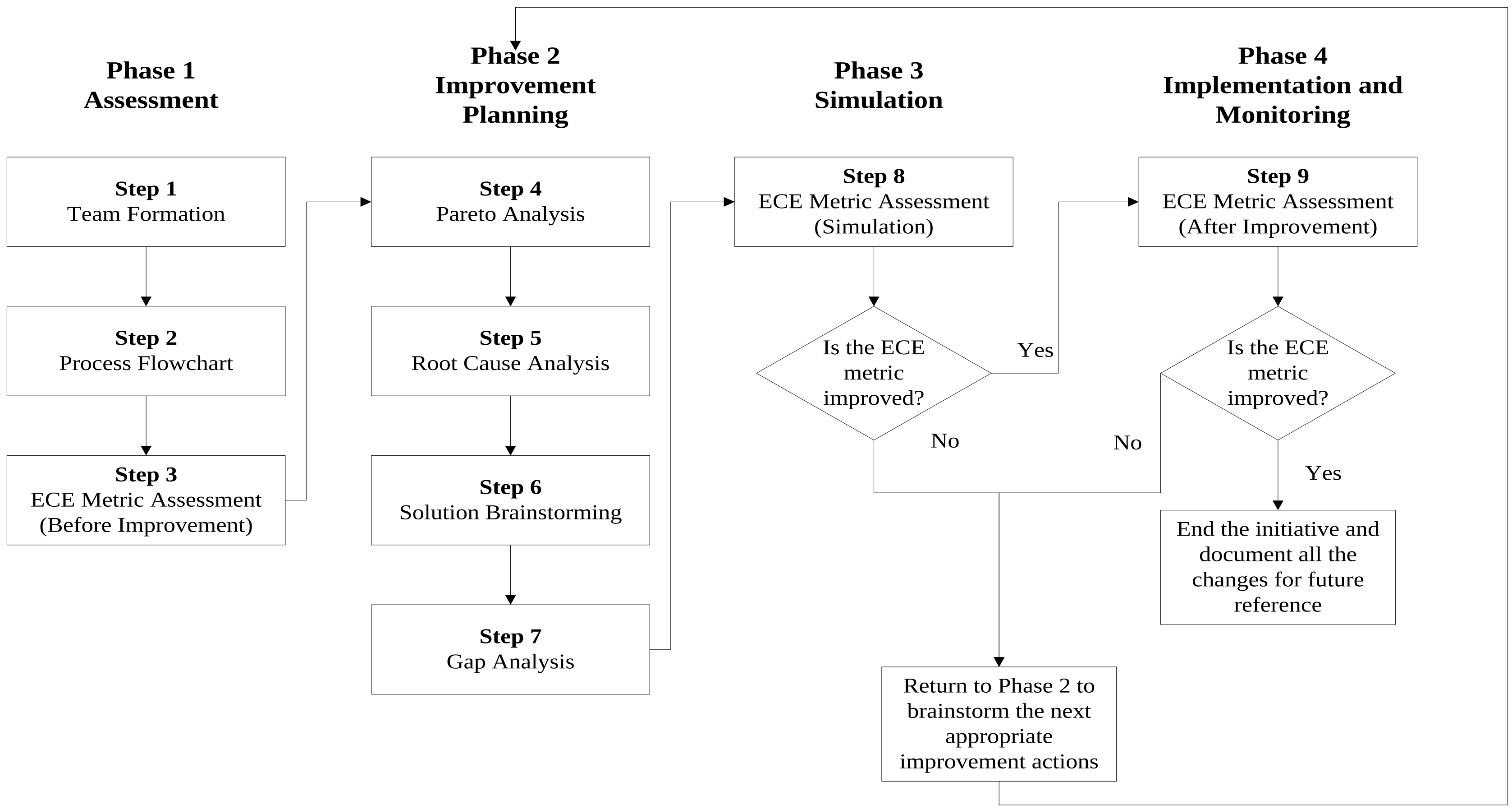

Figure 4.6: Equipment cost efficiency framework (ECEF)

4.3.1 Phase 1 – Assessment

The Assessment Phase of the ECEF encompasses three key steps: team formation, process flowchart, and ECE metric assessment before improvement (ECE_B). The Assessment Phase is critical to determining the success of the improvement initiative. The ECE_B, which quantifies the operational and financial performance of the equipment, is used to prioritise areas of improvement.

Sep 1 – Team Formation

The Assessment Phase commences with the formation of a multidisciplinary team, comprising individuals who possess a comprehensive understanding of the manufacturing system. The presence of competent team members facilitates the identification of best practices and improvement opportunities. The ideal multidisciplinary team may include members from equipment, process, production, planning, purchasing, or supplier departments.

Step 2 – Process Flowchart

The process flowchart is a graphical representation of all processes involved, from beginning to end, including inputs and outputs at each stage. The visual and logical depiction of the process flowchart helps in understanding the processes involved in the analysed equipment. The use of process flowcharts is a widely accepted practice to identify weaknesses that impact the operational and financial performance of the equipment (Mozaffari et al., 2013).

Step 3 – ECE Metric Assessment (Before Improvement)

In the final step of Phase 1, the ECE metric before improvement (ECE_B) is used to assess the extent to which the current operational performance (OEE, T_{LT}, T_{CT}) and financial performance (K_{EC} and K_{MC}) of the equipment are impacted by OEE losses. At this stage, K_{IC} is not yet available. If multiple equipment are analysed, the equipment with the lowest ECE_B should be prioritized for improvement. In the case where multiple equipment have the same ECE_B, the equipment with the lowest OEE should be given the highest priority for improvement.

4.3.2 Phase 2 – Improvement Planning

The Improvement Planning Phase is comprised of four steps that aim to analyse the underlying causes of low ECE_B and derive the most cost-effective improvement actions to enhance the ECE metric of the critical equipment.

Step 4 – Pareto Analysis

Pareto analysis is a data analysis tool that prioritises the most significant factors contributing to low ECE_B. It is based on the Pareto principle, which suggests that 20% of the factors cause 80% of the problems. A Pareto chart visually displays the relative significance of each factor by comparing it with others. This step helps to increase the effectiveness of the initiative by focusing on the primary factors affecting low ECE_B.

Step 5 – Root Cause Analysis

Root cause analysis is a method used to determine the sources of a problem by identifying the factors and root causes that lead to low ECE_B. This step involves defining the problem statement, understanding the underlying causes that result in low ECE_B, and determining the root causes of the problem (Reid and Smyth-Renshaw, 2012). While a conventional manifestation of root cause analysis often results in a cause-and-effect diagram, commonly known as a fishbone fishbone diagram, it is imperative to recognise that root cause analysis extends far beyond the creation of this graphical tool. It entails a systematic and exhaustive investigation aimed at uncovering the intricate relationship between the effects and causes of a problem (Abbasi et al., 2020). This method is not confined to the mere creation of visual representations; rather, it involves a comprehensive examination of the interconnected factors contributing to the identified problem.

Step 6 – Solution Brainstorming

Solution brainstorming is the process of listing down potential improvement actions to address the root causes identified in the preceding step. To ensure ease of tracking, each proposed improvement action should be labelled with the specific root cause it addresses. The pros, cons, and estimated K_{IC} for each improvement action should also be detailed for further analysis, as shown in Table 4.1.

Table 4.1. Sample of solution brainstorming

Improvement action	Root cause 1	Root cause 2	Root cause 3	Pros	Cons
Increase the headcount	✓	✓	✓	Provide better manning ration	Incur additional operating cost
Use the spare part from an alternative supplier	✓		✓	Longer lifespan	Induce higher spare part cost by MYR 4,000
Increase the preventive maintenance frequency		✓	✓	Increase the OEE of the equipment	Incur additional preventive maintenance downtime

Step 7 – Gap Analysis

In Step 7, gap analysis is performed to determine the most appropriate improvement actions to enhance the ECE_B. This analysis involves four components: (1) the current state, which lists the root causes identified through root cause analysis; (2) the future state, which encompasses the expectations set by the organisational management; (3) the gap, which analyses the discrepancy between the current and future states; and (4) the to-do list, which enumerates the improvement actions that will fulfil the expectations. Figure 4.7 presents a sample of gap analysis. If the organisational management does not agree with the analysis and/or improvement actions, project team should revisit the improvement planning phase of the ECEF to re-analyse the root cause and brainstorm new, appropriate improvement actions.

Table 4.2: Sample of gap analysis

Objective	• List down what to achieve from the gap analysis
Current state	• List down all the root causes that result in the deficiencies of ECE_B
Future state	• Include all the desired expectations
Gap	• List down all the differences between current and future state
To-do	• Enumerate the workable improvement actions

4.3.3 Phase 3 – Simulation

The Simulation Phase is aimed at evaluating the potential impact of the selected improvement actions on the ECE_B before actual implementation. This is a critical step that helps avoid costly rework.

Step 8 – ECE Metric Assessment (Simulation)

Simulation is used to determine the effect of the selected improvement actions on the ECE metric without any negative consequences (Soares do Amaral et al., 2022). The outcome of the ECE metric assessment from simulation (ECE_S) provides a quantitative evaluation of the equipment operational and financial performance of the improvement actions. In this step, the estimated K_{IC} for each improvement action can be calculated.

Additionally, the same improvement actions may result in lower K_{EC} and K_{MC}. However, these new values may not be available until the actual implementation of the improvement actions. Nonetheless, the financial performance of the improvement actions can still be evaluated based on the current K_{EC} and K_{MC} along with the estimated K_{IC}. The objective of the improvement actions is to increase the OEE of the equipment, which in turn should reduce K_{EC} and K_{MC}. Hence, the current K_{EC} and K_{MC} provide the worst-case scenario for the ECE_S assessment.

If the ECE_S assessment is less than ECE_B, the project team should revisit the improvement planning phase to determine the root cause and come up with alternative improvement actions.

4.3.4 Phase 4 – Implementation and Monitoring

The Implementation and Monitoring Phase of the ECEF is centred on Step 9, which involves monitoring and evaluating the effectiveness of the improvement actions. This phase is crucial in quantifying the impact of the improvement actions by comparing the ECE_B and equipment cost efficiency after improvement (ECE_A).

Step 9 – ECE Metric Assessment (After Improvement)

Upon the implementation of the simulated improvement actions, the effectiveness of the improvement is monitored over time by evaluating the ECE_A. This step utilizes the actual values of K_{EC}, K_{MC}, and K_{IC} to assess the impact of the improvement actions. The effectiveness of the improvement actions is confirmed when the ECE_A is higher than the ECE_B, indicating the success of the initiative. Conversely, if the opposite effect is observed, the framework project team must revisit the Improvement Planning phase to brainstorm alternative and more effective improvement actions.

4.4 Summary

This chapter introduces the development of the ECE metric and its accompanying framework. The ECE metric within the framework procides a comprehensive evaluation of the criticality of both the operational and financial performance of equipment. Rather than relying solely on either operational or financial performance to prioritise improvement effort, the ECE metric considers multiple criteria in determining the priority for improvement, resulting in a more refined priority setting.

The ECE metric has been integrated into a framework that also includes other intuitive and straightforward methodologies, such as process flowcharting, Pareto analysis, root cause analysis, solution brainstorming, gap analysis, and simulation. The methodologies are organised in a sequence within the framework, providing project team with a systematic approach to identify cost-effective improvement actions aimed at enhancing both the operational and financial performance of equipment.

The validity of the ECEF is demonstrated through three case studies, which will be presented in Chapter 5.

CHAPTER FIVE

CASE STUDY

5.0 Overview

The present chapter endeavours to validate the efficacy of the ECE metric and its framework through the examination of three distinct case studies. To this end, the chapter is structured into five sections. Section 5.1 provides a comprehensive introduction of the case study. Subsequently, the three case studies are presented in section 5.2, 5.3, and 5.4, respectively. Finally, the final section 5.5 summarises the Chapter 5.

5.1 Introduction of Case Study

The applicability of the ECE metric and its framework for real-world manufacturing environments has to be validated. As discussed in Section 3.1.4 (page 46), the multiple-case study is one of the best methods for evaluating the ECE metric and its framework. The multiple-case study validates the ECE metric and its framework at three different companies with different backgrounds, which include tyre flap, semiconductor, and medical devices. They are all located in Perak, Malaysia. The following Sections 5.2, 5.3, and 5.4 will detail the background of each case study company.

5.2 Case study 1 – Medical Device Manufacturer

The initial case study was conducted at a medical device manufacturing facility located in Perak, Malaysia. The luer tube holder assembly equipment (LTH), which was chosen for the study, was selected due to its low OEE. The LTH is a semi-automated apparatus utilized in the assembly of the luer tube holder, which plays a crucial role in preventing needle-stick injury and ensuring a secure connection to blood collection tubes. The manufacturer operates over 50 LTHs, and a production line composed of 15 LTHs was selected for the purpose of this study. The study adhered to the ECEF from inception to conclusion, and the methodology used to enhance the ECE metric of LTHs through the implementation of the ECEF will be outlined in subsequent sections.

5.2.1 Phase 1 – Assessment

Step 1 – Team Formation

A team composed of experts from various disciplines, including product development, process engineering, equipment maintenance, production operations, quality control, planning, and procurement, was established. The composition of this initiative team is summarised in Table 5.1.

Table 5.1: Initiative team structure of LTH improvement

Project champion	Operation manager
Stakeholder(s)	Equipment manager
Leader	Equipment section manager
Team members	Equipment engineer
	Production executive
	Planning
	Quality engineer
	Procurement executive

Step 2 – Process Flowchart

As depicted in Figure 5.1, the process of assembling a LTH comprises three stages. Firstly, the tube holder is introduced into the input bowl of the LTH. Subsequently, the tube holder is aligned on the linear pick-up track of the LTH, which serves to arrange the tube holders in a manner that enables their transfer to the assembly station through the action of the pick-up heads. At the assembly station, the torque module engages in tightening the luer onto the tube holder. In case of under-torquing, the error will be detected by the vision inspection system. Conversely, if overtightening leads to cracking, the air leak test will identify the issue. This test is a reliable, non-destructive and repeatable method to determine the presence of any leakage post assembly. Finally, upon successful passage through both the vision inspection and air leak test, the assembled tube holder is packaged and prepared for shipment.

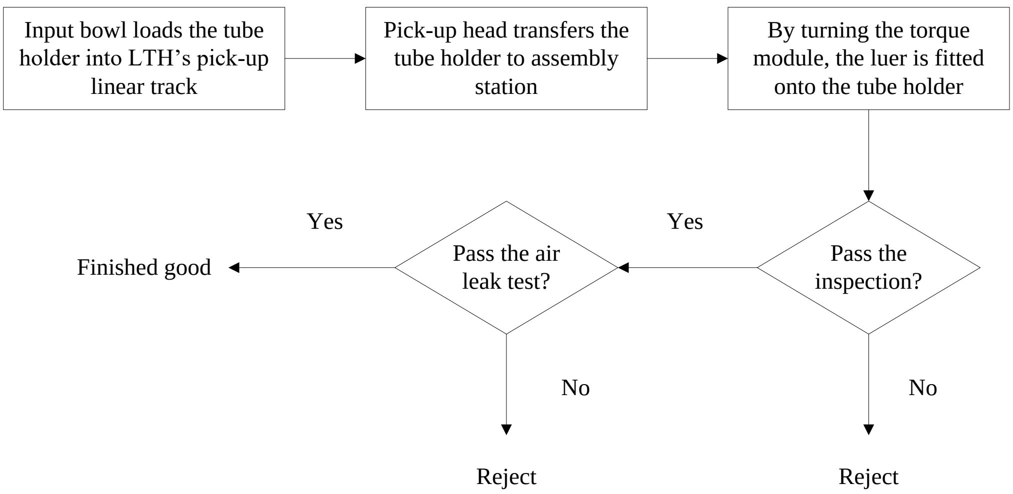

Figure 5.1: LTH operating process flow

Step 3 – ECE Metric Assessment (Before Improvement)

The calculation of the ECE_B requires the evaluation of certain operational and financial performance metrics. The operational metrics include T_{LT}, T_{CT}, and OEE, while the financial metrics are K_{EC} and K_{MC}. In the case study company, the T_{LT} is defined as 3,510,000 seconds, calculated over a three-month period by multiplying the daily working hours (15) by the number of working days (65). The T_{CT} varies among different LTH, with LTH 1, 2, 10, 11, and 12 having a T_{CT} of 6.7 seconds, while LTH 3 to 9 and 13 to 15 have a T_{CT} of 3.4 seconds. This difference in T_{CT} is attributed to the different features installed in LTH 1, 2, 10, 11, and 12, which cause a nearly 100% slower T_{CT} when compared to newer LTHs.

Table 5.2 presents the summary of the ECE_B for various LTHs over a three-month interval. The results indicate that LTH 8 exhibited the highest criticality of OEE and K_T among all the LTHs, while LTH 1 had the highest criticality of ECE_B. This divergence in priorities prompted further investigation. Upon close examination of the data, it was observed that LTH 1 had a higher cost per unit compared to LTH 8. The slower features of LTH 1, 2 10, 11, and 12 led to a substantial increase in T_{CT}, resulting in a decrease in productivity and subsequently increasing the cost per unit and ECE for these LTHs. As such, direct comparisons of equipment based on these metrics proved to be inappropriate. To address this, an alternative approach of analysing LTHs separately based on their features was adopted, leading to the prioritisation of LTH 1 and LTH 8. The management of the case study company eventually agreed to prioritise LTH 1 for improvement, as still LTH 1 incurred a higher wastage of K_{EC} and K_{MC} in the assembly of a single luer tube holder, surpassing the OEE benchmark. Furthermore, the case study company recognised that analysing LTH 1 alone would suffice after understanding the reasons for the differences among LTH 1, 2, 10, 11, and 12 compared to other LTHs.

