

**AN ADAPTIVE ANALYTICAL APPROACH FOR LEAN
AND GREEN FRAMEWORK**

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Abstract

The recent global supply chain has exposed the industrialists in a tough position when dealing with uncertain global issues such as political changes, fluctuation on foreign exchange, raw material supplies and recession. As these challenges are inevitable, the industrialists constantly seek for alternative solutions to stay competitive in the market. The recent advancement in Industry Revolution 4.0 (IR4.0) can bring many advantages and benefits to the industrialist. As new technology required high investment cost and development of new talent, many industrialists are not confident in investing in the technology especially during the bad economy time. Therefore, the development of adaptive lean and green (L&G) framework is to build the industrialist's confidence with the elements of IR4.0 to enhance operational and environmental performance while transitioning the industry towards IR4.0. Based on the real-time condition, the L&G model incorporates both quantitative and qualitative data input for both process improvement and de-bottlenecking. The model emphasized on a data-driven approach to address process optimization and debottlenecking challenges. Industry case studies are used to demonstrate the application of the developed model in each chapter. The L&G framework has reflected an improvement of 18.25% in process improvement. Meanwhile, the debottlenecking strategy reflects the possible pathways with the consideration of operation, economic and environment to enable the industrialist to be flexible and adaptive towards the uncertainty in the global economy. The performance of the L&G model is highlighted at the end of each chapter.

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List of Abbreviation and Variables

Abbreviation

4M1E	MP, MY, MC, MT and EV
A	Availability
A_C	Attributive element for carbon emission (CO ₂ -eq tonnes/h)
Adagrad	Adaptive gradient
Adam	Adaptive moment estimation
A_E	Attributive element for electrical power generated (MW)
A_H	Attributive element for heat energy produced (MW)
AHP	Analytic hierarchy process
ANP	Analytic network process
A_{Opex}	Attributive element for operating expenditures (m.u./year)
Avg.	Average
BOTA	Bottlenecking tree analysis
BP	Backpropagation
BSP	Bottleneck stopping point
C	Mass fraction of carbon dioxide within the stream
CapEx	Capital expenditures
CHP	Combine heat and power
CI	Consistency Index
CO ₂	Carbon dioxide
CR	Consistency ratio
DCS	Distributed control system

DfE	Design for Environment
DLE	Dry low emission
DLGI	Debottlenecking lean and green index
DMAIC	Define, Measure, Analyse, Improve and Control
EE	Employee empowerment
EIA	Energy Information Administration
EMS	Environmental Management System
ENV	Improve Working Environment
Equip.	Equipment
ER	Employee rewards
ET	Employee rewards
ET	Employee training
EV	Environment
EV_GWP	Carbon Emission
EV_HL	Heat Loss
EV _{co2}	CO ₂ footprint indicator
EV _{sw}	Solid waste performance indicator
EV _{ww}	Wastewater performance indicator
Exp	Exponential
F_C	Flowrate of carbon dioxide containing stream
F_E	Generation rate of electrical energy (MW)
F_H	Production rate of steam (ton/h)
F_N	Flowrate of natural gas that is being consumed (MMSCFD)
FPS	Ford production system

FR	Fix resources
FR_OEE	Overall equipment effectiveness in FR
FSR	Flexible resources
FSR_AB	Employee absent indicator in FSR
FSR_CS	Employee competency rate indicator in FSR
FSR_KPI	Employee KPI indicator in FSR
FSR_MU	Total material used indicator in FSR
FSR_OPEX	Operation cost indicator in FSR
FSR_OT	Employee overtime indicator in FSR
FSR_PP	Total product produced indicator in FSR
FSR_SA	Employee safety competency indicator in FSR
FSR_TP	Operation profit indicator in FSR
GDP	Gross domestic product
GHG	Greenhouse gases
GM	Green manufacturing
GRC	Grey relational coefficient
GT	Gas turbines
HRSG	Heat recovery steam generator
IC	The state and time dependant investment cost
II	Initial investment
IR4.0	Industry Revolution 4.0
ISO	International Standard Organization
JCM	Joint Crediting Mechanism
JIT	Just in Time
KPI	Key performance index

L&G	Lean and green
LCA	Life cycle assessment
LGI	Lean and green index
LGI _{actual}	Actual operation LGI
LGI _{target}	Target LGI
LM	Lean manufacturing
Log	Logarithmic
M	Estimation of maintenance cost per year correlated to the feed capacity (m.u./MMSCFD year)
MC	Machine
MCDM	Multi-criteria decision making
ME	Machinery enhancement
Min.	Minimum
ML	Machine learning
MMBtu	Million British thermal unit
MP	Manpower
MP _{AB}	Total average absent day indicator of MP
MP _{CR}	Total average competency rate indicator of MP
MP _{KPI}	Total average KPI achievable indicator of MP
MP _{LT}	Total average late check in time indicator of MP
MP _{OT}	Total average overtime indicator of MP
MP _{SC}	Total average safety competency rate indicator of MP
MRP	Material requirement planning system
MT	Material
MT _{DI}	Product to defect indicator of MT

MT _{IN}	Material inventory indicator of MT
MT _{RD}	The rate of recyclable defects indicator of MT
MT _{RE}	Resource consumption efficiency indicator of MT
MY	Money
MY _{OC}	Total operation cost indicator in MY
MY _{TP}	Total profit indicator of MY
NG	Natural gas
NGO	Non-governmental organization
NIS	Negative-ideal solution
NP	The state and time dependant net profit
NPV	Net present value
OEE	Overall equipment effectiveness
OpEx	Operating expenditures
Opt.	Operation
OSH	Occupational Safety and Health
P	Performance efficiency
PDCA	Plan, Do, Check, Act
P_E	Price of electrical energy per year (m.u./MW year)
P_H	Price of heat energy per year (m.u. h/ton year)
PIS	Positive-ideal solution
P_N	Price of natural gas (m.u./ MMSCFD year)
PP	Payback period
Prod.	Production
Q	Quality product
RBF	Radial basis function

RD	Operation R&D
RI	random index
RMSE	Root mean square error
ROI	Return on investment
SAW	Simple additive weighting
SCADA	Supervisory control and data acquisition
SD	Strategy and direction
SDG	Sustainable development goal
SGD	Stochastic gradient descent
SME	Small and medium-sized enterprise
SMED	Single minute exchange die
SOP	Standard operating procedure
SWP	Global warming potential
TOPSIS	Technique for order preference by similarity to ideal solution
TPM	Total productive maintenance
TPS	Toyota Production System
TSS	Total sum square
WWII	World War II

Variables

Δ_{ij}^{-max}	Maximum value of Δ_{ij}^{-}
Δ_{ij}^{+max}	Upper limit of Δ_{ij}^{+}
$\widehat{m}_t$	Computed bias-corrected first moment estimate
$\widehat{v}_t$	Compute bias-corrected second raw moment estimate
$\frac{\partial L_R}{\partial w_R}(t)$	Gradient calculated with a random value from the data set
Δ_{ij}^{-min}	Minimum value of Δ_{ij}^{-}
Δ_{ij}^{+min}	Lower limit of Δ_{ij}^{+}
$hr_{opt,month}$	Total working hours per month
AB_{avg}	Average absent day per employee monthly
A_m	Available alternatives for MCDM selection
CS_{avg}	Average employee competency rate per employee monthly.
C_n	Criteria of n indicator
$G_i(t)$	Squared gradient over time, t
KPI_{avg}	Average KPI achievable per employee monthly.
M_{ANP}	Matrix of ANP
MP_{ABn}	Average total absent day
MP_{CRn}	Average competency rate
$MP_{KPI n}$	Average KPI achievable
MP_{LTn}	Average late check in time

MP_{OTn}	Average overtime per employee
MP_{SCn}	Average safety competency rate
OT_{avg}	Average employee OT obtained per employee in a month.
P_{ij}	For i th alternative and j^{th} indicator
SA_{avg}	Average safety awareness rate through safety assessment
$day_{opt.month}$	Total working day per employee.
e_j	Output entropy of j^{th} indicator
g_j	Calculation of variation coefficient of j th indicator
g_t	Loss function
$k_{EV,i}$	Weight of sub-indicator, i of EV
$k_{MC,i}$	Weight of sub-indicator, i of MC
$k_{MP,i}$	Weight of sub-indicator, i of MP
$k_{MT,i}$	Weight of sub-indicator, i of MT
$k_{MY,i}$	Weight of sub-indicator, i of MY
k_i	Weight for sub indicator on current month
k_i	Weight of i sub-indicators
k_{i+1}	New weight for the sub indicator in next time step
k_{i-1}	Weights for sub indicators on last time step
m_t	Updated biased first-moment estimate
v_t	Updated biased second raw moment estimate
w_{EV}	Weight of main indicator for EV

w_{MC}	Weight of main indicator for MC
w_{MP}	Weight of main indicator for MP
w_{MT}	Weight of main indicator for MT
w_{MY}	Weight of main indicator for MY
w_c^i	Combine weight, i of ANP and entropy
w_i	Weight for main indicator on current month
w_{i+1}	New weight for the main indicator in next time step
w_{i-1}	Weights for main indicators on last time step
w_j	Weight of entropy
x_j^{Best}	PIS in terms of criteria j
x_j^{Worst}	NIS in terms of criteria j
x_n	Position of the cell in the matrix in the “ n ” project stage
$\frac{\partial L}{\partial w}(t)$	Gradient in time step, t
n	The number of sources.
w_{EV}	Weight environment
w_{fs}	Weight for fix resource
w_{fsr}	Weight of flexible resource
$M(x_n)$	DLGI at the cell position of x_n
S	Number of steps taken in project stages
q	d-dimensional vector with binary value in any dimension.
β	The distinguish coefficient used to control the resolution scale of the problem

η	Learning rate
ϵ	Smoothing factor

Chapter 1: Introduction

The industrial revolution has brought tremendous advancement to the industry especially the manufacturing sector. The increase in production waste including solid and environmental waste, many countries are struggling to manage waste. Therefore, with the advancement in technology, the global markets leaders are advancing to adaptive lean and green strategy. The lean and green approach is a combination of lean approach and green approach. Both approaches encourage the elimination of operational and environmental waste that reduce resource wastage and environmental impact respectively. On top of that, the adaptability of the strategy relies on the big data obtained from the manufacturing process. Thus, the big data obtained from the manufacturing sector will be used as the fundamental for process improvement and debottlenecking planning.

1.1. Problem Background

Since the first industrial revolution, the manufacturing industry has been contributing massively to the global economy. It is undeniable that the manufacturing sector is one of the main economic pillars in many developing and developed countries. Many industry players are struggling from uncontrollable factors and competition such as political influence, economic stability, technology advancement, regulator restructuring and environmental pressure (Issa, Chang and Issa, 2010). The sustainability of the manufacturing industry is highly dependant on the feasibility of economy and environment.