Table 5.2. The ECE_B of LTH over the past 3 months

LTH	T_{LT} (s)	T_{CT} (s)	OEE (%)	K_{EC} ($)	K_{OC} ($)	K_{MC} ($)	K_{IC} ($)	K_T ($)	CPU ($/pc)	OEE Losses	ECE_B ($/pc)
1	**3510000**	**6.7**	**70.6**	**38855**	**5775**	**6247**	**0**	**45102**	**0.1865**	**-0.0024**	**-0.000207**
2	3510000	6.7	73.0	36777	5579	5553	0	42330	0.1751	-0.0019	-0.000156
3	3510000	3.4	74.2	35822	5320	5641	0	41463	0.0870	-0.0017	-0.000069
4	3510000	3.4	77.5	33590	5763	5197	0	38787	0.0814	-0.0011	-0.000043
5	3510000	3.4	66.4	41321	5005	6615	0	47936	0.1006	-0.0033	-0.000153
6	3510000	3.4	84.3	25321	5562	3958	0	29279	0.0614	-0.0001	-0.000003
7	3510000	3.4	80.3	29584	5523	3678	0	33262	0.0698	-0.0007	-0.000022
8	3510000	3.4	65.4	43321	5819	7310	0	50631	0.1063	-0.0035	-0.000173
9	3510000	3.4	75.8	33899	5884	5105	0	39004	0.0819	-0.0014	-0.000054
10	3510000	6.7	72.7	34877	5388	5625	0	40502	0.1675	-0.0020	-0.000154
11	3510000	6.7	73.2	35529	5316	5558	0	41087	0.1699	-0.0019	-0.000149
12	3510000	6.7	71.7	36995	5405	5945	0	42940	0.1776	-0.0022	-0.000179
13	3510000	3.4	74.5	33228	6022	5927	0	39155	0.0822	-0.0017	-0.000063
14	3510000	3.4	72.1	37844	5961	5974	0	43818	0.0920	-0.0021	-0.000089
15	3510000	3.4	77.3	32865	5664	5063	0	37928	0.0796	-0.0012	-0.000043

LTH: Luer tube holder assembly equipment; T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{OC}: operating cost; K_{MC}: maintenance cost; K_{IC}: improvement cost; K_T: total cost; CPU: cost per unit; ECE_B: equipment cost efficiency before improvement

5.2.2 Phase 2 – Improvement Planning

Step 4 – Pareto Analysis

The LTH is semi-automated equipment and has error logs can be accessed through the operating system. Additionally, information about any associated downtime can also be retrieved through the operating system. Depending on the type of downtime, the downtime affects the operating time in different ways. The downtime affects the availability of the equipment by reducing the overall operating time, the performance of the equipment by reducing the net operating time and the quality of the product by reducing the valuable operating time. Therefore, extracting the downtime from the LTH's system and adopting the conventional OEE definition helps identify the most relevant OEE losses. As shown in Figure 5.2, the Pareto analysis showed that over 80% of the LTH 1 downtime was related to the luer drop, air leak test failure, and tube holder drop. The downtime of air leak test failure caused high defect and rework losses. The luer drop and tube holder drop downtime caused high equipment failure losses and idling and minor stoppage losses.

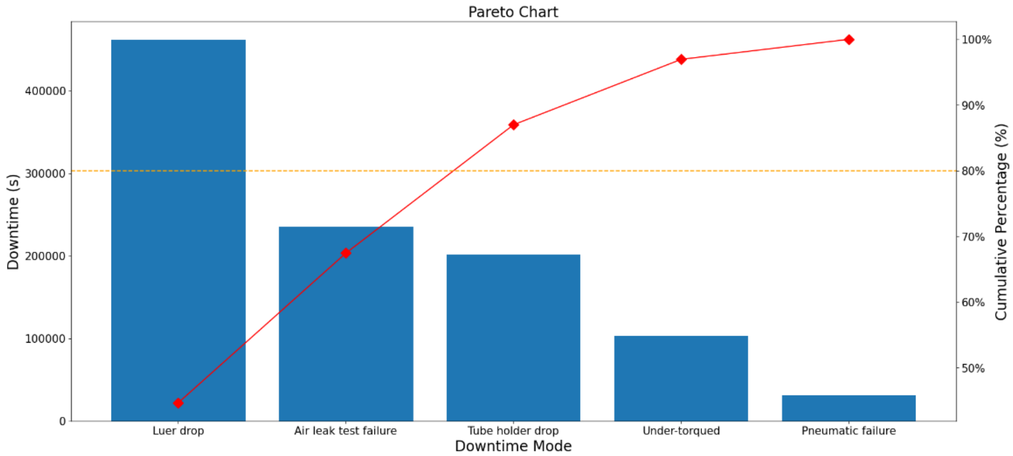

Figure 5.2: LTH 1 downtime Pareto analysis

Step 5 – Root Cause Analysis

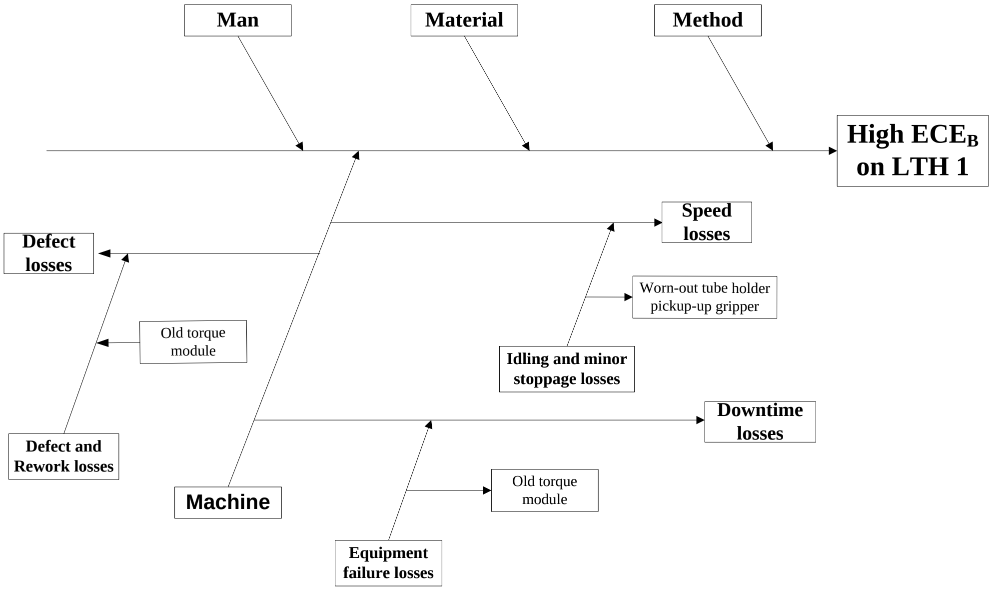

Figure 5.3. Root cause analysis of high ECE$_B$ in LTH 1 using fishbone diagram

Figure 5.3 illustrates the root cause analysis outcome in fishbone diagram. The equipment failure losses, idling and minor stoppage losses, and defect and rework losses yielded low availability, performance, and quality, which eventually caused low OEE and high ECE$_B$ in LTH 1.

The root cause of high equipment failure losses and defect and rework losses in LTH 1 is the old torque module. Unlike other LTHs, LTH 1 has a unique torque module inherited from its prototype concept, which requires more steps to assemble the luer into the tube holder. The process of fitting a luer onto the tube holder starts from the luer separator, which segregates a single piece of luer from the luer linear track. Meanwhile, the tube holder pick-up head transfers a tube holder to the assembly station. When the tube holder is held firmly by the gripper at the assembly station, the torque module fits the luer on the tube holder by turning the flange of the luer. The old torque module had the disadvantage of requiring more precise adjustment of the mechanical position to fit the luer into the tube holder because there were more steps involved. As a result, there was a high possibility of misalignment between the luer and tube holder, leading to the luer dropping down when the torque module released it. This misalignment not only caused the luer to strike or scratch the body of the tube holder but also resulted in damage to both the luer and tube holder. This not only incurred longer assembly time but also induced a higher defect rate. It is evident from these drawbacks that LTH 1 suffers from a detrimental impact on its financial and operational performance. In contrast, the new torque module in other LTHs functions differently, as the luer is straight picked up from the luer linear track and fitted to the tube holder by straight picking up the luer.

The primary cause of high idling and minor stoppage losses in LTH 1 is the worn-out tube holder pick-up gripper, which is equipped with silicone grips designed to securely hold test tubes without causing surface damage. However, after repeated use, the silicone grips become worn and fail to grip and drop the test tubes during assembly, triggering an alarm by the sensor at the assembly station. As a result, the operating system of LTH 1 halts the equipment and the operator must annually insert a test tube to clear the alarm. These frequent stoppages negatively impact the OEE and ECE_B of the system.

Step 6 – Solution Brainstorming

Utilising the fishbone diagram to meticulously pinpoint the underlying causes, the initiative team was able to propose six effective improvement actions to mitigate the losses stemming from equipment failure, defect and rework, and idling and minor stoppage.

In an effort to address current losses related to equipment failure and defect and rework, various improvement actions were recommended. One such improvement action entailed the replacement of the outdated torque module with a new, optimised design. The new design, which featured a streamlined luer and tube holder assembly, was found to be highly effective in reducing assembly time, thereby increasing efficiency and productivity. However, the implementation of this improvement strategy incurred a cost of MYR 50,000. Additionally, an effort was made to optimise the mechanical positioning of the luer within the tube holder. While this approach resulted in no cost, it was not a sustainable solution as issues with misalignment were expected to persist. Another proposed improvement action was to increase the operator headcount to manage stoppages, however, this approach was deemed unfavourable due to the additional costs and lack of permanency.

In an attempt to mitigate idling and minor stoppage losses, several improvement actions were proposed. One such strategy was the replacement of worn-out silicone grippers in the tube holder pick-up head, which was found to be a cost-effective and easy-to-implement solution. However, this incurred a cost of MYR 5,000. To sustain the improved performance, the initiative team proposed a preventive maintenance strategy, where the silicone gripper would be replaced semi-annually, regardless of its condition. This would result in an additional cost of MYR 5,000 per six-month period. Another proposed strategy was to transition from silicone to rubber grippers, which offer improved resistance to abrasion and are more economical. However, it should be noted that the use of rubber may result in potential contamination of the surface of the tube holder, and should be considered carefully before implementation.

Table 5.3 is a summary of improvement actions, along with a listing of the pros and cons of each action. The table serves as a helpful tool for decision-making, as it presents a clear overview of the potential benefits and drawbacks of each improvement action. This allows individual and teams to weigh the options and make informed choices about which actions to implement.

Table 5.3. Proposed improvement actions for enhancing the ECE_B of LTH 1

No	Improvement action	RC1	RC2	Pros	Cons
1	Replace the worn-out silicone gripper in the tube holder pick-up head		✓	A cost-effective and practical improvement measure	The cost of improving LTH 1 by replacing all silicone grippers is MYR 5,000
2	Incorporate the replacement of the silicone gripper into the current half-yearly preventive maintenance schedule		✓	Uphold the consistency of operational performance for LTH 1	A MYR 5,000 improvement cost will be incurred during each preventive maintenance
3	Replace the silicone gripper with a rubber alternative		✓	Rubber is a more economical and abrasion-resistance alternative to silicone	There is a possibility of rubber contamination on the surface of the tube holder
4	Upgrade the outdated torque module to the latest design utilised by other LTHs	✓		Enhance assembly cycle time and achieve a more uniform performance	To upgrade the old torque module to the new design, an improvement cost of MYR 50,000 will be incurred
5	Further optimise the mechanical positioning to accommodate the insertion of the luer into the tube holder	✓		This action will not incur any additional costs	Misalignments will occur inevitable
6	Increase the number of operators to manage any stoppages	✓		Minimise stoppage losses by promptly responding to alarms	Increasing the headcount is a containment action to address the issue

RC1: old torque module; RC2: Worn-out tube holder pick-up gripper

Step 7 – Gap Analysis

The present study conducted a gap analysis in conjunction with the management of a medical device manufacturer to identify opportunities to improve the ECE_B of LTH 1. The management conveyed the need for implementing effective, permanent improvement actions that do not compromise the quality of the final product. Three such actions were identified: replacing the worn-out silicone gripper in the tube holder pick-up head, incorporating the replacement of the silicone gripper in the current half-yearly preventive maintenance schedule, and replacing the old torque module with a new design. These actions were deemed to align with the expectations of the management of the case study company. The outcome of the gap analysis is summarised in Table 5.4.

Table 5.4: The gap analysis for improving the ECE_B of LTH 1

Objective	• To improve the ECE metric of LTH 1
Current state	• Old torque module • Worn-out tube holder pick-up gripper
Future state	• Improve the ECE metric of LTH 1 by implementing effective and permanent improvement actions without compromising the quality of the final product
Gap	• The maintenance of the silicone gripper in the tube holder pick-up head was not conducted on a regular basis • The design of the assembly station can be simplified through the replacement of the torque module
To-do	• Replace the worn-out silicone gripper in the tube holder pick-up head • Incorporate the replacement of the silicone gripper in the current half-yearly preventive maintenance • Upgrade the outdated torque module to the latest design utilized by other LTHs

5.2.3 Phase 3 – Simulation

Step 8 – ECE Metric Assessment (Simulation)

In order to optimise the operational and financial performance of LTH 1, the present study proposed three improvement actions with an associated cost of MYR 55,000. The proposed actions were expected to enhance both the OEE and ECE_B of LTH 1. However, to confirm the cost-effectiveness of these proposed actions, a simulation was conducted. The simulation calculated the ECE_S by simulating an increase in OEE from 70.6% (the current OEE of LTH 1) to 85.0% (a world-class OEE). The results of the simulation, as illustrated in Figure 5.4, indicate that the ECE_S was more beneficial than the ECE_B when the MYR 55,000 improvement actions increase the OEE to a minimum of 78.0%.

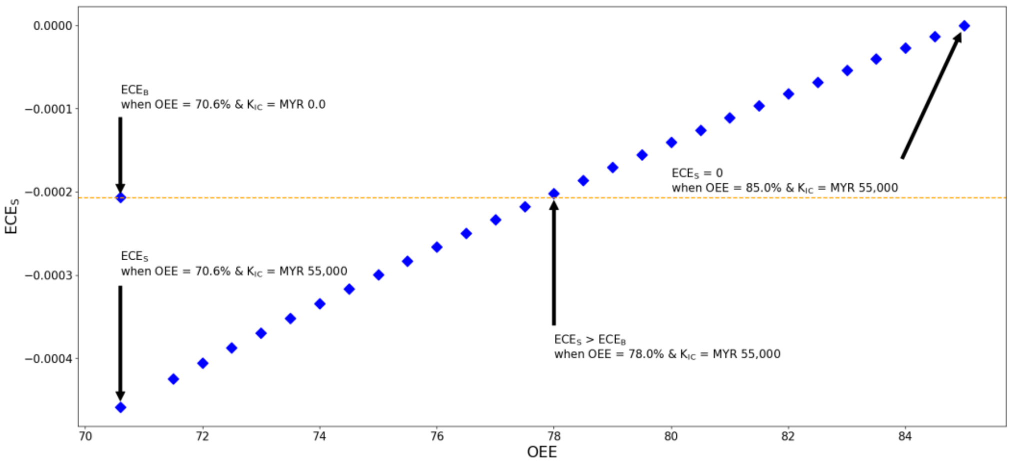

Figure 5.4. ECE_S of LTH 1 simulation with different OEE

The present study proposed three improvement actions to reduce the downtimes associated with luer drop, air leak test rejects, and tube holder drop. To assess the potential impact of these actions on the OEE, a series of simulations were conducted. These simulations, labelled as Simulations 1, 2, and 3, were designed to simulate the OEE with downtimes of 10%, 20%, and 30% less than the existing downtimes respectively. The results of these simulations are presented in Table 5.5. The simulation results indicate that the OEE could be improved by up to 78.3% when downtimes associated with luer drop, air leak test rejects, and tube holder drop were reduced by 30% as compared to the existing downtimes. Additionally, through the examination of other LTHs, the initiative team gained confidence that these downtimes could potentially be reduced by more than 30%.

Table 5.5. LTH 1 downtime and OEE simulation

Downtime	**Luer drop (s)**	**Air leak test rejects (s)**	**Tube holder drop (s)**	**Under-torqued (s)**	**Pneumatic failure (s)**	**Total downtime (s)**	**OEE (%)**
Existing	461080.0	235110.0	201562.0	102732.0	31456.0	1031940.0	70.6
Simulation 1	414972.0	211599.0	181405.8	102732.0	31456.0	942164.8	73.2
Simulation 2	368864.0	188088.0	161249.6	102732.0	31456.0	852389.6	75.7
Simulation 3	322756.0	164577.0	141093.4	102732.0	31456.0	762614.4	78.3

Simulation 1: OEE with downtimes of 10% less than the existing downtimes; Simulation 2: OEE with downtimes of 20% less than the existing downtimes; Simulation 3: OEE with downtimes of 30% less than the existing downtimes

5.2.4 Phase 4 – Implementation and Monitoring

Step 9 – ECE Metric Assessment (After Improvement)

In order to validate the sustainability of the proposed improved actions, an evaluation of the ECE_A was conducted following their implementation. Table 5.5 illustrates the results of this evaluation, which demonstrated that the K_{IC} was higher than anticipated due to the discovery and replacement of additional worn-out parts within the LTH 1. Despite this, the management of the medical devices manufacturer deemed it necessary to absorb the additional costs associated with this increased K_{IC} in order to more accurately assess the effectiveness of the implemented improvement actions. Furthermore, it was observed that the replacement of the outdated torque module with a new design led to a reduction in downtime associated with under-torquing, as well as improved fine-tuning and/or accurate micro-stepping. This unexpected improvement in ECE_A was observed to be higher than the results predicted by ECE_S. A comparison of the pre- and post-improvement metric (Table 5.6) revealed that the additional investment in these improvement actions led to significant improvement in the K_{EC}, K_{MC}, OEE, and ECE metric by 24.2%, 35.6%, 15.3%, and 77.7% respectively. This is a clear indication of the effectiveness of the implemented improvement actions in improving the operational and financial performance of the LTH 1.

Table 5.6. Comparison of the ECE_B and ECE_A of LTH 1

	Pre-improvement	**Post-improvement**	**Improvement**
T_{LT} (s)	3510000	3510000	No change
T_{CT} (s)	6.7	3.4	Reduce by 49.3%
OEE (%)	70.6	81.4	Improve by 15.3%
K_{EC} ($)	38855	29453	Reduce by 24.2%
K_{MC} ($)	6247	4023	Reduce by 35.6%
K_{IC} ($)	0	57820	NA
K_T ($)	45102	91296	Increase by 102.4%
Cost per unit ($/pc)	0.0861	0.0884	Increase by 2.7%
OEE Losses	-0.0024	-0.0005	Reduce by 79.2%
ECE ($/pc)	-0.000207	-0.000046	Improve by 77.8%

T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{MC}: maintenance cost; K_{IC}: maintenance cost; K_T: total cost; ECE: equipment cost efficiency

5.3 Case study 2 – Tyre Flap Manufacturer

The second case study was conducted at a tire flap manufacturing facility located in Perak, Malaysia. The tire flap, made by moulding premixed compounded rubber through the use of a semi-automated tyre flap vulcaniser (TFV), serves to protect the inner tube of the tire from damage caused by the rim. Such protection helps prevent tire blowouts and other tire-related incidents that may result in harm or death. The TFVs were selected for improvement due to their substantial impact on the quality, productivity, cost, and delivery of the tire flap. The facility operates 26 TFVs, and a module of 5 TFVs was designated for the purposes of this study. The ECEF was employed throughout the study, and the methodology of enhancing the ECE metric of the TFVs through the application of the ECEF will be thoroughly discussed in subsequent sections.

5.3.1 Phase 1 – Assessment

Step 1 – Team Formation

A multidisciplinary team was constituted, comprising members from the areas of production, process, maintenance, planning, quality, and procurement. The composition of the initiative team is summarised in Table 5.7.

Table 5.7. Initiative team structure of TFV improvement

Project champion	Operation manager
Stakeholder(s)	Production manager and equipment manager
Leader	Senior equipment engineer
Team members	Equipment technician Production supervisor Planning control Purchasing executive

Step 2 – Process Flowchart

The procedure for moulding a tyre flap, as demonstrated in Figure 5.5, entails six stages carried out by the TFV. In order to prevent under-curing faults originating from unsanitary moulds, the first step in the process is to clean the mould. Subsequently, the pre-mixed compounded rubber is introduced into the mould. Upon completion of the vulcanisation process, the vulcanised tyre flap is removed from the TFV by the operator for a final evaluation. It is noteworthy that all stages, except for the vulcanisation process, are executed manually. Although some of the stages of the process are executed manually, such as cleaning the mould and introducing the pre-mixed compounded rubber into the mould, the vulcanisation process itself is carried out by the equipment. Therefore, while the equipment does require some level of manual intervention, it also has an automated component, which classifies it as a semi-automated equipment.

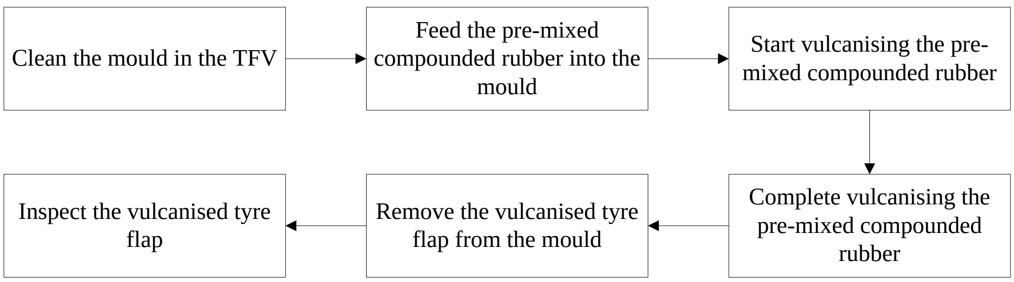

Figure 5.5: TFV operating process

Step 3 – ECE Metric Assessment (Before Improvement)

The calculation of the ECE_B for all five TFVs necessitated the use of operational performance metrics, namely T_{LT}, T_{CT}, and OEE, as well as financial performance metrics, including K_{EC} and K_{MC}. The TFV is a semi-automated equipment, and manual collection of accurate OEE data can be problematic. In this case study, the total T_{LT} was established as 1,872,000 seconds (calculated by multiplying 8 hours of daily working hours by 65 days), while the T_{CT} for vulcanising a tyre flap was determined to be 120 seconds. The average daily quantity of good tyre flaps produced by each TFV over a 3-month period was recorded as the quantity good (Q_G).

The K_{EC} and K_{MC} values were obtained from the financial records of the case study company. The K_{EC} represents the depreciation cost of the TFV over a 3-month period, calculated by dividing the difference between the acquisition cost and salvage value by the useful life of the TFV. The five TFVs were manufactured by the same company but purchased at different times, with varying acquisition costs, resulting in differing K_{EC} values for each TFV. The K_{MC} represents the expenditures incurred by the case study company for 3 months on maintenance activities, including preventive and corrective maintenance, on all five TFVs. It also encompasses the cost of parts replaced during these activities, with different values for each TFV due to variations in preventive and corrective maintenance performed.

Table 5.8 summarises the ECE_B of the analysed TFVs over a 3-month period. Among the TFVs, TFV 5 displayed the highest criticality in terms of ECE_B, leading to its prioritisation for improvement, a decision endorsed by the management of the case study company. The ECE_B results highlighted that, in comparison to the world-class OEE, TFV 5 dissipated MYR 0.0063 of K_{MC} and K_{EC} for every vulcanised tyre flap.

Table 5.8. The ECE_B of TFVs over the past 3 months

TFV	T_{LT} (s)	T_{CT} (s)	OEE (%)	K_{EC} ($)	K_{OC} ($)	K_{MC} ($)	K_{IC} ($)	K_T ($)	CPU ($/pc)	OEE Losses	ECE ($/pc)
1	1872000	120	72.5	19535	4941	4334	0	23869	1.5301	-0.0020	-0.0031
2	1872000	120	76.6	17125	4471	4216	0	21341	1.3680	-0.0013	-0.0018
3	1872000	120	65.3	22555	5516	4556	0	27111	1.7379	-0.0035	-0.0061
4	1872000	120	73.1	17600	4641	4375	0	21975	1.4087	-0.0019	-0.0027
5	**1872000**	**120**	**64.7**	**22200**	**3557**	**4348**	**0**	**26548**	**1.7018**	**-0.0037**	**-0.0063**

TFV: tyre flap vulcaniser; T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{OC}: operating cost; K_{MC}: maintenance cost; K_{IC}: improvement cost; K_T: total cost; CPU: cost per unit; ECE_B: equipment cost efficiency before improvement

5.3.2 Phase 2 – Improvement Planning

Step 4 – Pareto analysis

The utilization of TFV, despite being semi-automated equipment, still enables the operating system to document error logs and downtimes. The adoption of the conventional definition of OEE allows for the categorization of downtimes that impact OEE availability, performance, and quality into respective OEE losses. A Pareto analysis (Figure 5.6) indicates that a majority (over 80%) of the TFV 5 downtime was attributed to idling time, mod cleaning, and under-cured defect. These factors resulted in high idling and minor stoppage losses, as well as high defect and rework losses.

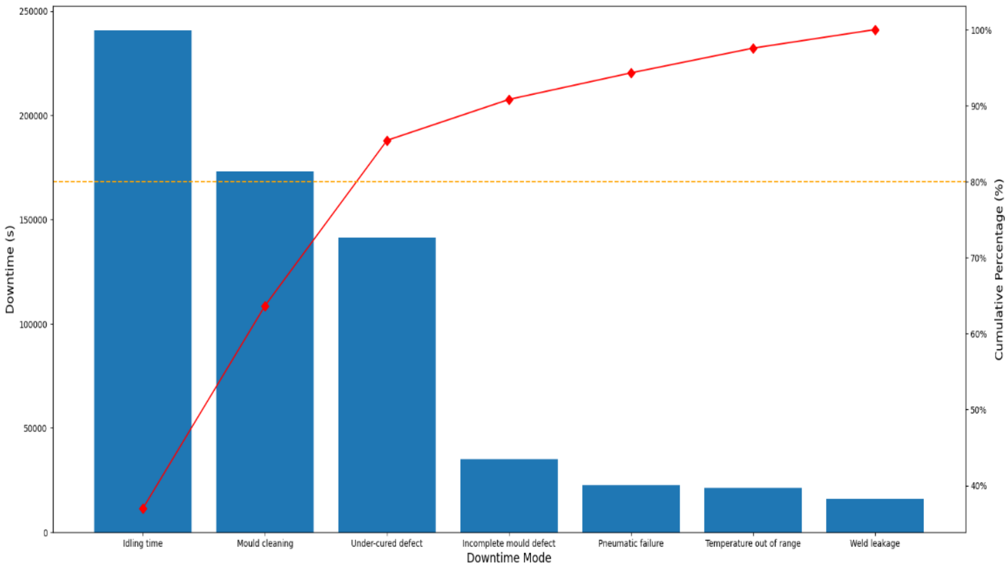

Figure 5.6. TFV 5 downtime Pareto analysis

Step 5 – Root Cause Analysis

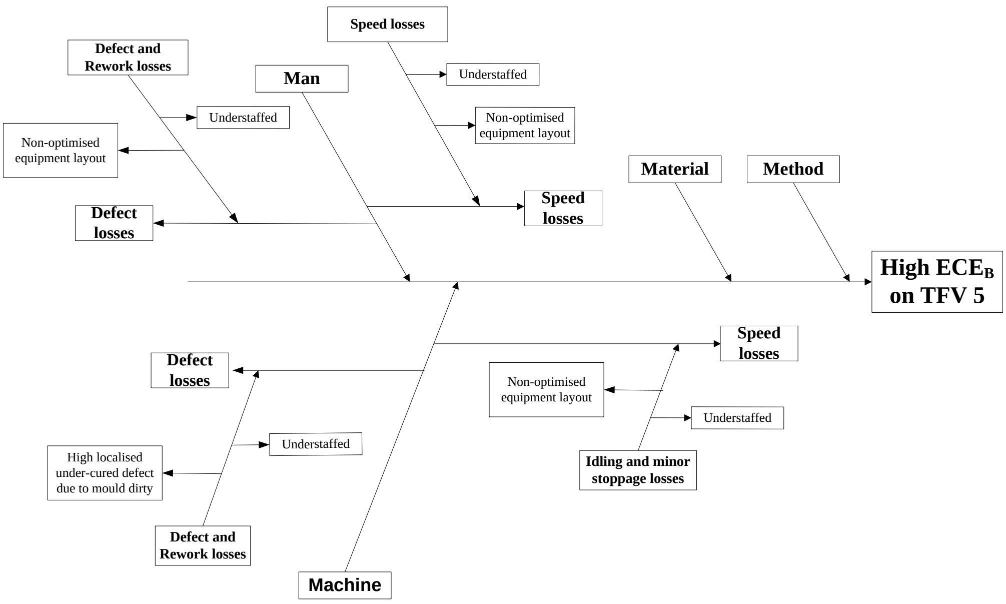

Figure 5.7. Root cause analysis of high ECE$_B$ in TFV 5 using fishbone diagram

Figure 5.8 presents the results of a root cause analysis in the form of a fishbone diagram, aimed at determining the reasons for the high ECE$_B$ in TFV

5. The analysis revealed that low OEE and high ECE_B were attributed to factors such as idling and minor stoppage losses, as well as defect and rework losses. The underlying causes were identified as a suboptimal equipment layout, inadequate staffing levels, and elevated local rates of under-cured defects due to dirty moulds.

Figure 5.8 provides a staffing analysis for the five TFVs in the manufacturing line. Three headcounts, consisting of one leader and two operators, were assigned to oversee all TFVs. While TFVs 1, 2, 3, and 4 were staffed by a minimum of two headcounts, TFV 5 was operated solely by the line leader. The leader or operators were required to clean the mould thoroughly before inserting the compounded rubber, and to attend other TFVs during the vulcanising process. The suboptimal equipment layout resulted in inefficiencies related to transport, motion, and waiting, while inadequate staffing levels exacerbated the issue and contributed to elevated local rates of under-cured defects due to insufficient cleaning of the moulds.

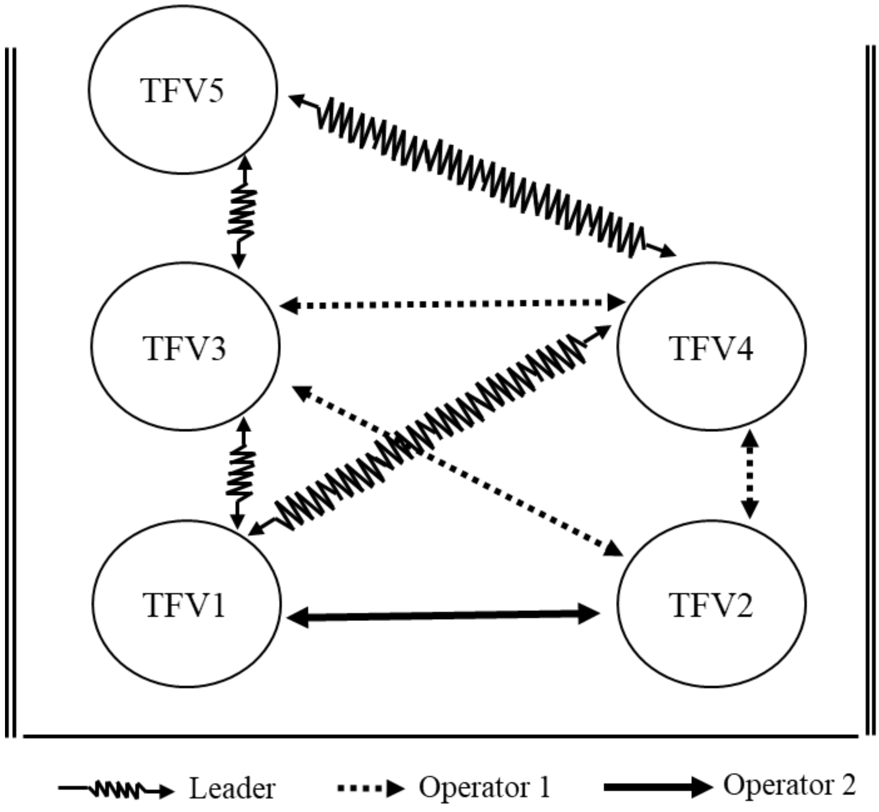

Figure 5.8. TFV layout

Step 6 – Solution Brainstorming

As depicted in Figure 5.8, a fishbone diagram was utilized to analyse the root causes that resulted in high ECE_B in TFV 5. The high idling and minor stoppage losses and defect and rework losses were attributed to several factors, including understaffing, prolonged equipment idling, non-optimised equipment layout, and high local under-cured defects caused by insufficient mould cleaning.

To address these root causes and minimise the frequency of these losses, six improvement actions were proposed. These actions include increasing operator headcount, relocating TFV 5 to reduce operator walking distance, optimizing the TFV operating process, investing in new mould technology that requires less frequent cleaning, automating the mould cleaning and/or vulcanised tyre flap inspection process, and optimizing moulding parameters.

Each of these improvement actions has its own unique benefits and drawbacks, such as cost implications and potential impact on performance. The proposed improvement actions and their respective pros, cons, and cost implications are summarised in Table 5.9 for ease of reference.

Table 5.9. Proposed improvement action for enhancing ECE_B of TFV 5

No	**Improvement action**	**RC 1**	**RC 2**	**RC 3**	**RC 4**	**Pros**	**Cons**
1	Increase the number of operators	✓	✓	✓	✓	Achieve higher performance and lower defect rates	Incur additional operation costs
2	Relocate TFV 5 between TFV 1 and TFV 2	✓	✓	✓	✓	Minimise the distance between TFVs	Incur equipment relocation cost (approximately MYR 2,500 per TFV)
3	Adjust the operating process of the TFV	✓	✓	✓	✓	Optimise the workload of operators without incurring additional costs	Achieve limited results
4	Replace the existing mould with a newer technology				✓	Require less frequent cleaning of moulds without compromising quality	Incur higher tooling cost (approximate MYR 15,000 per mould)
5	Automate the process of cleaning the mould and/or inspecting vulcanised tyre flaps	✓				Decrease the reliance on human resources	Incur higher equipment cost (approximately over MYR 100,000)
6	Investigate the feasibility of optimising the moulding parameters				✓	Decrease the frequency of mould cleaning and defect rates	Impact the quality of moulded tyre flap, which increases the moulding time and reduces the good products

RC1: non-optimised equipment layout; RC2: high equipment idling time; RC3: understaffed; RC4: high localised defect due to mould dirty

Step 7 – Gap Analysis

The gap analysis (Table 5.10) was conducted in conjunction with the management of the tyre flap manufacturer. The management expressed a desire to enhance the performance of TFV 5 ECE_B without incurring significant cost or expanding the workforce. To meet these expectations, two improvement actions were proposed and deemed sufficient: the reassignment of tasks within the TFV operating process and the relocation of TFV 5 between TFVs 1 and 2.

Table 5.10: The gap analysis for improving the ECE_B of TFV 5

Objective	• To improve the ECE metric of TFV 5
Current state	• Non-optimised equipment layout • High equipment idling time • Understaffed • High localised defect due to mould dirty
Future state	• Improve the ECE metric of TFV 5 without increasing the current operator-to-equipment ratio and without investing a large sum of money
Gap	• Improve TFV layout optimisation • Streamline TFV operational processes
To-do	• Move TFV 5 to a location between TFVs 1 and 2 • Modify the current TFV operational process

5.3.3 Phase 3 – Simulation

Step 8 – ECE Metric Assessment (Simulation)

The current study endeavours to propose two improvement actions, which a cost of MYR 2,500, aimed at optimising the operational efficiency and financial performance of TFV 5. It is hypothesized that the implementation of these proposed actions would result in a significant enhancement in both the

OEE and ECE_B of TFV 5. In order to confirm the cost-effectiveness of the proposed actions, a simulation was carried out. The simulation calculated the ECE_S by simulating an increase in the OEE from its current level of 64.7% to a world-class level of 85.0%. The results of the simulation, as depicted in Figure 5.9, indicate that the ECE_S was more advantageous than the ECE_B when the improvement actions increased the OEE to a minimum of 66.2%.