The manufacturing sector is one of the main energy consumers that contribute to global warming and climate change indirectly. Despite the

awareness of global warming is on the rise, this does not reduce the global demand for manufactured goods. Lam *et al.* (2017) predicted that the world energy consumption will grow by 48 % until 2040. However, Max *et al.* (2013) pointed out that the world population growth rate started to fall. Despite the reduction in growth rate in population growth, the demand for better quality lifestyle has spurred the manufacturing industry to produce better products.

The rise in global competition has forced the industrialists to seek for new technology and approach for process improvement. One of the easiest ways to improve organisation performance is through good practises such as lean and green (L&G) management. L&G management allows the organisation to improve both operation and environment aspect together. Despite many L&G tools have been developed, the industrialists are still depending on the expert to guide the improvement process.

The paradigm shift in Industry 4.0 (IR4.0) emphasizes on digitalisation where data-driven technology can provide in-depth know-how to improve performances. Mike (2016) highlighted that 73% of the data obtained from the organisation goes unused for analytics. Besides that, some facilities still rely on manual data logging method which could not capture the operation data precisely. Due to financial constraint and lack of confidence, many organisations do not prioritise data-driven technology as a necessity for process improvement. The need for government support in industrial digitalisation is critical to enhancing a country's economy through the manufacturing sector. Besides, as the manufacturing facility operates in a very dynamic condition, the lack of instrumentation and data collection tools will consume more resource

for troubleshooting. This can be a resource-consuming and unproductive way that will degrade the competitiveness of the company.

1.2. Problem Statement

UNIDO (2019) highlighted that the global manufacturing output has been decelerating since 2018 primarily due to tariff and trade tension between the economic dominant countries (i.e. United States, Europe and China). The effect of uncertainty in the global economy can affect the manufacturing output significantly. This situation can cause a demand gap which impacts the industrialist massively in terms of operation and financial efficiency. Besides that, the initiation of IR4.0 has also demonstrated its benefits in improving the operational efficiency that comes with huge investment.

Many big manufacturers who are financially capable can grasp the technology advantage to increase their value among their competitors. On the other hand, smaller and conventional operated manufacturers are less likely to invest in new technology as they are bound by the global economic fluctuation. This has created an unsustainable competition where the small-scale manufacturers are lack of confidence in investing in new technology during a bad economy hence lowering their competition level. In the long run, lower operation efficiency will result in unsustainable business competition. It is important to note that the total output of the manufacturing industry can cause a direct impact on a country's gross domestic product (GDP) (Stephen, 2016).

Based on the literature study, there is a lack of systematic implementation of L&G framework that can be easily accessible and beneficial to the industrialist, especially user friendly to the engineers and operators. Many studies have demonstrated the application of tools but lack of the integration of

tools with machine learning models. This research aims to close the gap between conventional and modern manufacturers to increase the organisation value and business sustainability without compromising the environment. The lack of knowledge and talent have caused the industrialist to step back from investing in new IR4.0 technology. The need for an adaptive analytical L&G framework is required to assist the industrialist to maintain sustainable competition during tough times.

The adaptive L&G analytical framework serves the purpose in addressing several challenges as below:

- a) Dynamic analysis on process improvement based on real-time data
- b) Increase the industrialist's application with a data-driven approach in the transition to IR4.0
- c) Incorporate lean and green aspect into process optimisation and de-bottlenecking
- d) Improve business competition and sustainability

1.3. Research Objectives and Scopes

The main objectives of this research are to develop an adaptive analytical L&G framework for the industry. To develop the adaptive L&G framework, the research objectives are listed as below:

1.3.1. Objective 1 - Development of Lean and Green Index

There is a lack of appropriate tools in establishing L&G performance in the manufacturing sector. The need to develop a lean and green index (LGI) for process benchmark and performance monitoring is necessary.

The LGI represent an organisation's L&G performance to ease communication and performance monitoring.

1.3.1.1. Research Scope

- a) Identify the basic requirement of operation through an interview with industrialists. Understanding their process requirement based on L&G approach.
- b) Establish a generalised L&G checklist that consists of the fundamental requirement of the manufacturing industry such as manpower, machine, money, material and environment aspect.
- c) Develop the formulation of LGI by considering the process data input and the priority of the performance indicator.

1.3.2. *Objective 2 - Development of Lean and Green Framework*

The lack of a systematic approach to implement L&G practises in the industry. The development of the L&G framework with a systematic guideline based on operational and environmental improvement will help the industrialists to improve operational performance.

1.3.2.1. Research Scope

- a) Establish discussion and collect information from the industrialist on their operation behaviour to develop the systematic flowchart to implement L&G approach.
- b) Collect information from the industrialist on their decision-making approach to develop a quantitative

method to analyse the decision-making strategy for process improvement.

- c) Carry out decision-making analysis to identify the priority of the performance indicator in the facility.

1.3.3. Objective 3 – Development of Adaptive Analytical Approach.

The adaptive analytical approach is required to overcome the challenges of a statistical model. The adaptive model deals with real-time data analysis by incorporating machine learning method to perform continuous process improvement. Thus, improving the industry based on the actual condition.

1.3.3.1. Research Scope

- a) Explore the possibility and method of machine learning approach such as gradient descent optimiser into L&G framework for real-time process improvement.
- b) Establish the step by step approach by integrating the adaptive analytical approach into L&G framework.
- c) Validate the machine learning approach with a case study.

1.3.4. Objective 4 – Development of Ensemble Solver for Adaptive Analytical Approach

Objective 4 focuses on the development of ensemble solver for the adaptive model. The enhancement of the adaptive model includes the qualitative and quantitative data obtained from the organisation.

Besides, the adaptive model is improved with ensemble solver for higher analysis performance.

1.3.4.1. Research Scope

- a) Improve the complexity and efficiency of the adaptive L&G model by exploring more machine learning optimiser model to form an ensemble solver.
- b) Incorporate a data-driven approach into decision-making strategy to improve the reliability of the adaptive model.

1.3.5. *Objective 5 – Data-Driven De-Bottlenecking Analysis*

A systematic debottlenecking pathway is critical for capacity increment planning. A de-bottlenecking strategy is required to analyse the process based on equipment capacity, investment and environmental aspect to establish process retrofit for the industry. The debottlenecking strategy emphasized on a data-driven approach to address process de-bottlenecking challenges.

1.3.5.1. Research Scope

- a) Understand the needs and future expansion of the organisation through interview and data collection.
- b) Develop an ensemble machine learning solver for L&G de-bottlenecking approach. With the different condition, the ensemble solver will response effectively with the best optimum solution.

- c) Build the ensemble solver based on the data-driven method as the design of production capacity increment is solely based on equipment datasheet.

1.4. Research Contribution

Refer to “List of Publication”, this work has developed the adaptive analytical L&G framework to improve the performance of combine heat and power (CHP) plant with different capacity. The improvement in the performance of the CHP plant can be observed in the case study demonstrated in chapter 5, 6 and 7 while chapter 8 demonstrates the enhanced BOTA approach to overcome debottlenecking challenges. Besides that, the outcome of this research has also been published in several Q1 journals such as Journal of Cleaner Production, Chemical Engineering Science and, Renewable and Sustainable Energy Reviews.

Chapter 2: Literature Review

Chapter 2 focuses on the literature review for the adaptive lean and green framework. This chapter is divided into several sections to introduce and explore the potential of key areas in this research. The fundamental of lean manufacturing will be covered in the next sub-section followed by green manufacturing, lean and green manufacturing, multi-criteria decision making, adaptive modelling and debottlenecking strategy.

2.1. Lean Manufacturing

The lean practice is discovered as a significant element in manufacturing since the first industrial revolution. The lean manufacturing (LM) approach is commonly used to eliminate non-value-added activities and procedures to the final product (Nawanir *et al.*, 2018). Figure 2-1 presents the important milestones of LM along with the development of the industrial revolution. LM kick-started back in early 1800 by Eli Whitney during the first industrial revolution when machinery was first introduced in the manufacturing sector (History, 2018). He invented the concept of interchangeable parts which allowed more unskilled workers to get involved in the production of the musket (History, 2018). It was a break-through as the musket manufacturing was only handled by skilful craftsman back then. Eli Whitney's introduction of the interchangeable part had successfully improved the economics of scale of the production line. In the late 1890s, F.W. Taylor introduced the time study to reduce processing time (Strategosinc, 2016). The time study measures and analyses the amount of time required by a worker to complete a specific task using a stopwatch (Lopetegui *et al.*, 2014). The time study established a

standard time for a specific process. Frank and Lilian Gilbreth then introduced Process Charting and Motion Study in 1900. Process Charting is a visualisation tool to identify the area for improvement (Gilbreth, 1921). On the other hand, the motion study method is developed to reduce the motion required for a task (Lopetegui *et al.*, 2014). Then, time study and motion study were integrated and improved as method engineering. The method engineering evaluates the involvement and effectiveness of human-being in executing a task (Industrial Timestudy Institute, 2017). These innovators were considered as the initiators for the idea of waste (e.g. motion and waiting) elimination which were then reflected in the seven (7) wastes of LM.

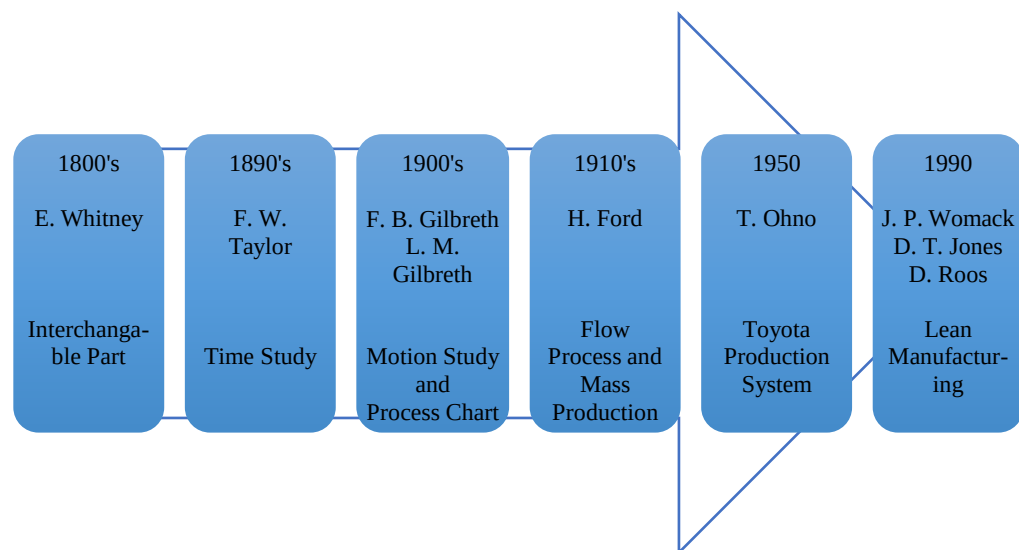


Figure 2-1: Revolution of lean manufacturing

In the early of 1910 where the second industrial revolution took place, Henry Ford integrated the elements of interchangeable parts with standard work into a flow of production known as an assembly line (History, 2019). Ford production system (FPS) has made an advancement in the manufacturing industry by mass production of Model T, the first affordable car to the market

(History, 2019). Rene (2009) stated that Ford's effort in improving the manufacturing production cost had been revolutionary. Furthermore, the FPS approach was the main factor contributing to the allied victory of World War II where bombers were produced at the rate of one plane per hour (Garrett, 2015). Ford was considered the first practitioner of LM.