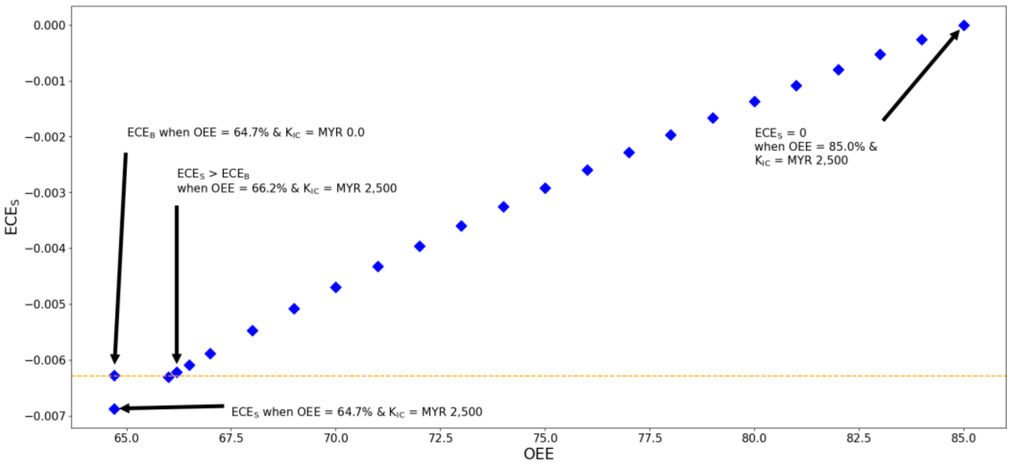

Figure 5.9. ECE_S of TFV 5 simulation with different OEE

The present study proposed two improvement actions aimed at minimising the downtimes caused by non-optimised equipment layout, prolonged equipment idling time, understaffing, and high localized defects due to mould contamination. To evaluate the potential impact of these actions on the OEE, a series of simulations were conducted. These simulations, labelled as Simulations 1, 2, 3, and 4, were designed to simulate the OEE with downtimes of 5%, 10%, 15%, and 20% less than the existing downtimes, respectively. The results of these simulations are presented in Table 5.11 and indicate that the OEE could be improved by up to 66.2% if downtimes associated with idling time, mould cleaning, and under-cured defects were reduced by 5% compared to the existing downtimes. Furthermore, the examination of the proposed improvement actions gave the initiative team confidence that these downtimes could potentially be reduced by more than 20%.

Table 5.11. TFV 5 downtime and OEE simulation

	Idling time (s)	Mould cleaning (s)	Under-cured defect (s)	Others (s)	Total downtime (s)	OEE (%)
Existing	240537.0	173133.8	141414.6	105731.0	660816.0	64.7
Simulation 1	228510.2	164477.1	134343.9	105731.0	633061.7	66.2
Simulation 2	216483.3	155820.4	127273.2	105731.0	605307.5	67.7
Simulation 3	204456.5	147163.7	120202.4	105731.0	577553.2	69.1
Simulation 4	192429.6	138507.0	113131.7	105731.0	549798.9	70.6

Simulation 1: OEE with downtimes of 5% less than the existing downtimes; Simulation 2: OEE with downtimes of 10% less than the existing downtimes; Simulation 3: OEE with downtimes of 15% less than the existing downtimes; Simulation 4: OEE with downtimes of 20% less than the existing downtimes

Based on the approach adopted, the proposed improvement actions were expected to not only address the downtime issue in TFV 5, but also reduce the equipment idling time for other TFVs, thereby improving their OEE and ECE metric. In order to assess the overall impact of these improvement actions, the management of the tyre flap manufacturer decided to incur the cost of relocating TFV 5 to a new location. The new operating process and layout for TFV 5 were simulated, and the operators were trained accordingly. Upon completion of the relocation, the functionality of TFV 5 was confirmed, and the project team initiated the measurement of ECE_S. The results, as presented in Table 5.12, indicate that the ECE_S of TFV 5 improved by 55.7% after the improvement actions, despite the increased cost of MYR 2,500 incurred by the relocation. The results of the ECE_S affirm the effectiveness of the improvement actions.

Table 5.12. Comparison of the ECE_B and ECE_S of TFV 5

	Pre-improvement	**Post-improvement**	**Improvement**
T_{LT} (s)	1872000	1872000	No change
T_{CT} (s)	120	120	No change
OEE (%)	67.7	75.4	Improve by 16.4%
K_{EC} (\$)	22200	22200	No change
K_{MC} (\$)	4348	4348	No change
K_{IC} (\$)	0	2500	NA
K_T (\$)	26548	29048	Increase by 9.4%
Cost per unit (\$/pc)	1.7018	1.8621	Increase by 9.4%
OEE Losses	-0.0037	-0.0015	Reduce by 59.5%
ECE (\$/pc)	-0.0063	-0.0028	Improve by 55.7%

T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{MC}: maintenance cost; K_{IC}: maintenance cost; K_T: total cost; ECE: equipment cost efficiency

5.3.4 Phase 4 – Implementation and Monitoring

Step 9 – ECE Metric Assessment (After Improvement)

The validity of the sustainability of the improvement action was assessed by evaluating the ECE_A following the implementation of the improvement actions. Three months after improvement, the results were documented in Table 5.13, which demonstrated the ECE_A. The management of the tyre flap manufacturer opted to pay off the K_{IC}, incurred by relocating TFV 5, instead of amortizing it during the simulation step, which led to no recorded K_{IC} after the improvement actions were put in place. The higher ECE_A in comparison to the simulation ECE_S was due to the operators' increased familiarity with the new operating process and layout of TFV 5 during the simulation. Table 5.13 shows that the K_{EC}, K_{MC}, OEE, and ECE of TFV 5 improved by 13.5%, 8.1%, 14.9%, and 74.6%, respectively, compared to the values before and after the improvement actions. The success of the improvement actions in reducing wastage in K_T (sum of K_{EC}, K_{MC}, and K_{IC}) was evident through the achievement of the ECE metric. Additionally, the same improvement actions resulted in increased OEE and ECE in other TFVs, as demonstrated in Table 5.14. The trends indicated that the initiative was successful, as the improvement actions were both under control and sustainable. The initiative was concluded after documenting the changes and results for record-keeping and future reference purposes.

Table 5.13. Comparison of the ECE_B and ECE_A of TFV 5

	Pre-improvement	**Post-improvement**	**Improvement**
T_{LT} (s)	1872000	1872000	No change
T_{CT} (s)	120	120	No change
OEE (%)	67.7	77.8	Improve by 14.9%
K_{EC} ($)	22200	19200	Reduce by 13.5%
K_{MC} ($)	4348	3995	Reduce by 8.1%
K_{IC} ($)	0	2500	NA
K_T ($)	26548	23195	Reduce by 12.6%
Cost per unit ($/pc)	1.7018	1.4869	Reduce by 12.6%
OEE Losses	-0.0037	-0.0011	Reduce by 70.3%
ECE ($/pc)	-0.0063	-0.0016	Improve by 74.6%

T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{MC}: maintenance cost; K_{IC}: maintenance cost; K_T: total cost; ECE: equipment cost efficiency

Table 5.14. The ECE_A of TFV over the past 3 months

TFV	**T_{LT} (s)**	**T_{CT} (s)**	**OEE (%)**	**K_{EC} ($)**	**K_{MC} ($)**	**K_{IC} ($)**	**K_T ($)**	**CPU ($/pc)**	**OEE Losses**	**ECE ($/pc)**
1	1872000	120	77.4	18453	3944	0	22397	1.4357	-0.0012	-0.0017
2	1872000	120	78.7	15945	4016	0	19961	1.2796	-0.0009	-0.0012
3	1872000	120	70.4	20372	3986	0	24358	1.5614	-0.0024	-0.0038
4	1872000	120	77.4	16051	4025	0	20076	1.2869	-0.0012	-0.0015
5	1872000	120	77.8	19200	3995	0	23195	1.4869	-00011	-0.0016

TFV: tyre flap vulcaniser; T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{MC}: maintenance cost; K_{IC}: improvement cost; K_T: total cost; CPU: cost per unit; ECE_B: equipment cost efficiency before improvement

5.4 Case study 3 – Semiconductor Manufacturer

The last case study presented in this research was conducted in a semiconductor manufacturing company located in Perak, Malaysia, with a specific focus on improving the OEE of its pick and place handler (PNP) system.

Out of the 150 PNPs installed by the company, a module of 12 PNPs was selected as the subject of the study. The implementation of the ECEF was carried out from the initiation to the completion of the project, and the subsequent subsections will provide a detailed account of the application of the ECEF to enhance the PNP system's ECE metric.

5.4.1 Phase 1 – Assessment

Step 1 – Team Formation

A team comprising individuals from various departments, including product, process, maintenance, production, planning, quality, and procurement, was established for the case study. The structure of this initiative team is summarised in Table 5.15.

Table 5.15: Initiative team structure of PNP improvement

Project champion	Operation manager
Stakeholder(s)	Maintenance manager and production manager
Leader	Maintenance section manager
Team members	Maintenance engineer Equipment technician Production supervisor Planning control Quality engineer Procurement executive

Step 2 – Process Flowchart

The process of testing a device utilising PNP is detailed in Figure 5.10 and comprises of 9 sequential steps. The pickup arm 1 retrieves the untested device from the loading station and transfers it to the input transfer station. The pickup arm 2 then conveys the device to the input shuttle for transportation to the testing area. The plunger then inserts the device into the test socket, which provides the electrical connection necessary for conducting electrical testing. Upon completion of the electrical testing, the plunger dispenses the tested device onto the output shuttle. The pickup arm 3 then moves the device to the output transfer station, and finally, pickup arm 4 classifies the device based on the test results into either the good or rejected tray at the output station.

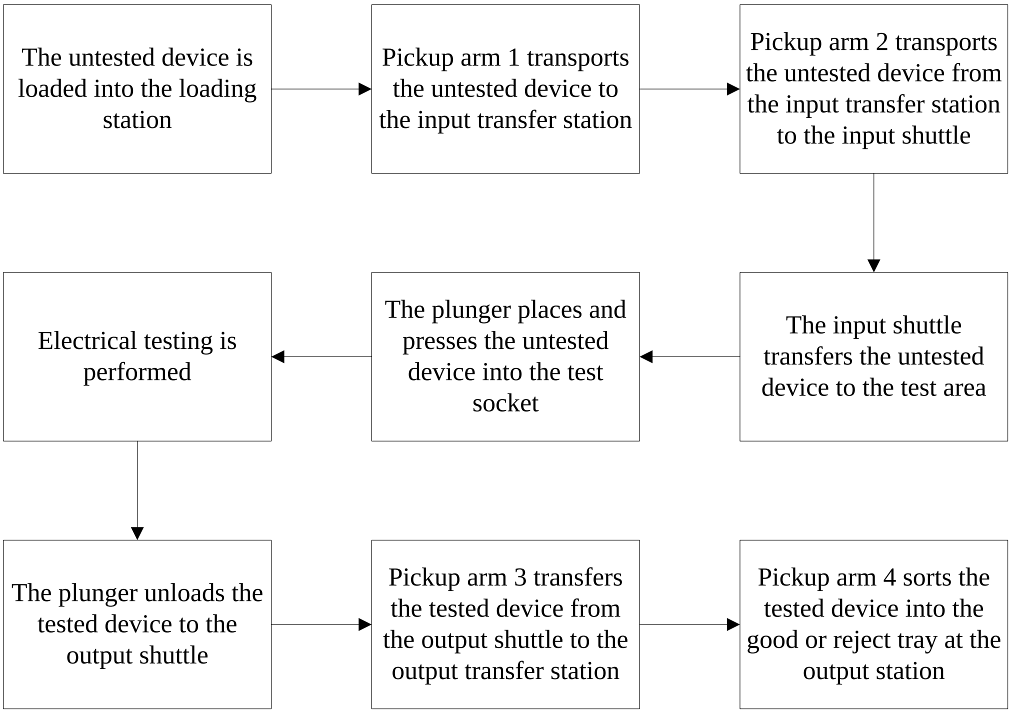

Figure 5.10: PNP operating process flow

Step 3 – ECE Metric Assessment (Before Improvement)

In the present study, the calculation of the ECE_B of the 12 PNPs required a comprehensive evaluation of the operational and financial performance metrics. The T_{LT} of the PNPs was calculated by multiplying the daily working hours, which were 24 hours (equivalent to 86,400 seconds), by the number of working days in a 3-month period, which was 91. The T_{CT} was established as the average of the cumulative test time and index time for all the devices tested on the PNPs over a 3-month period. The test time, a component of T_{CT}, is influenced by the complexity of the devices and the test fault coverage, while the index time is the time required to transfer the tested devices from the test station and replace them with fresh devices. The K_{EC} and K_{MC} were extracted from the financial records of the semiconductor manufacturer. The K_{EC} encompasses the monthly depreciation cost and spare parts cost of the PNPs, with the depreciation cost being calculated as the division of the difference between the PNP acquisition cost and salvage value by its useful life. The K_{MC} represents the monthly expenditure incurred by the company for maintenance activities, including both preventive and corrective maintenance, on all PNPs.

Table 5.16 presents the summary of the ECE_B of all 12 PNPs for a 3-month period. From the data presented in the table, it was observed that PNP 2 had the highest ECE_B criticality among all the PNPs. Hence, it was prioritised for improvement, as agreed by the case study company management. The ECE_B also revealed that for the testing of a single device, PNP 2 dissipated MYR 0.0043 of K_{EC} and K_{MC}. This value was compared with the 85% world-standard OEE and was found to be relatively high.

Table 5.16. The ECE_B of PNPs over the past 3 months

Eqp	T_{LT} (s)	T_{CT} (s)	OEE (%)	K_{EC} ($)	K_{OC} ($)	K_{MC} ($)	K_{IC} ($)	K_T ($)	CPU ($/pc)	OEE Losses	ECE_B ($/pc)
PNP 1	7862400	1.35	60.0	31868	4012	11823	0	43691	0.0075	-0.49	-0.0037
PNP 2	**7862400**	**1.35**	**58.3**	**34088**	**4571**	**11857**	**0**	**45945**	**0.0079**	**-0.54**	**-0.0043**
PNP 3	7862400	1.35	61.7	31483	3120	11766	0	43249	0.0074	-0.44	-0.0033
PNP 4	7862400	1.35	59.3	33554	3837	11916	0	45470	0.0078	-0.51	-0.0040
PNP 5	7862400	1.35	60.8	31245	3201	11799	0	43044	0.0074	-0.47	-0.0035
PNP 6	7862400	1.35	61.3	30508	3357	11762	0	42270	0.0073	-0.45	-0.0033
PNP 7	7862400	1.35	61.6	29788	3298	11772	0	41560	0.0071	-0.45	-0.0032
PNP 8	7862400	1.35	62.7	29050	3640	11622	0	40672	0.0070	-0.42	-0.0029
PNP 9	7862400	1.35	63.0	29431	3567	11574	0	41005	0.0070	-0.41	-0.0029
PNP 10	7862400	1.35	64.7	28900	4088	11428	0	40328	0.0069	-0.37	-0.0026
PNP 11	7862400	1.35	62.6	30124	4178	11613	0	41737	0.0072	-0.42	-0.0030
PNP 12	7862400	1.35	62.8	29577	4022	11628	0	41205	0.0071	-0.42	-0.0029

PNP: pick and place; T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{OC}: operating cost; K_{MC}: maintenance cost; K_{IC}: improvement cost; K_T: total cost; CPU: cost per unit; ECE_B: equipment cost efficiency before improvement

5.4.2 Phase 2 – Improvement Planning

Step 4 – Pareto analysis

The PNP is a fully automated equipment system, which maintains records of error logs and their corresponding downtimes within its operating system. The type of downtime can impact the operating time, thereby affecting the availability, net operating time and quality of the equipment. To determine the most significant losses in terms of OEE, the downtimes must be extracted from the PNP's system, using the conventional OEE definition. A Pareto analysis, as shown in Figure 5.11, indicated that over 80% of the downtime for PNP 2 was related to input shuttle jams, output shuttle jams, plunger failure to pick up items, and low plunger pressure. These downtimes resulted in losses of speed and idling and minor stoppage.

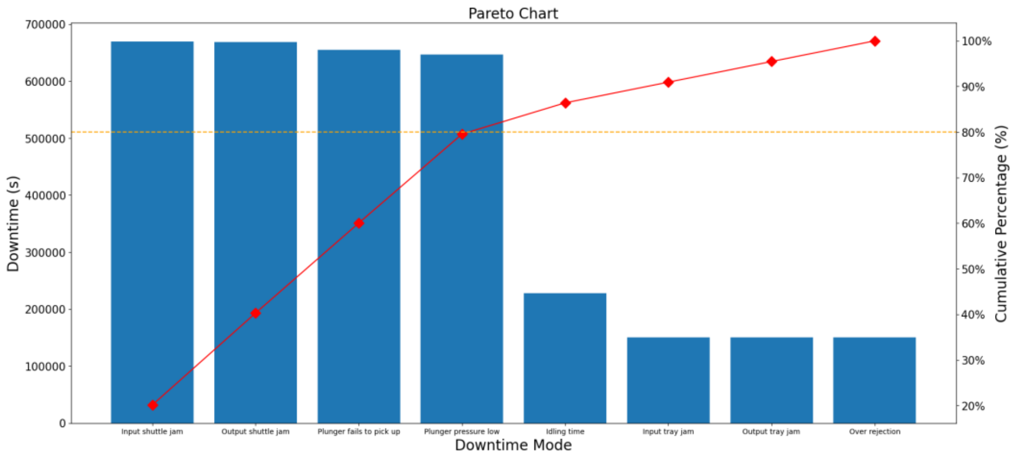

Figure 5.11: PNP 2 downtime Pareto analysis

Step 5 – Root cause analysis

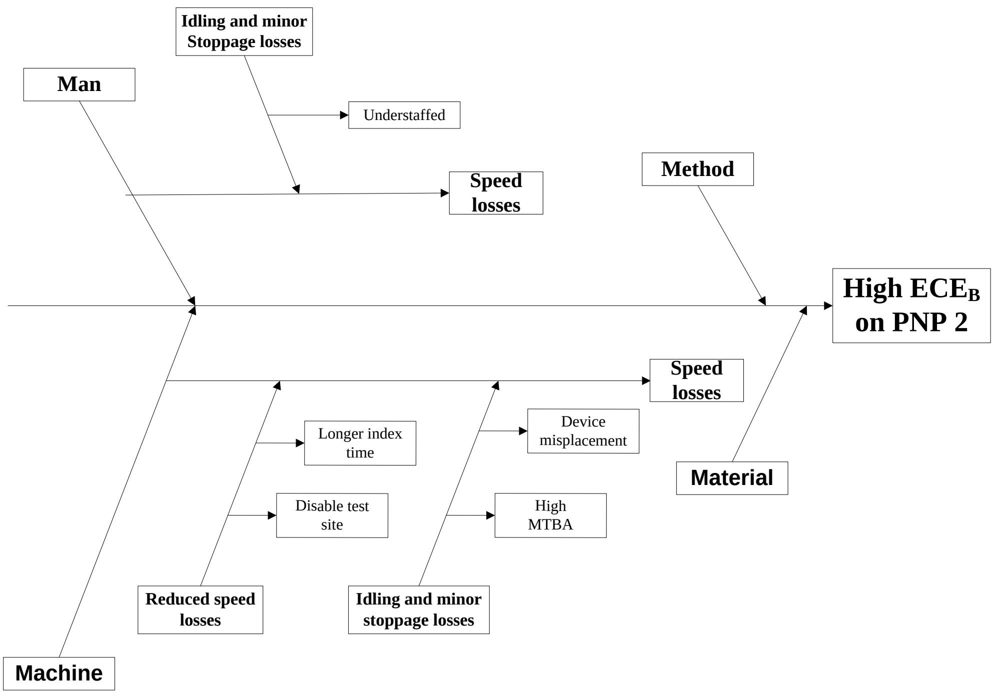

Figure 5.12: Root cause analysis of high ECE$_B$ in PNP 2 using fishbone diagram

Figure 5.12 displays a fishbone diagram analysis of the root causes behind the elevated ECE$_B$ in PNP 2. The analysis reveals that losses in idling, minor stoppages, and reduced speed led to a decrease in performance, OEE, and an increase in ECE_B in PNP 2. The underlying causes of high idling and minor stoppages are identified as: (1) Misalignment of the pickup arm 2, leading to misplacement of devices and consequent jams at the input shuttle during transfer from the input transfer station to the test area. (2) Oxidized input and output shuttles, causing frequent jams and elevated mean time between assistance for servicing the jams. (3) Inadequate technician support, leading to extended idling time as the available headcount could not promptly address the jams. The causes of high reduced speed losses are: (1) Insufficient maintenance of the plunger, resulting in low vacuum pressure, clogging of pipes, and wear and tear of mechanical parts that affect placement accuracy. This led to one or two disabled test sites and lower good quantity at lower parallelism. (2) An elevated index time, slowing down the speed of PNP 2, lowering good quantity and OEE, and increasing T_{CT} and ECE_B.

Step 6 – Solution brainstorming

In order to mitigate the idling and minor stoppage losses and reduced speed losses in PNP 2, the initiative team proposed nine potential improvement actions using the fishbone diagram (Figure 5.9). The objectives of the improvement actions for idling and minor stoppage losses were to: (1) Increase the headcount of technicians to provide a more timely response to jams, though this would increase overhead and reduce profitability, as well as pose a challenge for managing additional personnel in production. (2) Calibrate the pickup arm 2's placement accuracy through collaboration with the equipment manufacturer, which would cost MYR 5,000 as a K_{IC}. (3) Lubricate the input and output shuttle frequently to reduce the occurrence of jams, though this would lead to more frequent equipment downtime and disruptions to the production schedule. (4) De-oxidize the oxidized input and output shuttle, which would cost MYR 2,500 as K_{IC} and only extend the lifespan of the input and output shuttle by 1-2 years. (5) Replace the oxidized input and output shuttle with a new one, incurring a cost of MYR 15,000 as K_{IC} and providing a 3-4 year lifespan.

The proposed actions to address the reduced speed losses included: (1) Replacing worn-out consumable parts in the plunger to enable quad site testing, which would cost MYR 15,000 as K_{IC}. (2) Restoring the index time of PNP 2 to its standard setting and limiting access to the setting to maintain optimal speed.

Additionally, the team proposed improvement actions to improve the overall performance factor of OEE in PNP 2, including: (1) Integrating all previously proposed improvement actions into the current half-yearly preventive maintenance, which would cost at least MYR 10,000 as K_{IC} and result in additional equipment downtime. (2) Developing software to track the preventive maintenance schedule and lifespan of consumable parts in PNP 2, replacing the current manual tracking process and incurring a cost of MYR 10,000 as K_{IC}. Table 5.17 provides a summary of all proposed improvement actions, including their advantages, disadvantages, and corresponding K_{IC}.

Table 5.17: Proposed improvement actions for enhancing ECE_B of PNP 2

No	Improvement action	RC1	RC2	RC3	RC4	RC5	Pros	Cons
1	Increase the technician headcount	√	√	√			Provide more timely assistance to the jams	Incur additional operation cost and more difficult to handle more headcounts in the production floor
2	Re-target the pickup arm 2 position	√		√			Reduce the mis-contact occurrence	Cost approximately MYR 5,000 as K_{IC}
3	Grease the input and output shuttle frequent		√	√			Reduce the jam occurrence	Induce additional downtime and interrupt the production schedule more often
4	De-oxidise the oxidised input and output shuttle		√	√			Reduce the jam occurrence	Incur approximately MYR 2,500 as K_{IC}. After the de-oxidisation, the input and output shuttle can only last for another 1 to 2 years
5	Replace the oxidised input and output shuttle with a new one		√	√			3 – 4 years lifespan	Incur approximately MYR 15,000 as K_{IC}.
6	Replace the worn-out consumable parts in the plunger				√		Enable quad site testing at all times	Induce approximate MYR 15,000 as K_{IC}
7	Restore the index time to standard setting and restrict the access to the index time setting				√	√	Enable the PNP to operate at its optimum speed	Induce more jams if the PNP 2 is not restored back to its original condition
8	Enhance current half yearly preventive maintenance by including all the improvement actions taken to sustain the performance of PNP	√	√	√	√	√	Sustain the PNP operational performance	Induce longer downtime to service the equipment. Incur at least MYR 10,000 as K_{IC} for replacing the consumable parts in every preventive maintenance
9	Automate the preventive maintenance schedule and consumable parts lifespan tracking	√	√	√	√	√	Automate the manual tracking process	Incur approximately MYR 10,000 as K_{IC}

RC1: device misplacement; RC2: high MTBA; RC3: understaffed; RC4: disable the test site; RC5: longer index time

Step 7 – Gap Analysis

The semiconductor manufacturer's management conveyed their desire to improve the PNP 2 ECE_B without increasing headcount or investing substantial funds. To meet the management's expectations, the improvement initiative team prioritised short-term improvement actions, such as retargeting pickup arm 2, regularly greasing input and output shuttles, undergoing chemical de-oxidation for oxidized shuttles, replacing worn-out consumable parts, and restoring the index time to its standard setting. Table 5.18 provides a summary of the results of the gap analysis.

Table 5.18: The gap analysis for improving the ECE_B of PNP 2

Objective	• To improve the ECE metric of PNP 2
Current state	• Device miscontact • High MTBA • Understaffed • Disable test sites • Longer index time
Future state	• Enhance the ECE metric of the PNP 2, while maintaining current staffing levels and avoiding significant financial investments
Gap	• Improve preventive maintenance to enhance consistent performance sustainability in the PNP 2
To-do	• Retarget the position of pickup arm 2 • Grease the input and output shuttle frequently • De-oxidise the oxidised the input and output shuttle • Replace the worn-out consumable parts in the plunger • Restore the index time to the standard setting and restrict access to the index time setting

5.4.3 Phase 3 – Simulation

Step 8 – ECE Metric Assessment (Simulation)

The current study proposes five improvement actions with a cost of MYR 22,500 to optimise the operational efficiency and financial performance of PNP 2. The hypothesis is that the implementation of these actions will result in a significant enhancement in both OEE and ECE_B. To confirm the cost-effectiveness of the proposed actions, a simulation was carried out to calculate the ECE_S by simulating an increase in the OEE from its current level of 58.3% to a world-class level of 85.0%. The results of the simulation, as depicted in Figure 5.13, indicate that the ECE_S was found to be more beneficial than ECE_B when the improvement actions increased the OEE to a minimum of 65.0%.

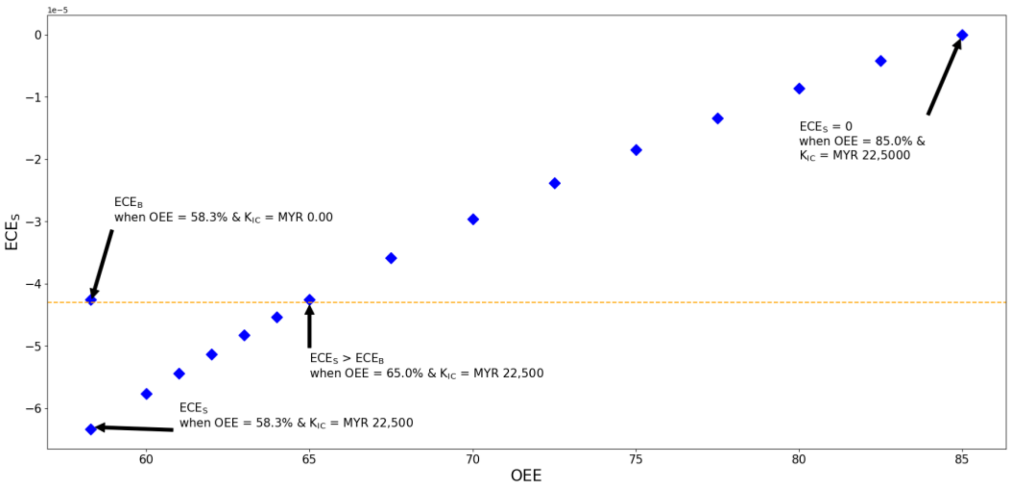

Figure 5.13. ECEs of PNP 2 simulation with different OEE

The present investigation posits five improvement actions aimed at reducing downtimes that result from device mis-contact, high MTBA, understaffed, disable the test site, and longer index time. To assess the effect of these improvement actions on the OEE, a set of simulations were performed. The simulations, designated as Simulations 1 through 6, were devised to reflect the OEE with downtimes that are 5%, 10%, 15%, 20%, 25%, and 30% lower, respectively, compared to the present downtimes. The results of the simulations are depicted in Table 5.19 and reveal that the OEE can be enhanced by as much as 65.3% if downtimes resulting from occurrences such as input shuttle jam, output shuttle jam, plunger fails to pick up, and plunger pressure low are diminished by 25% in comparison to the current downtimes. Furthermore, the analysis of the recommended improvement actions has instilled confidence in the initiative team that these downtimes can be reduced by more than 25%.

Table 5.19. PNP 2 downtime and OEE simulation

	Input shuttle jam (s)	**Output shuttle jam (s)**	**Plunger fails to pick up (s)**	**Plunger pressure low (s)**	**Others (s)**	**Total downtime (s)**	**OEE (%)**
Existing	559354.0	558470.0	545123.0	537054.0	1078620.0	3278621.0	58.3%
Simulation 1	531386.3	530546.5	517866.85	510201.3	1078620.0	3168621.0	59.7%
Simulation 2	503418.6	502623.0	490610.7	483348.6	1078620.0	3058620.9	61.1%
Simulation 3	475450.9	474699.5	463354.55	456495.9	1078620.0	2948620.9	62.5%
Simulation 4	447483.2	446776.0	436098.4	429643.2	1078620.0	2838620.8	63.9%
Simulation 5	419515.5	418852.5	408842.25	402790.5	1078620.0	2728620.8	65.3%
Simulation 6	391547.8	390929.0	381586.1	375937.8	1078620.0	2618620.7	66.7%

Simulation 1: OEE with downtimes of 5% less than the existing downtimes; Simulation 2: OEE with downtimes of 10% less than the existing downtimes; Simulation 3: OEE with downtimes of 15% less than the existing downtimes; Simulation 4: OEE with downtimes of 20% less than the existing downtimes; Simulation 5: OEE with downtimes of 25% less than the existing downtimes; Simulation 6: OEE with downtimes of 30% less than the existing downtimes

5.4.4 Phase 4 – Implementation and Monitoring

Step 9 – ECE Metric Assessment (After Improvement)

The ECE_S confirmed the efficacy of the implemented improvement actions, however, their long-term viability still required validation through the measurement of the ECE_A. As demonstrated in Table 5.20, the ECE_A was recorded for a period of three months following the improvement actions. In reality, the recorded K_{IC} was higher than the projected estimate due to the discovery and replacement of additional worn-out consumable parts in the plunger. Rather than amortizing the K_{IC} incurred from the improvement actions, the management of the semiconductor manufacturer elected to pay the K_{IC} in full during the assessment of the ECE metric, as the amount was considered relatively minor in the quarterly equipment maintenance budget. A comparison of the pre- and post-improvement scenarios (as shown in Table 5.17) reveals a significant improvement in the K_{EC}, K_{MC}, OEE, and ECE metric by 7.9%, 13.9%, 21.6%, and 37.2%, respectively. The improvement in OEE, K_{EC}, K_{MC} improved the PNP 2 ECE metric from MYR 0.0043 (ECE_B) to MYR 0.0027 (ECE_A). The additional investment in K_{IC} both improved the OEE and reduced the ECE metric, thus demonstrating the effectiveness of the improvement actions from both an operational and financial perspective.

Table 5.20. Comparison of the ECE_B and ECE_A of PNP 2

	Pre-improvement	**Post-improvement**	**Improvement**
T_{LT} (s)	7862400	7862400	No change
T_{CT} (s)	1.35	1.35	No change
OEE (%)	58.3	70.9	Improve by 21.6%
K_{EC} ($)	34088	31395	Reduce by 7.9%
K_{MC} ($)	11857	10209	Reduce by 13.9%
K_{IC} ($)	0	26050	NA
K_T ($)	45945	67654	Increase by 47.2%
Cost per unit ($/pc)	0.0079	0.0116	Increase by 46.8%
OEE Losses	-0.54	-0.23	Reduce by 57.4%
ECE ($/pc)	-0.0043	-0.0027	Improve by 37.2%

T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{MC}: maintenance cost; K_{IC}: maintenance cost; K_T: total cost; ECE: equipment cost efficiency

5.5 Summary

This present chapter outlines the examination and validation of the ECE metric and its corresponding framework through the examination of three distinct case studies conducted in various manufacturing environments. The results of the case studies revealed the successful validation of the ECE metric and its framework, as evidenced by the substantial accomplishments achieved. The solutions and outcomes obtained through the implementation of the ECE metric and its framework were recognized by the management of the companies involved in the case studies. The forthcoming chapter will delve into the specifics of the validation process.

CHAPTER SIX

DISCUSSION

6.0 Overview

This chapter presents an examination of the practicality of the ECE metric and its accompanying ECEF. This is based on the findings derived from three separate case studies. This chapter is structure into five sections, with each section serving a specific purpose. Section 6.1 assesses the validity of the ECE metric. Section 6.2 assesses the effect of OEE and K_T on the ECE metric. Section 6.3 compares the OEE and ECE metric in evaluating improvement initiatives. The advantages of the ECEF are explored in Section 6.4. Finally, Chapter 6 is summarised in the last section, Section 6.5.

6.1 Validation of the ECE Metric

The analysis of the correlation between OEE and K_{EC}, K_{MC}, K_{OC}, OEE losses, and cost per unit employed a comprehensive approach, utilising both Pearson and linear regression methods, alongside ANOVA regression analysis.

Pearson correlation analysis measures the linear relationship between continuous variables, producing correlation coefficients (r) from -1 to 1 (Schober et al., 2018; Li et al., 2022). Positive and negative r values represent corresponding correlations, while values close to zero suggest weak or negligible correlation. The accompanying probability value (p-values) indicate the statistical significance of the correlations. Low p-values indicate that the observed correlations are unlikely to have occurred by chance, further supporting the reliability of the correlation results.

Conversely, regression correlation analysis involves fitting a line through scatter plot data points, estimating dependent variable values concerning an independent variable, and providing an R-squared correlation coefficient. This coefficient ranges from 0 to 1, with 0 denoting a poor fit and 1 indicating a perfect fit (Kumari and Yadav, 2018; Schober et al., 2018).

Furthermore, ANOVA regression analysis explores the significance of the relationship between OEE and other variables. The F-statistic and associated probability value (PR(>F)) are essential statistical metrics, with the F-statistic gauging the model's fit to the data and the PR(>F) indicating the probability of obtaining observed results by chance (Kihm et al., 2022). Lower PR(>F) imply more significant relationships between dependent and independent variables. Additionally, ANOVA regression analysis provides the sum of squares (sum_sq) and degrees of freedom (df) information, which further quantifies the contribution of independent variables to the variance in OEE. By considering these metrics, ANOVA regression analysis provides valuable insights into the significance of the regression model and the impact of the independent variables on the dependent variable, OEE. The results from the ANOVA regression analysis complement the Pearson and linear regression findings, further bolstering the understanding of the intricate associations between OEE and K_{EC}, K_{OC}, K_{MC}, OEE losses, and cost per unit.

Table 6.1 outlines the established criteria for conducting hypothesis tests to evaluate the correlation between OEE and K_{EC}, K_{OC}, K_{MC}, OEE losses, and cost per unit. These criteria, encompassing null and alternative hypothesis, r, p-value thresholds, R-squared thresholds, F-statistics thresholds, and PR(>F) thresholds, serve as the basis for determining whether a correlation exists between OEE and each specific variable. This meticulously structured framework facilitates a systematic and robust evaluation of the relationship between OEE and vital factors within manufacturing environments, thereby illuminating the nuanced dynamics of these associations across diverse contexts and settings.