After World War II (WWII), Eiji Toyoda and Taichii Ohno visited Ford's production complex as FPS model contributed to the victory of WWII (Strategosinc, 2016). At that time, Ford's complex was producing 8,000 vehicles compared to 2,500 vehicles that Toyota had produced per day (Maynard, 2013). The visit then led to the development of the Toyota production system (TPS) initiated by Taichii Ohno before the third industrial revolution. TPS was established based on two concepts, which were Jidoka and Just in Time (JIT). Jidoka is known as one of the two main pillars in TPS which is defined as "automation with a human touch". Jidoka applies to any machine that is designed to make judgement by itself (TOYOTA, 2019). JIT is known as a production method where products are created to meet demand with no surplus production or storage requirement (Rouse, 2015). Taichii Ohno later introduced the "pull-flow production" which was able to generate a variety of products that could be reutilised in the process (Dekier, 2013). Toyota also recognized the importance of the quality circle which involves the participation of all employees contributing to the continuous improvement of the system (Villa and Taurino, 2013).

In the 1990s, James P. Womack, Daniel T. Jones and Daniel Roos introduced LM. LM was regarded as the successor of TPS (Dekier, 2013). The TPS and LM have similar philosophies where TPS focuses on the principles of

Toyota way and LM emphasize on continuous improvement methodology. The lean approach was defined with 5 principles (Table 2-1) and focused on eliminating 7 types of waste (Table 2-2).

2.1.1. *Lean manufacturing principles and tools*

The evolutions of manufacturing from the traditional method to the lean approach allow the industry to operate at higher efficiency and competitive way. Lean is a wide context and it covers various aspects of an operation. The 5 key principles of LM have laid down a systematic step for lean implementation. The 5 key principles are listed in Table 2-1. The principles of LM mainly focus on identifying the value-added and non-value-added components in a process flow.

Table 2-1: 5 Lean Principles Functions (Modified from Crawford, 2016)

Lean Principles	Principles Function
Define Value	To identify requirements for customer's need for a specific product. This value determines how much customer willing to spend on a service or product.
Identify Value Stream	Value stream identification allows the production team to understand the entire product life cycle. The goal is to identify the procedure or steps that do not add value to the product.
Create Smooth Value Flow	To smoothen the value flow, any steps that do not add value to the product will be eliminated. The intention is to allow raw material to flow through

	the process without any interruption and delivery to end-user smoothly.
Implement Pull Based Production	Pull based production approach is a demand-based production. The production of goods will only take place upon receiving an order from a client. This requires great production flexibility in managing the entire supply chain.
Strive for Excellent	Aim to perform continuous improvement by constantly reviewing the process to remove non-value-added procedures.

LM approach mainly focuses on improving the productivity of the operation through value creation by reducing 7 wastes from an operation. Table 2-2 provides a detail explanation of the 7 wastes.

Table 2-2: 7 waste of Lean Manufacturing

Waste	Description	Source
Over-Production	A product produced without a demand.	(Berg and Ohlsson, 2005)
Waiting	Waiting occurred between two different processes when the product is not being processed. Poor communication and uneven	(McBride, 2003; Bach, 2017)

workstation loading can contribute to the waiting factor.

Inventory	Excessive inventory can cause hidden operation problems that lead to cash flow constraint, longer lead time in obtaining items or storage of an obsolete product.
Motion	Motion is the excessive movement (McBride, 2003; Abe, 2015) of employee or machine that does not add value to the production. Excessive motion can result from a lack of standard operating procedure (SOP) and poor layout design.
Transportation	Transportation factor refers to the (Abe, 2015) movement of manpower, equipment, goods or products. Unnecessary movement can cause damage to the product during logistic handling.
Over-Processing	Over-processing is known as a product produced with a higher specification than required.
Defect	Defect is the product that does not meet the minimum requirement of a product. Defects can result from

poor quality control, inventory

control or machine breakdown.

The identification and elimination of non-value-added wastes in LM will be assisted by a series of lean tools (Liker and Meier, 2006). Many lean tools have been developed to support the implementation of lean management. However, the selection of appropriate lean tools (Table 2-3) can be challenging. For instance, some lean tools tend to have the same objectives on value creation and complement each other. For example, value stream mapping, bottlenecking analysis, Gemba analysis and continuous flow tools can be used to complement block diagram to achieve higher value. Some of the lean tools have the same function but exist with different names (i.e. process mapping is also known as value stream mapping). Mourtzis *et al.* (2016) highlighted that with appropriate modifications, lean tools can be applied to every enterprise. It is important to note that the misapplication of lean tools can cause additional wastage in resources.

To ease tools selection, Pavnaskar *et al.* (2003) proposed a classification scheme that matches the lean tools to the waste that needs to be eliminated. The scheme established a relationship between the lean tools and waste that guides the users to select the right tools. On contrary, Simona and Cristina (2015) concluded that an organization dependant on experience lean mentor to achieve significant results. The dependency on an experienced lean mentor to produce operational results from the lean approach requires time and lack of empowerment

to the employee. Therefore, the classification scheme will be able to empower the employee to take initiative to identify and apply appropriate lean tools for process improvement (Pavnaskar *et al.*, 2003).

Table 2-3: 25 Essential lean tools functions

Lean Tools	Tools Function	Source
5S	Workplace organization method that includes - Sort (Eliminate that which not needed) - Systemize (Organize remaining items) - Sanitize (clean and inspect work area) - Standardize (write standards of best practices in a work area) - Sustain (apply the standard, perform audit and training regularly)	leanproductio n.com (2017); Simona and Cristina (2015)
Andon	The main principle element of Jidoka. Real-time machine communication tools that notify the operator immediately to attend to a problem.	
Bottleneck	Identify the part of the manufacturing/process that limit the overall output of the process.	

Lean Tools	Tools Function	Source
Continuous Flow	The approach in discrete manufacturing where the product is produced from the start to complete without a stop.	leanproductio n.com (2017); Simona and Cristina (2015)
Gemba	Understand the location where value is generated.	
Heijunka	A strategy that leverage on the production ability to deal with unpredictable demand over a period of time.	
Hoshin Kanri	Policy deployment process to ensure manufacturing strategic is communicated consistently and align with company direction.	
Jidoka	An automated process that stops immediately when a defect is identified.	
Just-In-Time (JIT)	Inventory strategy to reduce inventory level, space requirement and improve cash flow through client demand.	
Kaizen	Continuous improvement strategy that encourages an employee to work proactively together to improve the manufacturing process.	

Lean Tools	Tools Function	Source
Kanban	Pull demand system that relies on a signal card to indicate when more goods are required. To create a smooth flow and reduce inventory.	leanproductio n.com (2017); Simona and Cristina
Key Performance Index (KPI)	An indicator used to track and encourage progress of employee towards company goal and target.	(2015)
Muda	Indicate the 7 wastes in lean manufacturing.	
Overall Equipment Effectiveness (OEE)	Benchmarking to track the improvement of operational performance.	(De Ron and Rooda, 2006)
Plan, Do, Check, Act (PDCA)	A methodology that continuously improves the production process.	(leanproductio n.com, 2017)
Root Cause Analysis	A method that focuses on identifying and solving the underlying problem.	
Single-Minute Exchange of Dies (SMED)	Reduce setup time or changeover of the machine.	

Lean Tools	Tools Function	Source
Six Big Losses	Provides a framework to cope with a common cause of waste from an equipment perspective such as - unplanned stop - planned stop - small stops - slow cycle - production rejects - startup rejects	(leanproduction n.com, 2017)
SMART Goals	Ensure that goals are defined accurately aligning with: - Specific - Measurable - Attainable - Relevant - Time Specific	
Standardized Work	Documented standard operating procedure for operation. Improvement can be documented and audit for continuous improvement.	
Takt Time	The rate of production that helps for production planning to cope with demand.	

Lean Tools	Tools Function	Source
Total Productive Maintenance (TPM)	Optimise equipment effectiveness, eliminate breakdown and promote autonomous maintenance by operators through day-to-day activities involving total workers	(leanproduction n.com, 2017)
Value Stream Mapping	Tools used to visually map the production flow to identify waste.	

The successful implementation of LM management has delivered positive results on operation performance such as 50% or greater increase in capacity with existing facilities, 50% improvement in quality and 60% reduction in cycle time (Zimmer, 2000). Czapke (2007) added that LM aims to create a smooth, high quality and well-organised operation with minimum waste. Reza et al., (2009) emphasized that lean is a culture for quality improvement that should be cultivated in the employee. The embedment of the LM element in the organisation can have a positive impact on cost performance where waste reduction is improved (Mcgrath and Doyle, 2007).

2.1.2. *Systematic implementation of Lean Manufacturing*

Generally, LM strives to improve an existing operation's productivity by eliminating non-value-added product. Despite the existence of various lean tools, the lack of proper guidance in selecting and matching

the suitable lean tools to target non-value-added stream can be resource consuming.

Many lean practitioners use a combination of individual lean tools to form combination method (i.e. combination of Six-Sigma and Agile). However, sustainable-focused work has received minimal attention despite Six-Sigma being one of the reliable tools in improving operational performance (Erdil, Aktas and Arani, 2018). Garza-Reyes (2015) developed a conceptual model to integrate lean, Six Sigma and green concept using Define, Measure, Analyse, Improve and Control (DMAIC) cycle.

A study revealed that human resources and management appeared to be the top-ranked critical success factor. Tortorella et al. (2016) discovered that a successful implementation of LM is highly dependent on the predominant culture within an organisation. A study has discovered that the human factor is the key to ensure successful implementation of the LM approach (Castillo-Pérez et al., 2019). Tortorella et al. (2016) further added that the management commitment in LM practises can have a positive influence on employee's attitude and behaviour. Therefore, a systematic implementation system of LM will require a top-down approach within the organization. In other words, empowerment of employee and lean approach implementation strategy should be taken into consideration carefully by an organisation to ensure successful implementation of LM.

2.2. Green Manufacturing

Green manufacturing (GM) is initiated in the early 1990s with the emerging of eco-innovation (Sezen and Çankaya, 2013). The eco-innovation is known as a novel production method which results in the reduction of environmental risk and negative impact of resources used in an organisation (Kemp and Pearson, 2007).

The GM is also known as sustainable manufacturing, referring to the business strategy that focuses on profitability through reactive and proactive environmentally friendly operation (Abdul-Rashid *et al.*, 2017). GM is regarded as an environmental and economical-driven approach to minimize waste stream through process design, consumption of products and materials (Dilip Maruthi and Rashmi, 2015). Handfield *et al.* (1997) stated that environmental caution and practice should be implemented in all value chain to make green approach successful. Mittal and Sangwan (2014) added that GM helps to achieve a better economic outcome without compromising the environment. Besides, the International Standard Organization (ISO) published the first Environmental Management System (EMS) standard internationally known as the ISO14001 to address the environmental issue (Agan, Acar and Borodin, 2013). The EMS system acts as a continuous improvement tool in providing a systematic method to manage an organization's environmental-related matters.

Furthermore, GM focuses on a closed-loop operation involving recycling and recuperation practices to reduce waste while implementing green technologies and optimised logistics for pollution prevention (Ferguson and Toktay, 2009). Sezen and Çankaya (2013) showed that GM can spur economic, environmental and social improvement through waste and cost reduction.

Taylor (1992) further illustrated that organisation embarked on green management and innovation can improve corporate image while satisfying consumer demand.

Additionally, Paul et al. (2014) stated that the cost of energy and resources are constantly increasing due to the rising demand. Therefore, energy-management is essential for the industry to address the increase in energy cost (Nukman *et al.*, 2017). By implementing GM, the industrialists explore the alternatives in production improvement without compromising the environmental performance.

2.2.1. Green Manufacturing Principles and Tools

The development of GM principles and tools are necessary to guide the industrialists in achieving better environmental performance. Anastas and Zimmerman (2003) proposed the 12 Principles of Green Engineering (Table 2-4) as the guidelines for green process design. They emphasized that the resources for energy and material used shall be non-hazardous inherently. Helu and Dornfeld (2012) then suggested a simplified framework that consists of 5 principles of GM as illustrated in Table 2-5. In the second principle, Helu and Dornfeld (2012) highlighted that the “vertical” refers to systems at any one level of details from the enterprise down to the process; the “horizontal” refers to systems at any one level of detail. In short, Helu and Dornfeld (2012) have simplified the principles that Anastas and Zimmerman (2003) proposed. Both frameworks focus on the evaluation of the manufacturing process based on product lifecycle with the consideration of energy and environmental emission.

Table 2-4: 12 principles of Green Principles (Modified from Anastas and Zimmerman, 2003)

No.	Definition	Description
Principle 1	Non-hazardous inherent rather than circumstantial	Strive to ensure all material and energy's input and output are inherently nonhazardous as possible.
Principle 2	Prevention over treatment	Waste prevention is prioritised compare to waste treatment.
Principle 3	Design for separation	The use of hazardous solvent is widely used in many separation processes. The separation process shall be designed according to the material and product characteristic to minimise the use of hazardous solvent with the consideration of energy consumption.
Principle 4	Maximise mass, energy, space and time efficiency	A process is considered inefficient when the mass, energy, space and time are underutilised. Space and time can be optimised along with mass and energy to eliminate waste.

No.	Definition	Description
Principle 5	Output-pull	The production is client demand dependant. The material and energy will only be consumed when there is a demand.
Principle 6	Conserve complexity	The material used in the production should have the complexity benefit without the need for modifying the existing process. Embedded entropy and complexity must be viewed as an investment when making design choices on recycle, reuse, or beneficial disposition
Principle 7	Durability rather than immortality	The product that lasts well beyond its commercial life normally will cause an environmental problem. The lifespan of a product should be considered during the product design stage. Product design goal should focus on durability instead of immortality.
Principle 8	Meet needs, minimise excess	The operation cost for material and energy can be high for an overdesigned system. To optimise the system to reduce resource wastage.

No.	Definition	Description
Principle 9	Minimise material diversity	Material diversification in multicomponent products should be minimised. The use of common material can ease product disassembly and value retention.
Principle 10	Integrate local material and energy flow	This focus on heat and material recovery on the existing process. Design of products, processes, and systems must include integration and interconnectivity with the available energy and materials flows.
Principle 11	Design for commercial “afterlife”	The recycling element should be incorporated into product design. This enables the current product to be utilized in the next generation product. Products, processes, and systems should be designed for performance in a commercial “afterlife”
Principle 12	Use renewable rather than depletable materials	The utilisation of material or waste as a feedstock into other processes as recycle/renewable source.

Table 2-5: Simplified 5 principles of Green Principles (Modified from Helu and Dornfeld, 2012)

No.	Definition	Description
Principle 1	A comprehensive systems approach must be used to evaluate and improve manufacturing processes from a green perspective	Principle 1 considers environmental impact as the impact may result from the process itself.
Principle 2	The system should be wholly viewed across both the vertical and horizontal directions	Vertical refers to system varying level of detail from the enterprise down to the process while horizontal refers to a system at the same level of detail. This approach is important as the environmental impact can be occur depending on the level of detail.
Principle 3	Harmful input and output of the system to the environment and humans should be minimised or removed	Identify the harmful input and output to be replaced with material that has a lower impact. An alternative way is to implement recycle, reuse and remanufacture to reduce harmful input required. Human activity dealing with harmful substance shall be reduced or eliminated if possible.

No.	Definition	Description
Principle 4	Net resource (i.e. energy and material) use should be lowered	Ideally, net resources should be zero so that resources may be used at a rate equal to the rate of replenishment in the environment. Aside from being practically impossible, this principle act as a guideline to control and reduce the consumption of resources.
Principle 5	Temporal effects on the system should always be considered	The temporal effect is known as a time-based effect. The environmental impact should be taken into consideration during the design stage to minimise the future impact.

Lele (2009) added that the product lifecycle design elements such as design, procure, manufacture, packing and distribution, product end of life and re-manufacturing need to be incorporated in GM practises. Vila et al. (2015) enhanced Lele's (2009) product lifecycle element into a detailed framework by adding method, tools and knowledge into product lifecycle design. The detailed framework is incorporated with three major sections such as design-development, manufacturing and services (Vila et al., 2015). In the production aspect, both Lele (2009) and Vila *et al.* (2015) focusses on resource management, production control, production, assembly and storage package.

Kim and Kara (2012) stated that 80% of the economic, social and environmental impact are determined during product or process design stage. With that, the Design for Environment (DfE) is introduced to include green element into process design. Generally, DfE establishes the guidelines to help the designer to reduce environmental impact (Cuerva *et al.*, 2014). Additionally, the life cycle assessment (LCA) evaluates the complete life cycle of the product to minimise the environmental impact (Ma *et al.*, 2012). The LCA is a quantitative tool that analyses the potential environmental impact throughout the entire life cycle of a product from raw material, production, use and disposal. Paul *et al.* (2014) highlighted the importance of LCA in minimising environmental pollution. Telenko *et al.* (2016) added that a comprehensive LCA requires highly detail data to describe the final product that can consume a significant amount of time. Therefore, DfE is often used as the guideline in the early design stage while LCA is used to reflect actual condition. Many of the DfE guidelines are the reflection of the lesson learned from LCA approach.

Other than the DfE and LCA method, energy consumption also plays a significant role in manufacturing. The utilization of green technology that improves environmental performance should be included during the design stage of a processing facility. Green technology such as photovoltaic, co-generation, biogas, etc. can improve the environmental performance of a factory (Paul *et al.*, 2014). Despite the green technologies have achieved certain technological maturity, it still occupied comparatively low market share (Yong, 2014). Yong

(2014) added that changes are required at the technology level, system perspective and knowledge, and paradigm shift to achieve higher market implementation for green technology. From DfE and LCA analysis, screening method can be used to evaluate new technologies that can improve environmental performance (Reich-Weiser *et al.*, 2010). Green technology can bring a positive impact on energy management and optimization performance in the factory. For instance, gas turbine co-generation system can reduce the operation cost without compromising the environmental emission.

Melnik *et al.* (2001) proposed a conventional material requirement planning system (MRP) that takes environmental impact into material planning. The MRP system provides a better understanding of potential waste stream generated from an operation in both quantitative and financial term. Hui *et al.* (2002) suggested using an analytic network model to evaluate the environmental hazards which focuses on analysing the impact produced from different types of manufacturing waste. Krishnan *et al.* (2004) developed an environmental value system analysis tools that assess the environmental performance through a “bottom-up” approach. The bottom-up approach allows the flexibility in the analysis of the environment, health and safety factor. Van Berkel (2010) discovered that industrial symbiosis allows industry to substitute high-quality resources (i.e. raw material and energy source) with lower quality substitute (waste). The substitution process will involve conversion, substitution and avoidance steps. The conversion step involves the collection of waste material from

a symbiosis partner's waste which is suitable to act as a feedstock or energy source that can be transported to the site. The substitution step uses alternative feedstock and requires process modification to compensate for alternative feedstock input. The final step emphasizes the reduction or elimination of waste that is generated and can harm the environment. This concept was proven by the *Verbund* concept by BASF corporation (BASF, 2020).

2.2.2. *Drivers for Green Manufacturing*

In GM, the green wastes can be classified into greenhouse gases (GHG), eutrophication, excessive resource usage, excessive power usage, pollution, rubbish, excessive water usage and poor health and safety. Many industrialists emphasized on technology to improve environmental performance. An interview was conducted with several companies from different sector (i.e. palm oil refineries, rubber processing facility and pharmaceutical company) on the application of green technology. The industrialists highlighted several important factors causing the delay in the implementation of a green approach. One of the main reasons is the management is unaware of the potential or possibility to improve the operational efficiency with the latest technological advancement. Besides, many employees are unaware of the new technology due to lack of exposure and training. Some of the engineers responded that only no or low-cost improvement is prioritised for process improvement (Cheng, 2018). Cheng (2018) added that the management is not confident with high-cost investment technology as they do not have experience and capable team to lead the project. This

also includes the influence of return on investment (ROI) in convincing the management. The industrialists tend to focus on individual or smaller component of energy-efficient equipment where it only contributes to a potential improvement of 2-5% (UNIDO, 2010). It became obvious that the primary concern of the industrialist in investing green technology was the lack of experience employee and availability of financial scheme. It is noticeable that the industrialists will be actively engaged in green technology when one successfully implemented a green technology project within the same industry sector.