Table 6.1. Summary of hypothesis testing requirements for correlation with OEE

Variable	**Null hypothesis (H0): No correlation**	**Alternative Hypothesis (H1): Correlation exists**
OEE and. K_{EC}	$r = 0$, p-value > 0.05, R-squared ≤ 0.1, F-statistics ≤ 2, $PR(>F) > 0.05$	$r \neq 0$, p-value < 0.05, R-squared > 0.1, F-statistics > 2, $PR(>F) < 0.05$
OEE and K_{MC}	$r = 0$, p-value > 0.05, R-squared ≤ 0.1, F-statistics ≤ 2, $PR(>F) > 0.05$	$r \neq 0$, p-value < 0.05, R-squared > 0.1, F-statistics > 2, $PR(>F) < 0.05$
OEE and K_{OC}	$r = 0$, p-value > 0.05, R-squared ≤ 0.1, F-statistics ≤ 2, $PR(>F) > 0.05$	$r \neq 0$, p-value < 0.05, R-squared > 0.1, F-statistics > 2, $PR(>F) < 0.05$
OEE and OEE losses	$r = 0$, p-value > 0.05, R-squared ≤ 0.1, F-statistics ≤ 2, $PR(>F) > 0.05$	$r \neq 0$, p-value < 0.05, R-squared > 0.1, F-statistics > 2, $PR(>F) < 0.05$
OEE and Cost per unit	$r = 0$, p-value > 0.05, R-squared ≤ 0.1, F-statistics ≤ 2, $PR(>F) > 0.05$	$r \neq 0$, p-value < 0.05, R-squared > 0.1, F-statistics > 2, $PR(>F) < 0.05$

OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{MC}: maintenance cost; K_{OC}: operating cost

6.1.1 The Correlation of OEE and K_{EC}

Figure 6.1 and Table 6.2 summarise the correlation analysis results between OEE and K_{EC}.

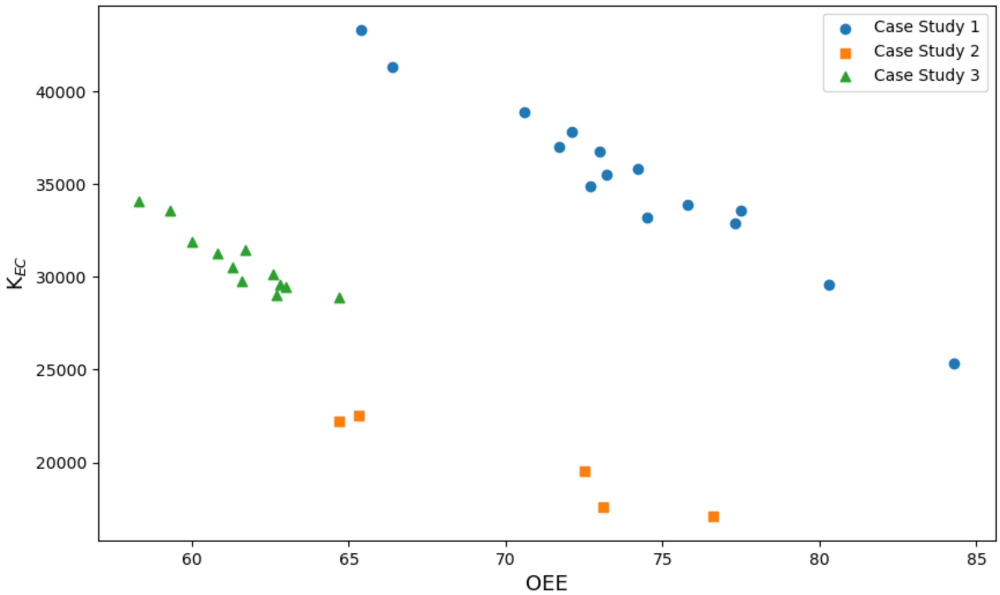

Figure 6.1. Correlation plot of OEE and K_{EC} for different case studies

Table 6.2. Summary of correlation analysis between OEE and K_{EC} for different case studies

Case study	r	P-value	R-squared	Sum_sq	df	F-statistic	PR(>F)
1	-9.797E-01	1.851E-10	9.599E-01	2.617E+08	1.0	3.109E+02	1.851E-10
2	-9.670E-01	7.150E-03	9.351E-01	2.377E+07	1.0	43.26E+01	7.150E-03
3	-9.323E-01	9.988E-06	8.692E-01	2.765E+07	1.0	66.45E+01	9.988E-06

Based on the analysis results, the outcomes of the correlation analysis between OEE and K_{EC} are consistent across the three case studies.

In case study 1, a strong positive correlation is evident, with a r of 0.9797. This signifies a substantial positive relationship between OEE and K_{EC}. The extremely low p-value (1.851E-10) indicates that this correlation is highly statistically significant. The R-squared value (0.9599) suggests that approximately 95.99% of the variability in K_{EC} can be attributed to variations in OEE. The substantial F-statistic (310.9) and its corresponding p-value (1.851E-10) emphasize the robustness and statistical validity of this correlation.

Case study 2 also reveals a strong positive correlation between OEE and K_{EC}, as reflected by a r of 0.9670. The associated p-value of 0.00715 indicates that this correlation is statistically significant. The R-squared value (0.9351) implies that approximately 93.51% of the variability in K_{EC} can be elucidated by changes in OEE. The notable F-statistic (43.26) and its corresponding p-value (0.00715) further underscore the reliability of this relationship.

Similarly, case study 3 presents a strong positive correlation, with a r of 0.9323, indicating a significant positive relationship between OEE and K_{EC}. The remarkably low p-value (9.988E-06) reaffirms the statistical significance of this correlation. The R-squared value (0.8692) suggests that around 86.92% of the variability in K_{EC} can be accounted for by variations in OEE. The high F-statistic (66.45) and its associated p-value (9.988E-06) accentuate the robustness and statistical validity of this correlation.

In summary, the correlation analysis outcomes regarding OEE and K_{EC} consistently demonstrate strong and highly significant positive correlations across the three case studies. These findings emphasize the substantial relationship between OEE and K_{EC}, implying that fluctuations in OEE are closely associated with variations in K_{EC}.

6.1.2 The Correlation of OEE and K_{MC}

The correlation analysis results between OEE and K_{MC} are shown in Figure 6.2 and Table 6.3.

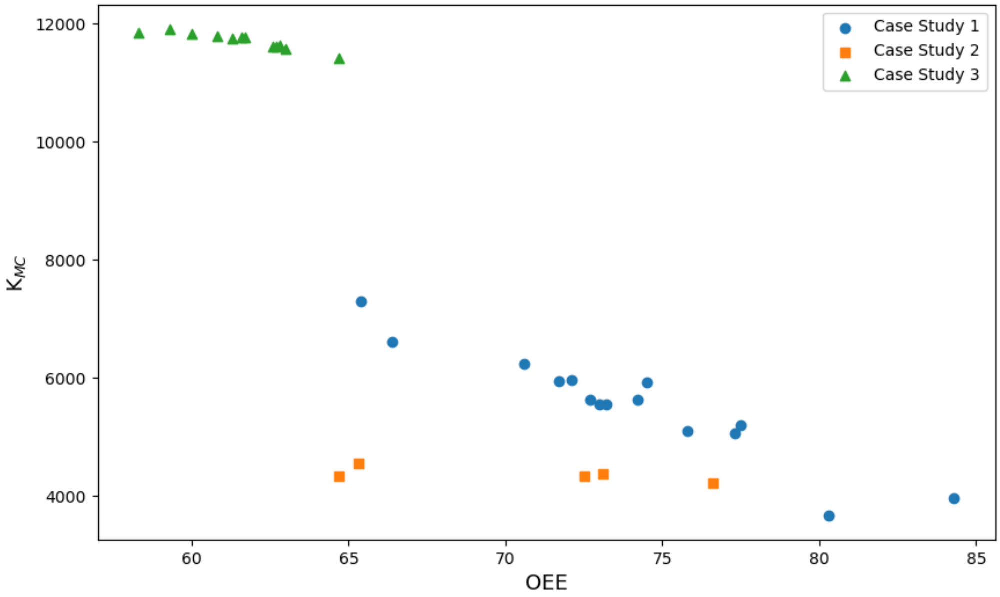

Figure 6.2. Correlation plot of OEE and K_{MC} for different case studies

Table 6.3. Summary of correlation analysis between OEE and K_{MC} for different case studies

Case study	r	P-value	R-squared	Sum_sq	df	F-statistic	PR(>F)
1	-9.489E-01	7.015E-08	9.004E-01	1.063E+07	1.0	1.175E+02	7.015E-08
2	-7.203E-01	1.700E-01	5.188E-01	3.114E+04	1.0	3.234E+00	1.700E-01
3	-9.408E-01	5.165E-06	8.852E-01	1.914E+05	1.0	7.709E+01	5.165E-06

Based on the analysis results, the outcomes of the correlation analysis between OEE and K_{MC} exhibit distinct variations across the three individual case studies.

Within case study 1, a robust negative correlation is evident, as denoted by a r of -0.9489. This indicates a substantial inverse relationship between OEE and K_{MC}. Notably, the low p-value (7.015E-08) underscores the high statistical significance of this correlation. The R-squared value (0.9004) suggests that approximately 90.04% of the variability in K_{MC} can be ascribed to fluctuations in OEE. The noteworthy F-statistic (117.5) and its corresponding p-value (7.015E-08) underscore the robustness and statistical validity of this correlation.

Conversely, in case study 2, a moderate negative correlation surfaces between OEE and K_{MC}, as reflected by a r of -0.7203. Nonetheless, the associated p-value of 0.170 highlights a lack of statistical significance. The R-squared value (0.5188) indicates that approximately 51.88% of K_{MC} variability can be elucidated by changes in OEE. The modest F-statistic (3.234) and its corresponding p-value (0.170) suggest a reduced statistical foundation for this relationship within case study 2.

Similarly, case study 3 reveals a notably strong negative correlation, with a correlation coefficient of -0.9408, signifying a significant inverse relationship between OEE and K_{MC}. The exceptionally low p-value (5.165E-06) reaffirms the statistical significance of this correlation. The R-squared value (0.8852) implies that around 88.52% of the variability in K_{MC} can be accounted for by variations in OEE. The prominent F-statistic (77.09) and its associated p-value (5.165E-06) further emphasize the robustness and statistical validity of this correlation.

The discrepancy in the OEE and K_{MC} relationship observed in case study 2 can be attributed to the presence of TFV 5, which exhibits relatively low K_{MC}

despite having the lowest OEE among all TFVs. This phenomenon arises due to fewer maintenance activities incurred by TFV 5, as it is frequently left idling due to insufficient coverage. To gain deeper insights into the relationship between OEE and K_{MC}, the analysis excluded TFV 5 from consideration. As depicted in Table 6.4, this adjustment reveals a stronger negative correlation between OEE and K_{MC}, highlighting that the presence of TFV 5 was influencing the OEE-K_{MC} relationship. By removing it from the analysis, a clearer negative correlation between OEE and K_{MC} emerges.

Table 6.4. Summary of correlation analysis of OEE and K_{MC} for case study 2

	r	**P-value**	**R-squared**	**Sum_sq**	**df**	**F-statistic**	**PR(>F)**
Include TFV 5	-7.203E-01	1.700E-01	5.188E-01	3.114E+04	1.0	3.234E+00	1.700E-01
Exclude TFV 5	-9.808E-01	1.922E-02	9.619E-01	5.736E+04	1.0	50.54E+00	1.922E-02

In conclusion, the results of the correlation analysis concerning OEE and K_{MC} reveal varying pattern across the three case studies. Case study 1 and 3 demonstrate pronounced and notably significant negative correlations, while case study 2 displays a moderate negative correlation that lacks statistical significance. Notably, the exclusion of TFV 5 from the analysis within case study 2 underscores the significance of identifying and addressing specific factors that influence the correlations between OEE and K_{MC}.

6.1.3 The Correlation of OEE and K_{OC}

Figure 6.3 and Table 6.5 summarises the correlation between OEE and K_{OC} in all three case studies.

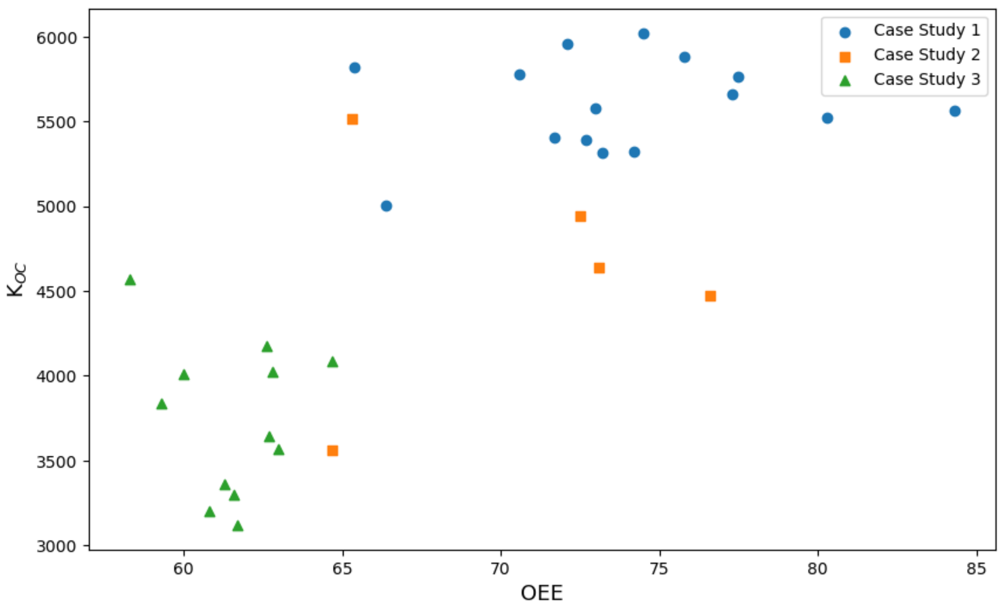

Figure 6.3. Correlation plot of OEE and K_{OC} for different case studies

Table 6.5. Summary of correlation analysis of OEE and K_{OC} for different case studies

Case study	r	p-value	R-squared	Sum_sq	df	F-statistic	PR(>F)
1	1.526E-01	5.872E-01	2.330E-02	2.566E+04	1.0	3.098E-01	5.872E-01
2	8.660E-01	8.898E-01	7.500E-03	1.545E+04	1.0	2.269E-02	8.898E-01
3	-1.609E-01	6.174E-01	2.590E-02	5.757E+04	1.0	2.658E-01	6.174E-01

Based on the provide analysis result, the relationship between OEE and K_{OC} in the three case studies yields distinct outcomes. In case study 1, the r between OEE and K_{OC} is 0.1526, indicating a relatively weak positive correlation. The p-value associated with this correlation is 0.5872, which is considerably high. This suggests that the observed correlation is not statistically significant. The R-squared value (0.0233) implies that only a minor proportion of the variance in K_{OC} can be explained by changes in OEE. The F-statistic (0.3098) and its associated p-value (0.5872) further reinforce the non-significant nature of the relationship in this case.

In case study 2, a r of 0.8660 is observed between OEE and K_{OC}. This indicates a strong positive correlation. However, the p-value (0.8898) is high, indicating that this correlation is not statistically significant. The R-squared value (0.0075) signifies that only a minimal amount of the variance in K_{OC} can be attributed to variations in OEE. The low F-statistic (0.0227) and its associated p-value (0.8898) substantiate the non-significance of the observed relationship.

In contrast, case study 3 exhibits a correlation coefficient of -0.1609 between OEE and K_{OC}. This suggests a weak negative correlation. Once again, the p-value (0.6174) is relatively high, indicating a lack of statistical significance. The R-squared value (0.0259) implies a limited explanatory power of OEE in relation to K_{OC} variance. The F-statistic (0.2658) and its corresponding p-value (0.6174) further reinforce the non-significant nature of the identified correlation.

In summary, the analysis across the three case studies collectively reveals that the associations between OEE and K_{OC} lack statistical significance. Despite variations in correlation strength and direction, the consistently high p-values indicate that the observed relationship are prone to chance fluctuations rather than indicative of meaningful connections.

6.1.4 The Correlation of OEE and OEE Losses

The results of the correlation analysis of OEE and OEE losses for three case studies are summarised in the Figure 6.4 and Table 6.6.

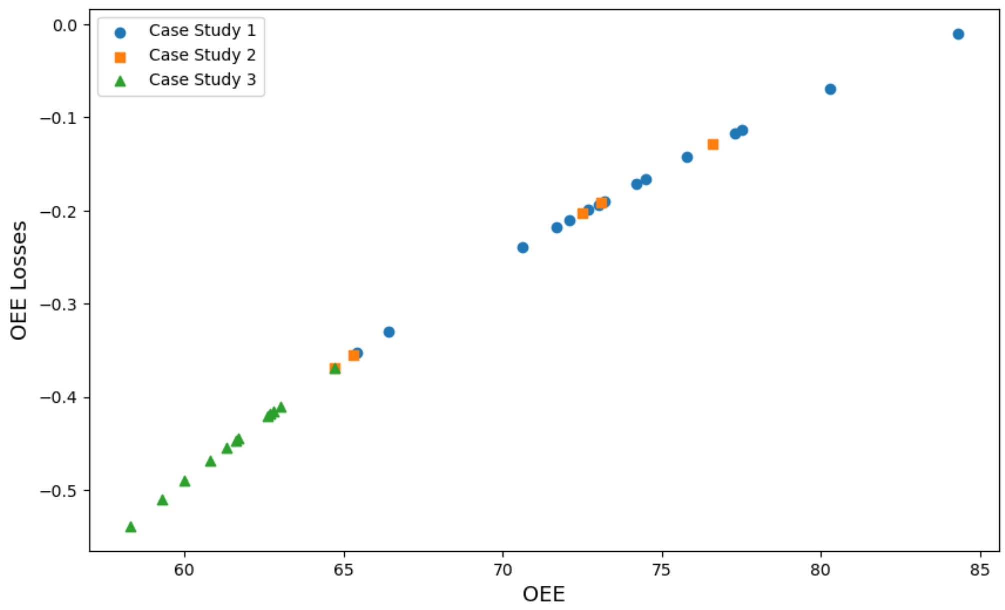

Figure 6.4. Correlation plot of OEE and OEE losses for different case studies

Table 6.6. Summary of correlation analysis of OEE and OEE losses for different case studies

Case study	r	p-value	R-squared	Sum_sq	df	F-statistic	PR(>F)
1	9.958E-01	5.056E-15	9.920E-01	1.092E-01	1.0	1.614E+03	5.056E-15
2	9.992E-01	2.487E-05	9.985E-01	4.541E-02	1.0	1.986E+03	2.487E-05
3	9.994E-01	4.143E-16	9.989E-01	2.452E-02	1.0	9.001E+03	4.143E-16

Based on the provided analysis results, it is evident that there is a remarkably strong and highly significant positive correlation between OEE and OEE losses across the three case studies.