According to the Energy Information Administration (EIA) (2016), the industry sector is consuming 54% of the world total delivered energy. BP (2018) indicated that the global primary energy consumption has increased by 2.2% in 2017. As the reliance on global energy source on fossil fuel and coal are still favourable, the energy generation sector has always been one of the major contributors to global warming and climate change. Generally, the main driving forces of GM are from the external driver such as legislation, corporate image, peer pressure and tax incentive. Álvarez-Gil et al. (2007) discovered that influence from the stakeholders such as supplier, customer, government agency, non-governmental organization (NGO) and shareholder create pressure and urgency on the organisation towards GM. Government regulation also plays a crucial role in promoting and advocating the industry towards GM practises (Zhu *et al.*, 2005). In promoting the green initiative, the government has offered tax incentive for the company with green practice such as investment tax allowance (MIDA, 2019).

Government support in providing green project funding and incentive will thrust the implementation and confident of the user for GM. Besides that, the Japan government has shown strong commitment and initiatives in the green approach. Japan has initiated the Joint Crediting Mechanism (JCM) to facilitate the implementation of green technology and system in some developing countries (JCM, 2017). Figure 2-2 illustrates a collaboration model of JCM structure. In exchange, Japan will benefit from the total GHG emission reduction or removal that contributes to Japan's emission reduction target (JCM, 2017). The green technology will not only reduce environmental pollution but also helps to reduce operation cost. Green technology such as cogeneration or tri-generation is considered to increase energy generation and consumption efficiency of the facility.

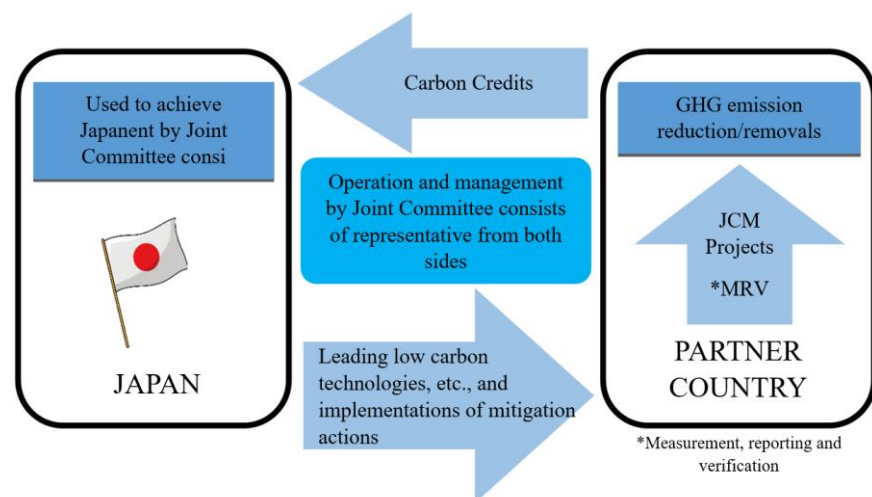


Figure 2-2: Japan's Joint Credit Mechanism Scheme (Modified from JCM, 2017)

Furthermore, Carter and Jennings (2002) discovered that customer pressure is influencing the company to invest in GM. The urge to incorporate GM management also corresponds to market pressure. A

study showed that customers are creating pressure and demand on the manufacturer for a green product (Hall, 2006). The company realised that corporate image can be improved through environmental related corporate social responsibility activity that can boost their presence in the market (Maloni and Brown, 2006).

There are many green tools and methods in assisting the company to achieve green. For instance, an ISO certified company needs to maintain the certification through continuous improvement practices. A study showed that an ISO 14001 certified companies are 40% likely to assess their suppliers' environmental performances and 50% likely require their suppliers to undertake specific environmental practices (Maloni and Brown, 2006). Some manufacturing industries are implementing the green approach in their operations without realizing.

GM approach mainly focuses on environmental pollution, manufacturing energy-efficient and waste management (Rehman and Shrivastava, 2013). Additionally, GM emphasizes the reduction of resources, energy and environmental emission of a company. Many countries around the world have put a priority on GM due to global warming. With the available technology, the government should advocate and support the industry for GM approach by offering financing and incentive aid.

2.3. Lean and Green Manufacturing

Both LM and GM approach have shown similar objectives towards minimization of non-value-added product. Both approaches form stronger synergy when applied simultaneously. The development of lean and green

(L&G) manufacturing approach has captured the industry and academics' interest since the past decade (Verrier *et al.*, 2016b).

Many research work has been done on the development of L&G application. Hines (2009) proposed to align green waste with lean waste to close the gap between L&G approach. Garza-Reyes (2015b) developed a conceptual L&G model to integrate lean, Six Sigma, and green. Garza-Reyes (2015b) also highlighted that the misunderstanding of L&G concept where “lean environment” means an environment that has already implemented a lean approach, instead of relating lean to a green environment. Verrier *et al.* (2016) proposed to incorporate lean waste and green waste together as one to further improve the operational performance.

Both LM and GM have exhibited a similar positive effect on operational and environmental performances (Galeazzo *et al.*, 2014). Hajmohammad *et al.* (2013) developed an extensive application for LM that helps organizations to incorporate rethinking capability in their processes with waste reduction in mind which can be transferable to GM.

According to Vachon and Klassen (2006), some researchers argued that LM has a positive environmental impact on environmental performance. Sawhney *et al.* (2007) discovered that factories operate with lean principles have a greater capability in reducing environmental impact. Organisations that practice LM approach demonstrated positive operation outcome towards higher efficiency and better environmental performance (Galeazzo *et al.*, 2014). Chiarini (2014) highlighted that the implementation of lean tools such as 5S, single minute exchange die (SMED) and total productive maintenance (TPM) can improve environmental performance. In Boeing, the LM program has

resulted in reduced environmental waste as process efficiency and quality improved (EPA, 2000). However, the LM study did not specifically address environmental waste as a main subject in the study. Some authors claimed that GM approach can improve production performance. According to Melnyk *et al.* (2002), GM exhibits a positive influence on the operation by creating a synergy between environmental and operation management. Jabbour *et al.* (2013) highlighted that the implementation of the environmental program (ISO14001) can positively impact the organization performance in various areas.

Generally, the L&G approach improves the efficiency and effectiveness of an operation outcome as compared to the individual approach. Dües *et al.* (2013) stated that lean is a catalyst to implement green while green may help in return to maintain a best-practice in lean. Bergmiller and Mccright (2009a) have developed a parallel L&G model where the implementation of the green approach may lead to lean effects as well. Hallam and Contreras (2016) added that L&G approach shares the same objectives in enhancing performance, product quality and time at reduced operation cost while creating values.

Dües *et al.* (2013) demonstrated the overlapping of L&G elements according to series of common attributes such as people and organization, waste reduction method, lead time reduction, supply chain relationship, key performance index (KPI) as well as common tools and practices in Figure 2-3. It is also important to note that both lean approach and green approach share common attributes, but they are defined differently. Based on Figure 2-3, it can be interpreted as lean is to maximize profit through cost reduction while green is to reduce environmental risks and impacts while improving the ecological efficiency of an organization. However, there can be a scenario where lean

practice emphasized on high resource utilization rate by frequently replenishing required item while green practice reduces replenish frequency to reduce environmental pollution. Therefore, Verrier *et al.* (2016) proposed to incorporate lean waste and green waste as a common waste for L&G approach to further enhance the symbiosis performance in the area of waste reduction.

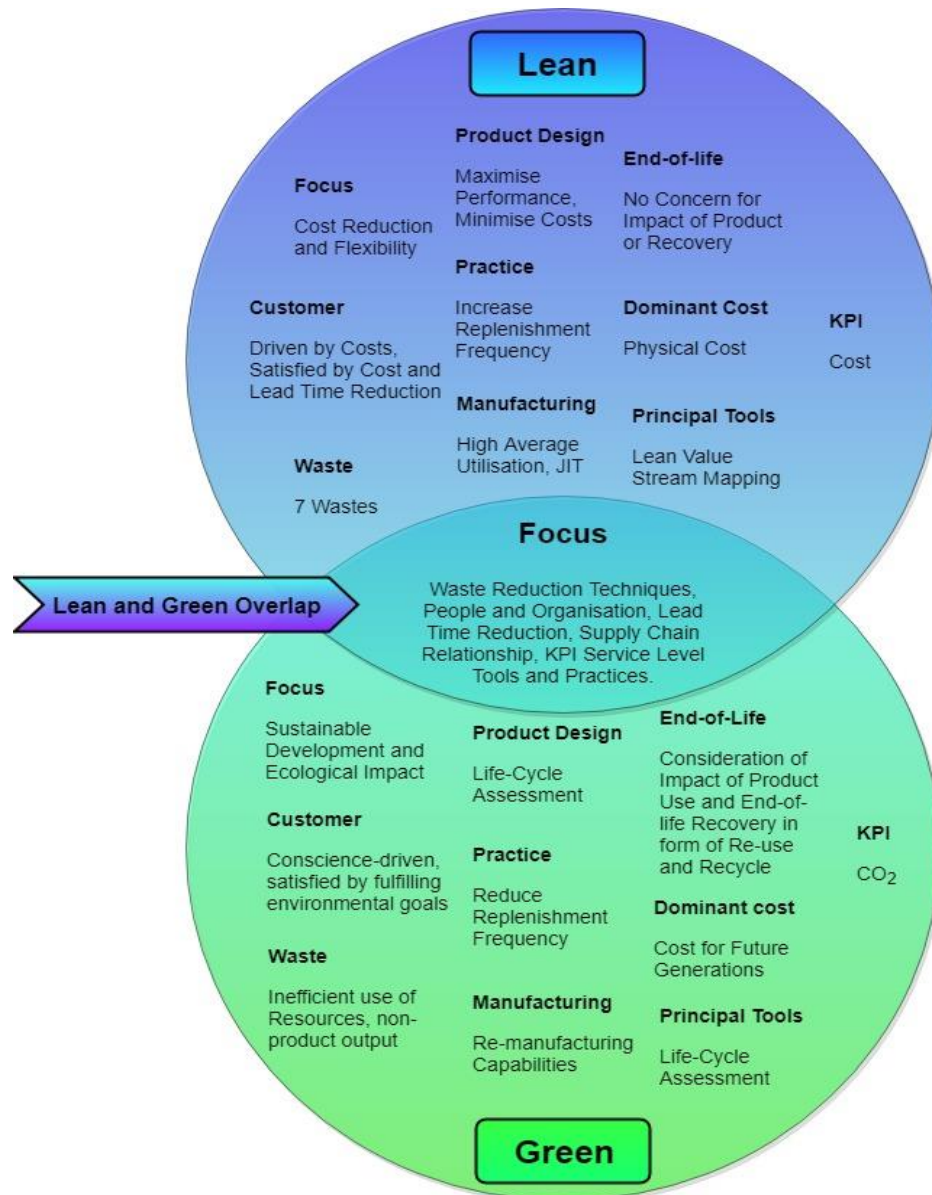


Figure 2-3: Relationship between lean and green approach (Modified from Dües *et al.*, 2013)

2.3.1. *Challenges in implementing Lean and Green Approach*

Many tools have been developed for the L&G approach but there is a lack of development on the measurement method and model for a specific process (Garza-Reyes, 2015b). Pampanelli *et al.* (2014) highlighted that there is a lack of approach to integrate L&G approach with the fundamentals principles together. Kurdve *et al.* (2014) emphasized that the lack of management responsibility and commitment in the L&G approach are the major hurdles in improving the organisation's performance. Having said that, the top-down management commitment is the key to implement L&G approach (Asif *et al.*, 2013).