In case study 1, the r between OEE and OEE losses is 0.9958, signifying an exceptionally robust positive correlation. The corresponding p-value of 5.056E-15 reinforces the high significance of this correlation. The R-squared value (0.9920) indicates that an overwhelming proportion of the variance in OEE losses can be accounted for by variations in OEE. This is reinforced by the substantial F-statistic value (1614.0) and its extremely low associated p-value

(5.056E-15), confirming the statistical reliability and meaningfulness of the established relationship.

Moving to case study 2, a r of 0.9992 between OEE and OEE losses suggests an even stronger positive correlation. The p-value (2.487E-05) reiterates the highly significant nature of this correlation. The R-squared value (0.9985) underscores the extensive explanatory capacity of OEE with respect to OEE losses. The substantial F-statistic (1986.0) and its corresponding p-value (2.487E-05) provide further evidence of the significance of this relationship.

Case study 3 continues to affirm this trend, with a correlation coefficient of 0.9994 between OEE and OEE losses, indicating a near-perfect positive correlation. The exceptionally low p-value (4.143E-16) reaffirms the statistical significance of this correlation. The R-squared value (0.9989) underscores the high proportion of OEE losses variance explicable by variations in OEE. The considerable F-statistic (9001.0) and its associated p-value (4.143E-16) underscore the robustness and statistical validity of this correlation.

In conclusion, the analysis outcomes across all three case studies consistently reveal a conspicuously strong and notably significant positive correlation between OEE and OEE losses. These findings underscore the substantive connection between the two variables, implying that variations in OEE are closely intertwined with shifts in OEE losses.

6.1.5 The Correlation of OEE and Cost Per Unit

Figure 6.5 and Table 6.7 summarises the correlation analysis between OEE and cost per unit in all three case studies.

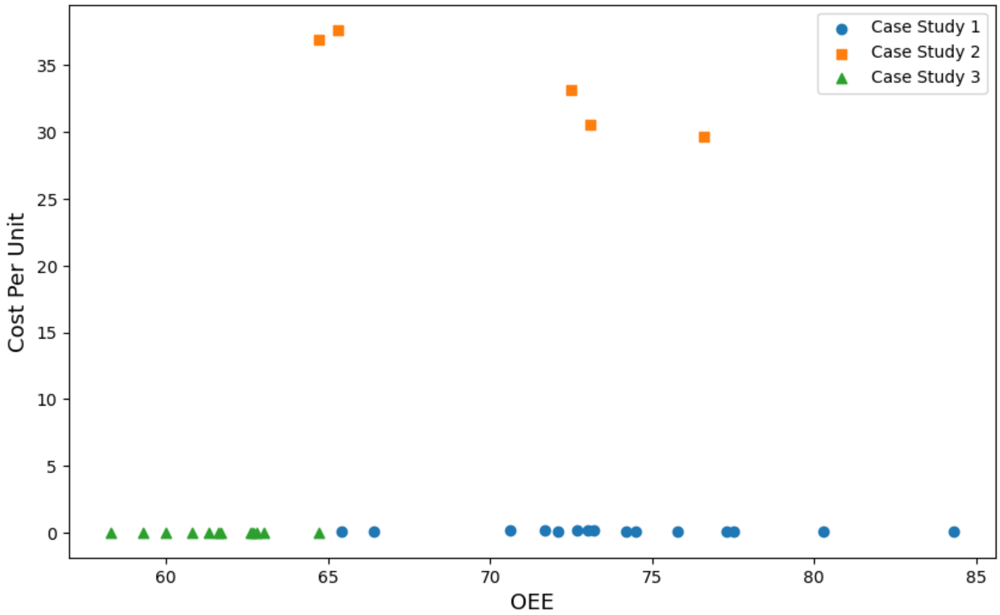

Figure 6.5. Correlation plot of OEE and cost per unit for different case studies

Table 6.7. Summary of correlation analysis of OEE and cost per unit for different case studies

Case study	r	p-value	R-squared	Sum_sq	df	F-statistic	PR(>F)
1	-4.773E-01	7.200E-02	2.278E-01	6.715E-03	1.0	3.835E+00	7.200E-02
2	-9.683E-01	6.735E-03	9.377E-01	4.923E+01	1.0	4.512E+01	6.735E-03
3	-9.434E-01	4.000E-06	8.900E-01	9.000E-06	1.0	8.086E+01	4.000E-06

The provide analysis results unveil a range of negative correlations between OEE and cost per unit across the three distinct case studies. In case study 1, the r between OEE and cost per unit is -0.4773, indicating a moderate negative correlation between these variables. However, the associated p-value of 0.072 reveals that this correlation lacks statistical significance. The corresponding R-squared value (0.2278) suggests that approximately 22.78% of the variability in cost per unit can be attributed to changes in OEE. The F-statistic (3.835) and its corresponding p-value (0.072) collectively underscore the absence of robust statistical support for the observed relationship.

Transitioning to case study 2, a more pronounced negative correlation emerges with a r of -0.9683, signifying a substantive negative association between OEE and cost per unit. Importantly, the low p-value of 0.006735 denotes a statistically significant correlation. Remarkably, the high R-squared value (0.9377) indicates that a substantial 93.77% of cost per unit variability can be ascribed to fluctuations in OEE. This strong connection is reinforced by the considerable F-statistic value (45.12) and its corresponding p-value (0.006735), emphasizing the statistical robustness of the relationship.

Case study 3 maintains this trend, revealing a noteworthy negative correlation characterized by a r of -0.9434. This reflects a robust negative relationship between OEE and cost per unit. The remarkably low p-value (4.000E-06) reaffirms the statistical significance of this correlation. The significant explanatory capacity of OEE is demonstrated by the substantial R-squared value (0.8900), suggesting that approximately 89% of cost per unit variance can be accounted for by OEE variations. The notable F-statistic (80.86) and its associated p-value (4.000E-06) further underscore the reliability and statistical validity of this relationship.

In comparison to case studies 2 and 3, case study 1 exhibits a weaker negative correlation between OEE and cost per unit. The higher cost per unit LTH 1, 2, 10, 11, and 12 is attributed to their slower features, resulting in a nearly 100% decrease in T_{CT} as compared to the other LTHs. This decreases in T_{CT} adversely affects the productivity of the LTH 1, 2, 10, 11, and 12, leading to an increase in the cost per unit. Therefore, comparing the equipment in this context is inappropriate. To dive deeper, the LTHs are analysed separately based on their features. As shown in Table 6.7, in the combined analysis, the LTH feature shows a relatively weak negative correlation with both OEE and cost per unit. However, upon examining the LTH with distinct feature in Table 6.8, a more pronounced negative correlation with both OEE and the cost per unit becomes evident. This underscores the significance of analysing fast and slow LTHs separately, as it offers more insightful understanding into their distinct influences on OEE and the cost per unit.

Table 6.8. Summary of correlation analysis of OEE and cost per unit for LTH with different features

LTH feature	r	p-value	R-squared	Sum_sq	df	F-statistic	PR(>F)
Fast	-9.883E-01	8.171E-08	9.767E-01	1.550E-03	1.0	3.350E+02	8.171E-08
Slow	-8.873E-01	4.462E-02	7.874E-01	1.740E-04	1.0	1.111E+01	4.462E-02

6.1.6 Summary of the ECE Metric Validation

Table 6.9 summarises the hypothesis tests conducted to analyse the correlation between various variables and OEE. For the relationship between OEE and K_{EC}, it was evident that a strong negative correlation existed, as indicated by the remarkably high r values. These findings consistently led to the rejection of the null hypothesis (H0: No correlation) and the acceptance of the alternative hypothesis (H1: Correlation exists) across all case studies.

Similarly, OEE and K_{MC} exhibited a significant negative correlation, with the null hypothesis rejected in favour of the alternative hypothesis for most case studies. However, case study 2 demonstrated a different outcome, suggesting that the relationship might vary under certain conditions, especially the equipment always stays idling.

The relationship between OEE and K_{OC} did not demonstrate a strong correlation, with the null hypothesis generally accepted across all case studies.

Notable, the association between OEE and OEE losses displayed a substantial positive correlation, consistently leading to the rejection of the null hypothesis for all case studies.

Lastly, OEE and cost per unit demonstrated a negative correlation, with the null hypothesis accepted for case study 1 and rejected for case studies 1 and 2. This indicates that specific factors, such as equipment features or operational conditions, could influence this relationship differently across different case studies. These results provide valuable insights into the factors affecting OEE in manufacturing settings, emphasising the variability of these relationships in diverse contexts.

In summary, the robust validation of correlation relationship has been achieved through Pearson correlation analysis, regression correlation analysis, and ANOVA regression analysis, reinforcing the connections between OEE and K_{EC}, K_{MC}, OEE losses, and cost per unit. This extensive validation bolsters the credibility of the ECE metric, substantiated by real-world manufacturing data. Furthermore, the correlation analysis reveals the nuanced nature of the relationship between OEE and K_{OC} across the studies, suggesting its unsuitability as a robust indicator for quantifying equipment's financial performance.

Table 6.9. Summary of hypothesis testing results for correlation with OEE

Variable	Case study	Correlation results: r (H0: = 0; H1: ≠ 0)	p-value (H0: > 0.05; H1: < 0.05)	R-squared (H0: ≤ 0.1; H1: > 0.1)	F-statistic (H0: ≤ 2; H1: > 2)	PR(>F) (H0: > 0.05; H1: <0.05)	H0: No correlation	H1: Correlation exists	Analysis
OEE and K_{EC}	1	9.80E-01	1.85E-10	9.60E-01	3.11E+02	1.85E-10	Rejected	Accepted	
	2	9.67E-01	7.15E-03	9.35E-01	4.33E+02	7.15E-03	Rejected	Accepted	
	3	9.32E-01	9.99E-06	8.69E-01	6.65E+02	9.99E-06	Rejected	Accepted	
OEE and K_{MC}	1	-9.49E-01	7.02E-08	9.00E-01	1.18E+02	7.02E-08	Rejected	Accepted	
	2	-7.20E-01	1.70E-01	5.19E-01	3.23E+00	1.70E-01	Accepted	Rejected	TFV's low K_{MC} despite its lowest OEE influences the correlation analysis. Excluding TFV 5 strengthens the negative OEE-K_{MC} correlation.
	3	-9.41E-01	5.17E-06	8.85E-01	7.71E+01	5.17E-06	Rejected	Accepted	
OEE and K_{OC}	1	1.53E-01	5.87E-01	2.33E-02	3.10E-01	5.87E-01	Accepted	Rejected	
	2	8.66E-01	8.90E-01	7.50E-03	2.27E-02	8.90E-01	Accepted	Rejected	
	3	-1.61E-01	6.17E-01	2.59E-02	2.66E-01	6.17E-01	Accepted	Rejected	
OEE and OEE losses	1	9.96E-01	5.06E-15	9.92E-01	1.61E+03	5.06E-15	Rejected	Accepted	
	2	9.99E-01	2.49E-05	9.99E-01	1.99E+03	2.49E-05	Rejected	Accepted	
	3	9.99E-01	4.14E-16	9.99E-01	9.00E+03	4.14E-16	Rejected	Accepted	
OEE and cost per unit	1	-4.77E-01	7.20E-02	2.28E-01	3.84E+00	7.20E-02	Accepted	Rejected	LTH 1, 2, 10, 11, and 12, with slower feature, impact the correlation analysis. Separating LTHs into slower and faster features unveils a stronger negative OEE-cost per unit correlation.
	2	-9.68E-01	6.74E-03	9.38E-01	4.51E+01	6.74E-03	Rejected	Accepted	
	3	-9.43E-01	4.00E-06	8.90E-01	8.09E+01	4.00E-06	Rejected	Accepted	

OEE: overall equipment effectiveness; K_{EC}: equipment acquisition cost; K_{MC}: maintenance cost; K_{OC}: operating cost

6.2 The Impact of the OEE and K_T on the ECE Metric

The relationship between the metrics of OEE, K_T, and ECE metric is depended on the particularities of each manufacturing operation. OEE and K_T are considered as key indicators of the ECE metric, yet it is challenging to discern which of the two has a greater impact.

OEE evaluates the overall effectiveness of the equipment by accounting for its availability, performance, and quality. A high OEE value represents an efficient operation and the production of high-quality goods, thus having a direct effect on the ECE metric though its impact on the production rate and product quality. On the other hand, K_T comprises K_{EC} and K_{MC}, and assesses the financial performance of the equipment. Both K_{EC} and K_{MC} influence the financial performance of the equipment and, therefore, the ECE metric.

To optimise the ECE metric, it is crucial to determine which aspect, the improvement of OEE or K_T, will result in the greatest impact. Although both OEE and K_T impact the ECE metric, the degree of their impact may vary based on the equipment, production process, and other factors. In the subsequent sub-sections, a comprehensive analysis and evaluation will be performed to determine the most appropriate focus for improvement. By continuously monitoring both OEE and K_T and implementing strategic improvements, manufacturers can enhance their overall equipment efficiency and financial performance, leading to an improvement in the ECE metric.

6.2.1 Understanding the ECE Metric and Its Relationship with OEE

The ECE metric is a performance metric employed in the manufacturing industry to evaluate the efficiency and effectiveness of equipment operations. This is achieved by comparing the cost per unit of good output for a given system to the cost per unit of good output for a system that operates at a world-class level of 85% OEE. The relationship between the current and 85% world-class OEE is expressed mathematically in Equation (26) of Section 4.2 (page 53). A negative ECE metric result suggests that the equipment is performing below the established benchmark of 85% world-class OEE, as indicated in Figure 6.6. Conversely, a zero ECE metric signifies that the equipment is operating at 85% OEE, the benchmark for world-class performance. Finally, a positive ECE metric value indicates that the equipment is operating at a level exceeding 85% world-class OEE. To attain either a zero or positive ECE metric, it is imperative to enhance the OEE to reach a minimum of 85%. However, it must be noted that a zero or positive ECE metric value cannot be attained simply by reducing the K_T without concurrently improving the OEE to a minimum of 85%.

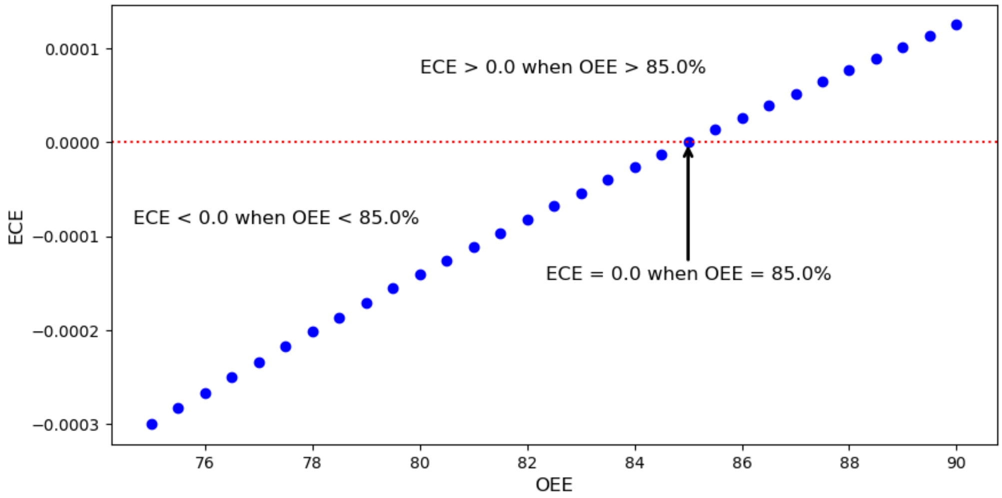

Figure 6.6. ECE metric value for OEE less than 85%, equal to 85%, and greater than 85%

6.2.2 Response of OEE and K_T to ECE Metric

Partial differentiation analysis is a mathematical tool used to determine the rate of change of one variable with respect to another. In this case, the partial derivatives of OEE and K_T with respect to ECE metric are calculated to determine how each of these variables influences the value of ECE metric. The partial derivative of a variable with respect to ECE metric represents the sensitivity of ECE metric to changes in that variable, and can be used to determine which factor has the greatest impact on ECE metric.

The partial derivatives of ECE metric with respect to OEE and K_T can be expressed mathematically using Equation (28) and (29). These equations capture the relationship between variables and allow for a quantitative assessment of the responsiveness of ECE metric to changes in OEE and K_T. By analysing the values of the partial derivatives, it is possible to determine which of these factors has a greater impact on ECE metric and to make informed decisions based on this information.

$$\frac{dECE_i}{dOEE_i} = K_{T_i} \cdot \left(\frac{T_{CT_i}}{T_{LT_i}}\right) \cdot \left[\frac{1}{0.85 \cdot OEE_i} - \frac{(OEE_i - 0.85)}{0.85 \cdot OEE_i^2}\right] \tag{28}$$

$$\frac{dECE_i}{dK_{T_i}} = \left(\frac{T_{CT_i}}{T_{LT_i}}\right) \cdot \left[\frac{(OEE_i - 0.85)}{0.85 \cdot OEE_i}\right] \tag{29}$$

The data regarding the T_{LT}, T_{CT}, K_T, and OEE of LTH 1, TFV 5, and PNP 2 prior to improvement, as obtained from case studies 1, 2, and 3, respectively, were analysed in order to determine the partial derivatives of ECE metric with respect to OEE and K_T. As indicated by the results presented in Table 6.10, across all three case studies, the partial derivative of ECE with respect to OEE was found to be substantially greater in magnitude than the partial derivative of ECE with respect to K_T. This suggests that, in terms of impact on ECE metric, small increases in OEE have a much more pronounced effect than small decrease in K_T.