The lack of L&G expert in the industry has been the challenge for the industrialist. To increase the implementation rate of L&G approach, a systematic approach should be introduced to support and allow the employee to understand the benefit of L&G. With that, Verrier *et al.* (2016b) summarised the correlation between the benefits and wastes of L&G approach for better understanding. Simon and Mason (2003) added that the L&G approach has many in common such as the way resources are consumed and focuses on maximizing waste reduction.

The synergy between L&G can impact the operation and environmental performance through effective management strategy with the proper aiding tools. The lean tools (i.e. Hoshin Kanri, Gemba, KPI, etc.) can help the organization to strategize the lean effect on the employee. In lean operation, tools such as TPM and root cause analysis

are critical to ensure smooth operation. Furthermore, the appropriate lean tools (i.e. kanban, 5S, PDCA, etc.) can be used to establish continuous improvement practice. On the green aspect, energy consumption can be easily reduced through optimisation and integration approach. An effective energy management system can reflect directly on the total operation cost reduced in the facility. Additionally, potential energy-saving opportunities can be identified through energy management. Besides that, environmental emission can be monitored and improved through operation and technology enhancement. As the manufacturing industry is driven by market demand, the need for industrialists to implement L&G approach is crucial in maintaining the operation and environmental performance during challenging times.

The implementation of L&G approach requires collaboration from all the stakeholders in the industry sector. Table 2-6 outlined the critical challenges that the industrialists are facing. To overcome the challenges, Cherrafi *et al.* (2017) emphasized the importance of providing education and training for the top management to improve their commitments and understanding for L&G. The barriers listed in Table 2-6 are evaluated by a group of experts based on a scale of “Low-Moderate-High”. The NGOs and academics can collaborate to develop workshop and internship program to promote L&G among industry practitioners and students. Besides, many industrialists are bound by fund constraint when implementing a new improvement in their facilities. The industrialist needs government support in gaining easier access to financial funding. Besides that, a proper data collection and

performance management system should be in place (Cherrafi *et al.*, 2017). This allows the organization to identify problems and evaluate the effectiveness of an action plan systematically. Cherrafi *et al.* (2017) added that recruiting a qualified and competent person to implement and improve L&G can be a challenging task too.

Table 2-6: Important barrier in implementing L&G approach (Cherrafi *et al.*, 2017)

No.	Barrier in Implementing L&G	Importance
1	Lack of environmental awareness	High
2	Fear of failure	High
3	Poor quality of human resources	High
4	Lack of expertise training and education	High
5	Fund constraints	High
6	Lack of statistical, lean and green thinking	High
7	Inappropriate identification of areas and activities to be “leaned and greened” and unreliable “data collection system”	High
8	Lack of Kaizen culture	High
9	Lack of visual and statistical control during L&G implementation	High

No.	Barrier in Implementing L&G	Importance
10	Lack of government support to integrate green practices	High
11	High cost	High
12	Lack of communication and cooperation between departments	Moderate
13	Lack of top management involvement in adopting L&G initiative	High
14	Resistance to change	High
15	Poor corporate culture separating environmental and continuous improvement decisions	High

2.4. Multi-Criteria Decision-Making Approach

In the development of L&G approach, the biases in decision making are reduced by considering both qualitative and quantitative dataset. Multi-criteria decision making (MCDM) method is a complex decision-making tool that converts quantitative and qualitative data input for decision making (Mardani *et al.*, 2015). The output of MCDM is expressed in terms of weight to represent the importance of the parameter. Teng *et al.* (2020) highlighted that the weight of the parameters is normally expressed in the range from 0 – 1. With that, a parameter with higher weight reflects a higher priority during decision making. Besides, there is also a combination of various integrations between MCDM methods such as GRA-TOPSIS and fuzzy-ANP. The combined MCDM approaches are normally used when an individual MCDM method is unable to

determine the accuracy of the performance of the alternative solution and ideal solution (Qibing and Anhua, 2010).

Generally, MCDM methods help decision-makers to analyse the relationship between prioritization of the alternatives and strength of the decision-maker. Pavan and Todeschini (2009) stated that the selection of MCDM method is highly dependent on the application. MCDM such as the analytic hierarchy process (AHP), simple additive weighting (SAW), technique for order preference by similarity to ideal solution (TOPSIS), entropy and case-based reasoning are the common tools used in decision making as illustrated in Table 2-7.

In the application of L&G approach, both expert inputs and historical data are taken into consideration to improve the organisation performance. The involvement of a human expert is important in the manufacturing sector, particularly in L&G initiative. Aniba *et al.* (2009) emphasized that the involvement of human expertise can help to reduce the complexity of the mathematical model of MCDM.

To encourage the use of MCDM tools in the industry, practical and user-friendly MCDM tools are considered. The decision-making strategy aims to combine both expert inputs combined with data-driven input to obtain a non-bias outcome. Mardani *et al.* (2015) reviewed that out of 393 application of MCDM case study, AHP is the most frequently used technique mainly due to its visual structure of hierarchy structure for decision making. The following sub-section focuses on the introduction of the AHP/ANP and GRA-TOPSIS method that will be used in utilised in the development of the L&G framework.

Table 2-7: Comparison of MCDM method

MCDM method	Pros	Cons	Application	Source
Analytic Hierarchy Process (AHP)	Easy to use, hierarchy structure can be adjusted easily, can be used on many application problems, not data-intensive	Can lead to inconsistency between judgement and ranking criteria, interdependence between criteria and alternatives can be problematic.	Policy strategy, resource management	Velasquez and Hester (2013)
Fuzzy Set Theory	Allow imprecise input, cope with insufficient information	Require numerous simulation before use	Engineering, environmental management, economics application	Zadeh (1965)

Table 2-7: Comparison of MCDM method (continue)

MCDM method	Pros	Cons	Application	Source
Case-Based Reasoning	Not data-intensive, can adapt to change in environment, can be improved over time	Sensitive to inconsistent data, requires many case study	Engineering design and business application	Daengdej <i>et al.</i> (1999)
Simple Additive Weighting (SAW)	Able to compensate among criteria, simple calculation, intuitive to decision-maker	Outcome does not always reflect real situation and outcome may not be logical	Water management, financial management	Qin <i>et al.</i> (2008)
Technique for Order Preferences by Similarity to Ideal Solution (TOPSIS)	Easy to use, simple process and make full use of allocated information	Difficult to weight and keep the consistency of judgement	Supply chain management, engineering, human resource, manufacturing system	Shih <i>et al.</i> (2007)

Table 2-7: Comparison of MCDM method (continue)

MCDM method	Pros	Cons	Application	Source
PROMETHEE	Incorporate uncertainty and fuzzy information	Depend on decision-maker to assign the weight. Complicated, users are limited to expert	Risk analysis, structural analysis	Brans and Vincke (1985)
Entropy	Highly reliable for information measurement and high accuracy in weight determination	Rely on data consistency	Material selection, process analysis	Shannon (1948)

2.4.1. *Analytic Hierarchy Process (AHP) / Analytic Network Process (ANP)*

AHP introduced by Thomas Saaty (1980), is an effective MCDM tool that is widely applied in the research arena as well as business applications over the past decades (How and Lam, 2017). The AHP analyses the issue/problem that can be structured in a hierarchy structure (i.e., top-down). It is a relative measurement that transforms both qualitative judgments as well as quantitative values into an objective measure (Ngan *et al.*, 2018). The AHP method reduces the complexity of the decision-making process by assigning weight to the performance indicators. It allows the decision-maker to model a complex problem which associates with multiple criteria and alternatives in a hierarchy structure to derive the final solution in a simple and systematic manner (Skibniewski and Chao, 2007). The mathematical simplicity of AHP allowed the method to be applied in business, engineering, health care, environmental science and various other fields. It adopts the concept of relativity to compare the element in pairs to determine its dominance relationship, which could be importance, preference, influence or dependence. The judgements of the pairwise comparison are mainly based on personal experience, expertise, situation and state of mind of the respondent (Yadav and Jayswal, 2013). This is different from most statistical tools which require significantly larger sample groups. AHP only required small sample size (i.e. 2 - 20) which have deep understanding and expertise on the subject matter (Baby, 2013). In terms of the applications in operation strategy, AHP has been adopted to evaluate fuel cell engines performance based on the properties of

different stages (i.e., steady-state, start-up, dynamic, safety) (Hou *et al.*, 2011). Govindan *et al.* (2014) applied the AHP model to evaluate and identify the key barriers for the green supply chain management. The model defined five main barriers and 47 specific barriers into a hierarchical model to study the key factors that hinder the achievement of green supply chains. In front end research, it is used to develop the systems for refurbishment building assessment scheme to prioritize factors such as energy, waste, economics, social and cultural and others for the reduction in energy consumption and carbon dioxide (CO₂) emission for building in Malaysia (Kamaruzzaman *et al.*, 2018).

On top of that, the general form of AHP known as the analytic network process (ANP) developed by Saaty (1980) to study the structural dependency of multiple criteria or level for decision making. As most real case studies do not only involve the unidirectional dependence, ANP overcomes the constraint of AHP to include inter-, inner- and feedback dependency of criteria of the problem. The supermatrix enables ANP to take in consideration of multiple relationships to propose the final criteria weights (Saaty, 2001). With the ANP approach, human expertise and experience which hardly can be quantified can be evaluated, prioritized and selected for process improvement.

2.4.2. Entropy

The entropy concept was first introduced by Rudolph Clausius in 1865 to measure the thermodynamics of the unavailability of a system's

energy by measuring the disorder (Daub, 1970). The concept of information entropy was first introduced by Shannon (1948) to measure the uncertainty in information formulated in terms of probability theory. Entropy method can measure the amount of useful information with the given dataset (Işık and Adalı, 2017). The smaller the indicator's entropy, the higher the entropy weight which reflects the indicator provides more useful information and impactful for decision making (Cui *et al.*, 2009). The application of entropy was used widely in many applications such as finance (Zhou *et al.*, 2013), engineering (Marvizadeh, 2013) and the economy.

The combination of ANP and entropy approach has been used utilised in many areas. As ANP collects subjective inputs from a human expert, the weight of the indicators can have bias. The biases of ANP will be compensated by the entropy method where the weight of the indicators is data-dependent. Many researchers have applied the combination of ANP and entropy in their work such as supply chain management (Liu *et al.*, 2018), investment risk management (Yuan *et al.*, 2019), policymaking in renewable energy (Yang *et al.*, 2018), production management (Mei *et al.*, 2016), etc. The combination of ANP and entropy will be demonstrated in Section 7.2.

2.4.3. GRA-TOPSIS

Grey relational analysis (GRA) has been used to address complex problems that contain incomplete information and convoluted interrelationship between a given list of criteria (Eraslan and Çağman, 2017). It is one of the most widely used grey system theory (Ju-Long,

1982), which have extended its utility to various fields such as the manufacturing industry (Kumari *et al.*, 2018), logistics companies (Lee, Lin and Shin, 2012), food security (Lin *et al.*, 2019), etc.

The technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is one of the well-established MCDM approaches to select the best options, based on a given list of criteria set. The earliest application of TOPSIS started in the early 1980s (Hwang and Yoon, 1981). Generally, TOPSIS ranks the alternatives based on its geometric distance from positive-ideal solution (PIS) (i.e. the solution that has the best performance of given criteria) and negative-ideal solution (NIS) (i.e. the solution that has the worst performance of given criteria) (Hwang, Lai and Liu, 1993). In short, the option that has the shortest geometric distance from PIS and the longest geometric distance to the NIS, is considered as the best alternative.

Recently, the integration between GRA and TOPSIS (or GRA-based TOPSIS) have been proposed to overcome the accuracy issues on the approximation of the geometric relationship between a given solution to the respective PIS and NIS (Qibing and Anhua, 2010). This hybrid method has been proposed by researchers to address various complex process system engineering (PSE) problems such as supplier selection challenges in supply chain management (Peng and Wang, 2011), equipment and process selections (Wang *et al.*, 2016), process debottlenecking (Teng *et al.*, 2020), etc.

2.5. Adaptive Analytical Approach

With the development of IR4.0, the industrialists need to continuously improve their adaptability on global economic change. The adaptability of an organisation can be enhanced with the application of machine learning (ML). The application of ML has been extended into various areas such as image recognition (Joutou and Yanai, 2009), speech recognition (Graves, Mohamed and Hinton, 2013), supply chain management (Carbonneau *et al.*, 2008), techno-economic of biogas plant (Vondra *et al.*, 2019), thermal degradation optimisation of microalgae (Teng *et al.*, 2019) and maintenance management (Arcos Jiménez *et al.*, 2020).

The adaptability of the industry in IR4.0 requires the integration of the ML approach with human interaction. Ansari and Seidenberg (2016) highlighted that the human and machine should collaborate interactively through ‘mutual learning’. Mutual learning interaction can achieve vast improvement. However, it is noted that the capability between human and ML can have huge variance based on operation performance. Table 2-8 highlights the difference between human and ML.

Table 2-8: Capacity comparison between human and machine learning

Criteria	Human	Machine learning
Cost	Human cost is highly dependant on the employee’s qualifications, experience and expertise.	High investment cost, servicing cost and upgrading of computational parts

	This is a fixed expense for all organisation	(Ansari and Seidenberg, 2016).
Flexibility on task	Human flexibility is dependant on skills, experience and competency to perform a specific task. Physical and mental limitation. Humans are normally assigned with a fix working hours or shift.	ML's flexibility is highly dependant on the advancement of algorithms and model (Boelaert and Ollion, 2018). ML model can operate 24 hours a day (Ma and Zhai, 2019).
Data processing capability	Due to physical and mental limitation, human's data processing capability can cause (Bhatnagar, 2018): • Time-consuming in the data processing • Unreliable in information storage and retrieval • Inconsistent error detection and correction.	The computation advantages of ML can optimise data processing as below (Qiu <i>et al.</i>, 2016): • Efficient in data processing and storage with minimum time. • Reliable in large scale data storage • Consistent in error detection and correction.
Problem-solving	Good in solving an ill-structured problem. Can	Able to learn and formalise the troubleshooting process.

	deal with the ad-hoc condition. Establish a collaborative partnership to overcome problems if the problem is too critical.	Detect and recommend a solution based on repeated problems. Establish predictive action on standard problems based on continuous monitoring.
Performance variation	Dependant on the employee's qualifications, experience and expertise. Decision making highly depends on individual experience, qualifications, problem-solving ability and competency.	Performance variance is minimum. Decision making highly depends on data quality. However, the system performance can be improved by training the system with larger datasets.

Table 2-8 also illustrated several critical points of implementation of IR4.0 such as cost, performance flexibility, data processing and ability of problem-solving. Weichert *et al.* (2019) added that the ML approach is highly depending on the availability of large dataset. The techniques used in ML such as deep-learning can perform process optimisation efficiently with big-data. Therefore, the traditional process improvement approach can be improved by incorporating ML elements to increase the efficiency of process improvement. The advancement of IR4.0 and technology have also created a big gap between the well-established company and the SME. Safar *et al.* (2018) highlighted that many SME is challenged with limited resources (i.e. financial support and

incentive) to benefit from IR4.0. However, the SME needs to strengthen the adaptability for IR4.0. Despite the limitation of resources, the SME should take the initiative to enhance their adaptivity for IR4.0 in improving their production advantages. As data is one of the main pillars in IR4.0, the SME can utilize the data obtained within their organisation to improve their operational performance (Miragliotta *et al.*, 2018).

2.5.1. *Backpropagation method*

In ML, the backpropagation (BP) method is an optimisation algorithm that is developed based on the reverse mode of differentiation (Griewank, 2012). This method was then popularized with the application in the neural network to learn representation (Rumelhart *et al.*, 1986). The formulation and utilisation of BP in the network framework has been demonstrated by Lecun (1988). Gori and Maggini (1996) have illustrated the BP application in achieving optimal convergence. Generally, BP specifies a loss function and modify the weights iteratively according to the gradient of the loss function. The neural network consists of at least 3 layers of units namely input layer, at least 1 layer of hidden layer and output layer (Figure 2-4). The feed-forward step produces the output by processing the operation input data from input later passing through the hidden layer from the structure. The error between the feedforward outcome and the desired output will be backpropagated through the network to adjust the weight of each neuron (elements) in the layers to achieve the desired output. As BP is a

supervised learning algorithm, the desired output or expected outcome are specified as part of the network training (Solanki, 2012).

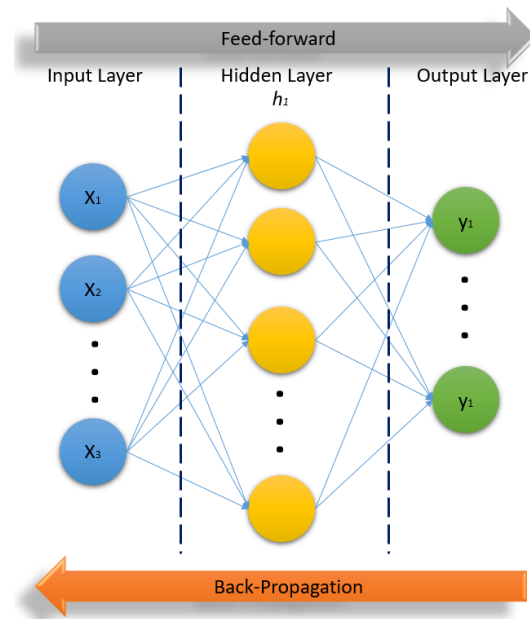


Figure 2-4: Simple neural network

The update function of BP in a neural network is implemented into the analytical model as shown in Figure 2-5. It is important to note that the response of human expert in process improvement is not as fast as the application in a neural network. The adaptive model is initiated with the human expert input followed by the BP approach to optimise the process. Therefore, the features (performance indicators) in the adaptive model need to be selected carefully. Comparing with the neural network, the time step used in the analytical model can vary from 1 week up to 1 month depending on the operation condition of the facility. This is highly influenced by the rate of collectable data.

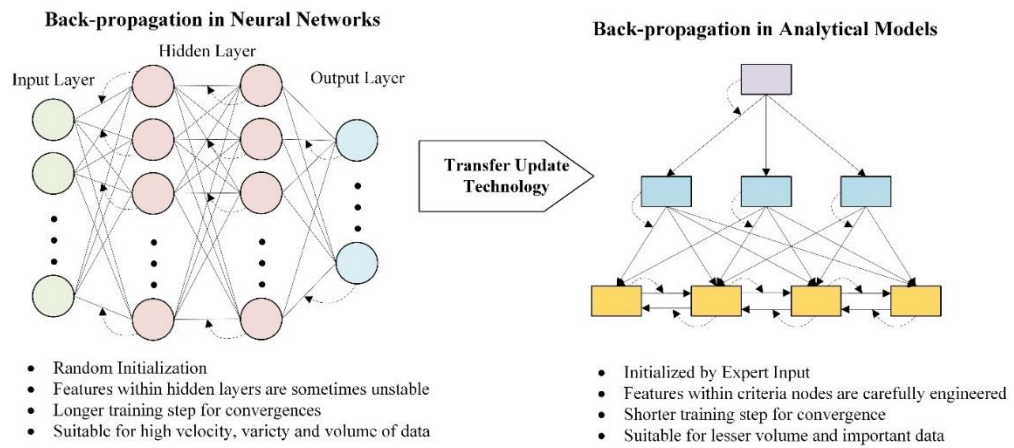


Figure 2-5: Terminology of backpropagation in adaptive analytical approach

By considering the limitation of the resources that the SME is experiencing, the adaptive model with BP can be a powerful tool to optimise the organisation performance based on existing operating conditions and the available data. This model can improve the organisation's performance according to its target.

2.6. De-bottlenecking strategy

Operation debottlenecking methods are derived from the root of process system design (Teng *et al.*, 2020). Generally, the heuristic approach to process synthesis is derived from the Onion model (Linnhoff and Boland, 1982) and the hierarchy of decision (Douglas, 1985). The Onion diagram proposed by Linnhoff *et al.* (1982) was then modified by Smith and Linnhoff (1988) for different processes. The hierarchy of decision mainly considered the mode and type of the processing system following by the heat exchanger network (Douglas, 1985).