Table 6.10 Comparison between the partial derivatives of ECE with respect to OEE and K_T

Eqp	**T_{LT} (s)**	**T_{CT} (s)**	**OEE (%)**	**K_T ($)**	$\frac{dECE_i}{dOEE_i}$	$\frac{dECE_i}{dK_{T_i}}$
LTH 1	3510000	6.7	70.6	45102	1.73E-02	-4.58E-07
TFV 5	1872000	120	64.7	26548	4.07E+00	-2.37E-05
PNP 2	7862400	1.35	58.3	45945	2.32E-02	-9.25E-08

Eqp: equipment; T_{LT}: loading time; T_{CT}: theoretical cycle time; OEE: overall equipment effectiveness; K_T: total cost; $\frac{dECE_i}{dOEE_i}$: partial derivative of ECE with respect to OEE; $\frac{dECE_i}{dK_{T_i}}$: partial derivative of ECE with respect to K_T

6.2.3 Summary of the Response of OEE and K_T to the ECE Metric

The present section endeavours to explore the interdependence between the metrics of OEE, K_T and ECE in the manufacturing sector. The objective of the study is to evaluate which of the two metrics, OEE or K_T, holds a higher correlation with the ECE metric, and thus, which parameter should be prioritised for improvement. To this end, a partial differentiation analysis was carried out to assess the rate of change of ECE metric with reference to both OEE and K_T. The results indicated that even a marginal improvement in OEE has a more substantial impact on ECE metric in comparison to a minimal reduction in K_T. This section concludes by emphasizing the significance of continuous monitoring of both OEE and K_T and the implementation of strategic measures aimed at enhancing equipment efficiency and financial performance, which will eventually result in an improvement in the ECE metric.

6.3 Advantages of Using the ECE Metric in Evaluation of Improvement Actions

The OEE primarily focuses on evaluating the operational effectiveness of improvement actions. The success of improvement actions is deemed satisfactory even if they only result in a marginal increase of 1-2% in the OEE, despite the significant investment of resources, such as MYR 100,000 in this case. On the other hand, the ECE metric takes into account not only the operational effectiveness but also the cost-effectiveness of improvement actions. Figures 6.7, 6.8, and 6.9 illustrate the ECE_A for LTH 1, TFV 5, and PNP 2 simulations with varying OEE values. In actuality, LTH 1, TFV 5, and PNP 2 received investments of MYR 57,820, MYR 2,500, and MYR 20,650 K_{IC}, respectively. The ECE metric considers an improvement action to be cost-effective only if it results in a corresponding increase in the OEE, leading to a situation where ECE_A is greater than ECE_B.

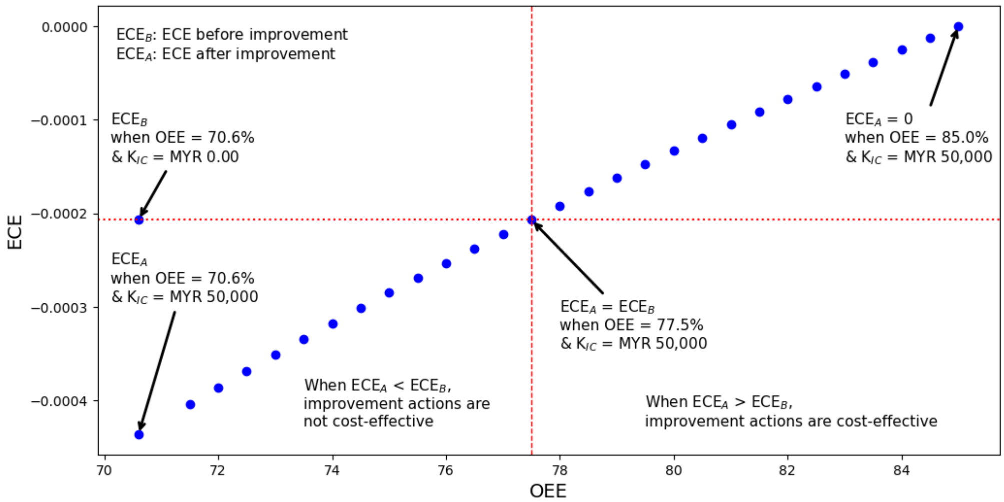

Figure 6.7. ECE_A of LTH 1 simulation with different OEE

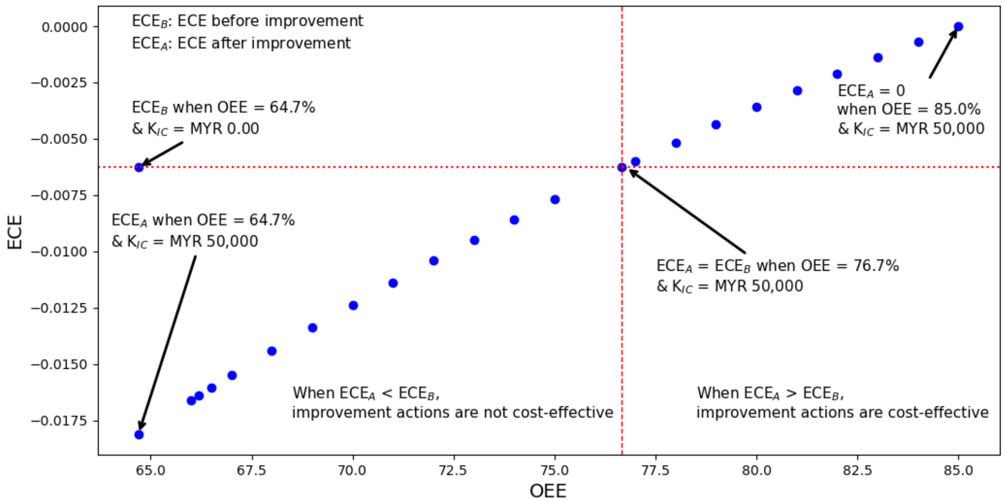

Figure 6.8. ECE_A of TFV 5 simulation with different OEE

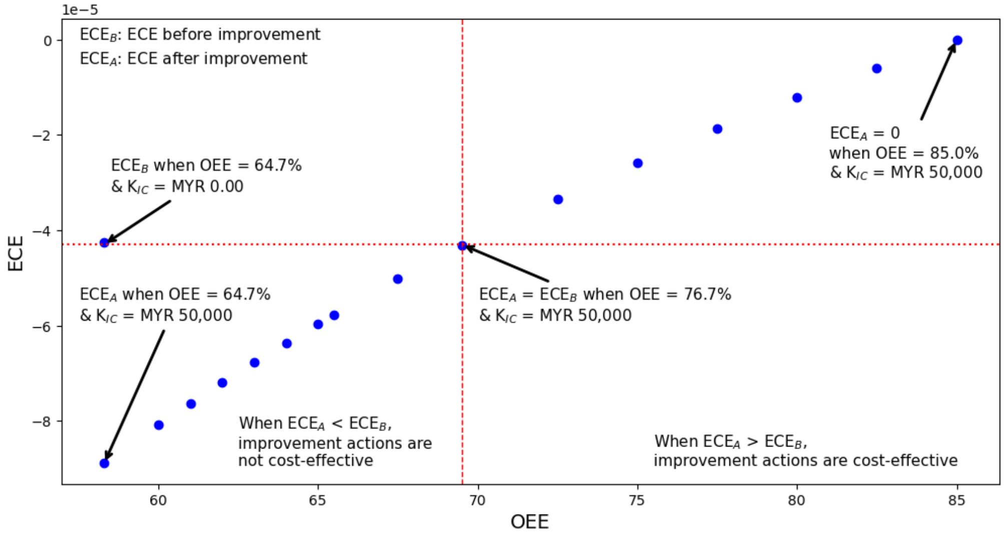

Figure 6.9. ECE_A of PNP 2 simulation with different OEE

The key difference between the OEE and ECE metric lies in their scope of evaluation. While the OEE focuses solely on the operational effectiveness of improvement actions, the ECE metric takes into account both the operational effectiveness and the cost-effectiveness of these actions. This comprehensive approach of the ECE metric provides a more comprehensive and significant advantage in evaluating the success of improvement initiatives in the manufacturing industry. The ECE metric ensures that investments made towards improving equipment efficiency are not only effective in increasing operational performance, but also financially sound, thereby optimising the financial performance and the overall return on investment. Thus, the use of the ECE metric provides a more informed and valuable evaluation of the impact of improvement actions, leading to better-informed decision-making and strategic planning.

6.4 The Benefits of Pareto Analysis, Root Cause Analysis, Solution Brainstorming, and Gap Analysis in the ECEF.

The previous discussions demonstrate the superiority of the ECE metric in evaluating the operational and financial performance of equipment. This comprehensive evaluation approach considers multiple criteria, which allows for a more informed determination of improvement priorities and a conclusive evaluation of the cost-effectiveness of improvement actions. Together with ECE metric, the implementation of the ECEF, consisting of the steps of Pareto analysis, root cause analysis, solution brainstorming, and gap analysis, provides practical guidelines for project team to derive cost-effective improvement actions.

The use of Pareto analysis in the ECEF provides a significant advantage in identifying the key areas for improvement. By focusing exclusively on the downtime that has the most significant impact on the unfavourable ECE_B of each prioritised equipment, the Pareto analysis enables a targeted and effective approach to addressing the root cause of equipment inefficiencies. Thus, in turn, leads to more effective and efficient improvement actions, as resources and efforts are directed towards the areas that will have the most significant impact on performance.

The root cause analysis, the next critical step builds upon the insights generated from Pareto analysis. Root cause analysis is the process of identifying the underlying causes of problems and inefficiencies. This process helps to identify the root causes of the downtime identified in the Pareto analysis and allows project team to design and implement targeted solutions to address the root cause of equipment inefficiencies. The combination of Pareto analysis and root cause analysis provides a powerful tool for improvement initiatives in the manufacturing industry, as it not only allows for a targeted and effective approach to addressing equipment inefficiencies but also ensures that solutions are designed to address the root cause of problems, leading to sustainable improvements in operational performance and financial performance.

Solution brainstorming is another critical step in the ECEF, which leverages the insights generated from root cause analysis. This step involves generating and evaluating potential solutions to address the root cause of equipment inefficiencies. Brainstorming sessions are an effective way to encourage creativity and innovation, and to encourage cross-functional collaboration among team members. The diversity of ideas generated during brainstorming sessions can lead to the discovery of new and innovative solutions that are cost-effective, efficient, and sustainable.

Gap analysis, as the next step in the ECEF, provides additional value by allowing project team to assess the current state of the equipment against desired or benchmarked performance levels. This evaluation provides insights into areas where performance gaps exist and helps project team to prioritize their improvement initiatives and allocate resources effectively. The gap analysis step in the ECEF ensures that improvement initiatives are aligned with the overall goals and objectives of the organisation, leading to a more strategic and effective approach to improving equipment performance.

In conclusion, the ECE metric and its accompanying ECEF provide a comprehensive and effective approach to evaluating the operational and financial performance of equipment. The ECEF, consisting of the steps of Pareto analysis, root cause analysis, solution brainstorming, and gap analysis, provides practical guidelines for project team to derive cost-effective improvement actions. The Pareto analysis identifies the key areas for improvement by focusing exclusively on the downtime with the most significant impact on the unfavourable ECE_B. The root cause analysis identifies the underlying causes of problems and inefficiencies and allows for targeted solutions to be designed and implemented. The solution brainstorming step encourages creative and innovative thinking to generate a wide range of potential solutions. Finally, gap analysis provides a structured and systematic comparison of the desired state and the current state to identify the gaps and design action plans to bridge these gaps. The combination of these steps in the ECEF provides a powerful tool for improvement initiatives in the manufacturing industry, leading to sustainable improvements in operational performance and financial performance.

6.5 Summary

This chapter explores the interdependence between the OEE, K_T, and ECE metric in the manufacturing sector. The results confirm the validity of the ECE metric through the discovery of an inverse linear relationship between OEE and K_{EC} and K_{MC}, as well as a direct positive correlation between OEE and cost per unit and OEE losses. The study also aimed to determine which of the two metrics, OEE or K_T, has a stronger correlation with ECE metric. The results shows that even minor improvement in OEE has a more significant impact on ECE metric compared to a reduction in K_T. The ECE metric provides a comprehensive evaluation of improvement actions, taking into account both operational effectiveness and cost-effectiveness. The ECEF, which incorporates key elements such as Pareto analysis, root cause analysis, solution brainstorming, and gap analysis, presents a set of practical guidelines for executing cost-effective improvement measures that result in lasting improvements in both operational and financial performance.

CHAPTER SEVEN

CONCLUSION

7.0 Overview

The present chapter offers a final conclusion on the development of the ECE metric and its accompanying framework. The chapter is structured into two sections. The first section, 7.1, provides the insights gained from the study of the ECE metric and framework. The second section, 7.2, recommends areas for future research to further advance the development of the ECE metric and its framework.

7.1 Closing Insights of the ECE Metric and its Framework

In the manufacturing industry, operational performance is a key determinant of financial performance, yet management often evaluates the effectiveness of operations solely based on financial performance indicators. The commonly used metric, OEE, provides information on the operational performance of equipment and helps organisation identify capacity issues. However, high OEE equipment is not always representative of financial performance, leading to the perception of OEE as a technical improvement that does not motivate its implementation within organisations.

To address the limitations of OEE, several financial metrics have been proposed that aim to link OEE to financial performance metrics such as K_P, K_R,

K_{EC}, K_{OC}, and K_{MC}. However, research suggests that these metrics are insufficient in accurately measuring the impact of OEE on financial performance, as OEE has no direct impact on K_P or K_R and the relationship between OEE and K_{OC} is complex and uncertain.

To address the aforementioned limitations, the ECE metric has been developed as a pioneering performance metric that combines operational and financial insights for equipment evaluation. In contrast to existing metrics, the ECE metric establishes a relationship between OEE and more relevant factors such as K_{EC}, K_{MC}, and K_{IC}. By comparing the cost per unit between current world-class OEE, the ECE metric quantifies the cost waste attributed to the six major OEE losses. Case studies have validated the relationship between ECE, OEE, K_{EC}, and K_{MC} Notably, the ECE metric is the first financial metric to consider the impact of improvement costs on both operational and financial performance. The case studies presented in this research demonstrates the effectiveness of the ECE metric approach in assessing equipment criticality and planning improvement actions. Utilising the ECE metric empowers project team to optimise both operational performance and financial outcomes, thereby fostering the long-term sustainability of organisations.

When integrated with a problem-solving framework that includes tools such as process flowchart, Pareto analysis, root cause analysis, solution brainstorming, gap analysis, and simulation, the ECE metric becomes even more practical and relevant in real-world manufacturing environments. The combination of the ECE metric and these tools provides a powerful tool for improvement initiatives in the manufacturing industry and results in sustained improvements in both operational and financial performance, as demonstrated by the case studies.

7.2 Recommendations for Future Research

Despite its promising attributes, the ECE metric and ECEF present certain limitations that merit acknowledgement. Firstly, the validation of ECE metric and its accompanying framework was confined to specific manufacturing environments, encompassing sectors like medical devices, tyre flaps, and semiconductors. For its broader applicability and generalizability, it is imperative to extend ECE metric and its accompanying framework validation across diverse manufacturing settings, utilising varied methodologies to glean insightful comparisons for future research endeavours.

Secondly, as demonstrated by the TFV 5 in case study 2, equipment frequently subject to idling may yield low OEE and K_{MC}. Although the ECE metric establishes a negative correlation between OEE and K_{MC}, situations involving frequent idling might render K_{MC} an inadequate reflection of equipment's operational performance, thereby affecting ECE metric accuracy. In the interim, a plausible solution could involve excluding idling or non-bottleneck equipment from ECE metric analysis. However, for future research, it is advisable to delve into the correlation between K_{EC} and/or K_{MC} in ECE metric specific OEE losses, facilitating a more comprehensive reflection of both operational and financial equipment performance.

An existing constraint of the ECE metric lies in its uniform treatment of operational and financial performance, potentially misaligning with varying priorities among different manufacturing industries. To address this limitation, future research could enhance flexibility by integrating the Analytical Hierarchy Process (AHP), a robust multi-criteria decision-making technique. AHP offers a structured approach to weigh and prioritise operational and financial performance metrics according to decision-makers' preferences. This incorporation of AHP empowers organisations to customise their evaluation process to cater to unique needs, thus facilitating well-informed decisions to optimise equipment performance.

Another noteworthy limitation of the ECEF involves its reliance on project team expertise during solution brainstorming. To overcome this hurdle, AHP can be employed as a supplementary tool. AHP provides a mathematical framework for multi-criteria decision-making, facilitating a structured assessment of objectives, elements, and improvement actions. This systematic approach empowers project team to methodically identify suitable improvement actions aligned with specific goals. Moreover, AHP considers the importance of criteria and allows for trade-off decisions among conflicting factors.

In conclusion, the ECE metric and ECEF show promise but have limitations. Their validation in specific manufacturing sectors calls for broader validation in diverse settings. Equipment idling challenges accurate assessment affecting the OEE-K_{MC} correlations. Temporarily excluding idling equipment and exploring correlations with K_{EC} and K_{MC} for OEE losses could offer solutions. The ECE metric's uniform treatment of operational and financial performance may not align with industry priorities. Integrating the AHP addresses this. Similarly, AHP can supplement the ECEF's reliance on project team expertise, systematically identifying suitable improvement actions. These limitations present refinement and research opportunities for more effective application across manufacturing contexts.

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