The debottlenecking strategy has been demonstrated in many literatures. Litzen and Bravo (1999) proposed a stair-step chart to identify the capacity of major equipment that needs to be debottlenecked. For instance, Tan, Andiappan

and Wan (2018) utilized an inoperability input-output model for the debottlenecking of the palm oil milling process. Koulouris, Calandranis and Petrides (2000) developed a throughput analysis and debottlenecking of a batch chemical process via process simulator (i.e., SuperPro Designer software). Tan *et al.* (2006) demonstrate the debottlenecking strategy for a batch pharmaceutical product with a computer-aided process design method. More recently, Besides, with the aid of the P-graph Studio software, How *et al.* (2018) include both the analytical hierarchy process (AHP) and waste reduction (WAR) algorithm for debottlenecking purposes.

In general, most of the research works consider single criterion during the debottlenecking process. For example, Liang, Kang and Liu (2016) had developed a debottleneck framework to illustrate an optimal hydrogen network to minimise the total annual cost. Andiappan, Ng and Tan (2017) developed a heuristic framework for retrofitting existing plant. However, the benefit-cost ratio was used as a sole indicator to justify the feasibility of the debottlenecking. Many researchers focused on the debottlenecking at conceptual design phase instead of on the retrofit condition. For instance, Heitmann, Schembecker and Bramsiepe (2017) developed a design framework for the early stages of plant design while Kasivisvanathan *et al.* (2014) proposed a step-by-step framework to identify bottlenecks of an integrated biorefinery plant. Besides, none of these works has covered the project scheduling and payback period which the debottlenecking activities.

Litzen and Bravo (1999) stated that the capacity debottlenecking is identified when the input capacity of an operating unit has reached its maximum

design capacity. This is known as a “bottleneck” within the process. The bottleneck can be resolved by replacing the unit, modifying the design, installing additional units and other retrofit techniques (Van Duc Long and Lee, 2011). By further increasing the overall capacity, another unit becomes the new bottleneck in the process. This process continuously repeats until essentially all the equipment within the facility has been replaced. This is equivalent to building a new facility, which is highly illogical for debottlenecking as building a new facility could potentially cost much lesser. Therefore, it is critical to plan what is the stopping point of the debottlenecking process.

2.6.1. *Integration of machine learning approach*

The ML relies on the backbone of neural networks to extract complex Big Data representation at a high-level of abstraction (Najafabadi *et al.*, 2015). Abiodun *et al.* (2018) highlighted the application of neural network areas including pattern classification, language processing, complex system modelling, optimisation, and prediction. Having said that, a huge amount of data is required to obtain higher accuracy in the data-analytical process. Lenz *et al.* (2018) applied a data-driven method in a smart manufacturing system focusing on cost optimisation for predictive maintenance system. Vondra *et al.* (2019) emphasized that data-driven methods can identify the techno-economic study of biogas plants more effectively. Teng *et al.* (2019b) extended the data-driven application in optimising thermal degradation of microalgae. Fast and Palmé (2010) highlighted that the application of neural network models in CHP plants can produce highly accurate predictions for condition monitoring and diagnosis.

The Bottleneck Tree Analysis (BOTA) was first proposed by Teng et al. (2020) for process capacity debottlenecking. The concept of the novel debottlenecking method emphasized the long-term sustainability instead of short-term goals (i.e. increase profit). The BOTA model decouples the problem using a graphical matrix and tree approach to achieve 3 objectives. Firstly, BOTA identifies multiple bottlenecks within multiple areas with varying operating capacities. Then, followed by evaluating long-term sustainability benefits and identify a pathway to achieve the most beneficial condition. Lastly, it identifies the most economically feasible schedule for the most beneficial condition.

From a process debottlenecking perspective, the major KPI that can be applied are money, material, machine and environment which reflected as economic, environment and operation. Dües et al. (2013) highlighted that financial indicator should include return on investment (ROI) or payback period (PP). When making decisions for equipment replacement, the consideration should be emphasized on product defects, quality and production capacity which relates to poor production output (Sullivan, McDonald and Van Aken, 2002). Teng et al. (2019) also highlighted the importance of considering product yield and quality for a continuous chemical process. In the batch manufacturing process, the average utilization factor of machine tools using operation time as a basis was used to reflect the effectiveness of operation (Metternich, Bechtloff and Seifermann, 2013). As for continuous processes, Ray (2015) suggested the measurement of utilization factor in terms of

production capacity. This approach of maximal capacity utilization is also implemented in Sony, Oita where equipment is constantly fully utilized and equipment investment is performed when required (De Haan, Yamamoto and Lovink, 2001).

The ensemble of a neural network is a set of multiple individual neural networks being trained to provide a combined prediction power based on either accuracy or diversity (Hansen and Salamon, 1990). Brown et al. (2005) highlighted that mathematical evidence has shown that model prediction accuracy can be improved in ensemble models by distributing the errors of the full input space into multiple individual base models.

By incorporating data-driven methods in the debottlenecking strategy, the best debottlenecking pathway can be identified effectively.

2.7. Research Gap

Due to the global economic fluctuation, many industrialists have shown lack of interest in investing in new technology. This has created a competition gap between the cash-rich organisation and the SME. Besides, the literature review has also reflected the lack of a systematic model in implementing the L&G approach. Therefore, this research focuses in developing a data-driven adaptive model to guide the industrialists towards L&G manufacturing for continuous improvement. Additionally, a data-driven debottlenecking strategy is also developed to identify the best de-bottlenecking path with the consideration of environment, commercial and operational constraints. By addressing these gaps,

the industrialist can enhance its competitiveness in the global market with proper operation planning with L&G approach.

2.8. Summary

This thesis will address the research gap in Section 2.6 by developing the adaptive analytic L&G model. The development of the adaptive model will be further explained in this thesis as below:

- Chapter 3 will highlight the research strategy and methodology in approaching the research gap.
- Chapter 4 focuses on the development of lean and green index (LGI) which acts as the benchmarking and continuous improvement indicator for the adaptive model.
- Chapter 5 highlights the detailed development of L&G framework. A case study will be presented to illustrate the application of L&G framework.
- Chapter 6 covers the development of adaptive L&G model. A case study will be demonstrated the functionality of the adaptive model.
- Chapter 7 further enhance the adaptive L&G model into an ensemble model that response more effectively. A case study will be illustrated the usage of enhance adaptive L&G model.
- Chapter 8 emphasized on the development of an enhanced de-bottlenecking model with debottlenecking lean and green index (DLGI) for L&G framework. A case study is used to reflect the performance of the de-bottlenecking model.
- Chapter 9 ends the thesis by highlighting the current research limitation and potential future works that can be improved.

Chapter 3: Research Strategy and Methodology

3.1. Introduction

Chapter 3 highlights the research strategy and methodology that is acquired in this research. This section covers the “cradle to grave” approach in the development of the adaptive L&G framework. This section summarises the contribution and novelty of each chapter that leads to the development of the adaptive L&G model.

3.2. Research Strategy and Methodology

This chapter encompasses the research strategy implemented in this research. The development of IR4.0 has created an implementation gap where many industrialists still rely heavily on manpower resource for daily production due to the high investment cost and lack of talent. The motivation of this research is to develop an adaptive (self-evaluation) L&G framework to improve both operation and environment performance. The state-of-the-art L&G framework incorporate machine learning method to execute a self-evaluation step for process improvement as a steppingstone for an organisation to transit towards IR4.0. The state-of-the-art L&G framework considers both human expert input and operation data for continuous process improvement and process de-bottlenecking to enhance the operation and environmental performance. Besides, industry collaborators are invited to contribute to the development of L&G framework through the identification of critical operation parameter, industry concerns and challenges, L&G framework implementation, and data validation.

Figure 3-1 demonstrates the adaptive L&G framework developed in this research work. Each chapter focuses on the development of a critical aspect of the adaptive L&G framework.

Chapter 4 focuses on the development of lean and green index (LGI). This chapter highlights the purpose of the development of LGI in L&G approach as a benchmarking and performance monitoring tool. Chapter 4 also illustrates the novelty and contribution of the L&G checklist and LGI which is the core of the L&G framework. The fundamentals of the L&G checklist established on 5 main factors including manpower, money, material, machine and environment. The 5 factors provide a comprehensive coverage on both L&G elements. On top of that, the recommended modification of L&G checklist for different industry application has also been highlighted.

Chapter 5 highlights the development of L&G framework. This chapter illustrates the effectiveness of L&G framework in laying out a systematic implementation path for an industrialist to optimise operational performance. The L&G framework layout a step by step procedure to guide the industrialist to carry out L&G approach. The framework provides a comprehensive approach in improving the facility performance by considering both quantitative and qualitative data obtained within the facility. The quantitative data includes operation data obtained from the facility while the qualitative data consists of input obtained from the employees or experts.

In Chapter 6, the adaptive analytical approach is introduced. The workflow of the adaptive analytical approach is developed to illustrate the capability of the approach in coping with dynamic industry problems. The adaptive analytic

model intends to perform process optimisation based on a dynamic condition. The adaptive model is developed based on the gradient descent approach which is implemented in a machine learning model. The adaptive model can react to a dynamic situation with respect with time for industry application. Thus, chapter 6 illustrate the outcome of the adaptive analytical model in continuous process improvement.

Moving on to Chapter 7, as the case study becomes more complex, the relationship between each component becomes more complicated. Therefore, the ensemble solver is developed to cope with higher complexity system. The ensemble solvers consist of several gradient descent optimisers (i.e., ADAM, Adagrad and stochastic gradient descent) that always select the best possible optimisation option to cope with industry challenges. The consideration of ensemble solvers includes the dynamic changes in operation behaviour, fluctuation in product demand and supply chain as well as environmental impact. Besides that, the analytic network process (ANP) has also been incorporated into the ensemble solver for complex decision-making approach. Chapter 7 distinct from Chapter 6 with the capability of solving higher complexity challenges with more sophisticated decision-making network.

Lastly, chapter 8 outlined the de-bottlenecking strategy. This chapter highlights the ensemble solver for de-bottlenecking strategy. As the progress towards the bottleneck of a facility is highly dependent on the expansion and development of the facility's output, a series of optimised debottleneck pathway should be established to allow the industrialist to react to dynamic global fluctuation. This enables the industrialist to have several de-bottlenecking pathways based on the existing operation and financial challenges of the facility. The ensemble solver

is developed based on neural network model where several activation functions such as sigmoid, linear and exponential function to simulate the function of the human brain in analysing the condition. As the model is developed, only the top 5 solutions are taken into consideration as the top de-bottlenecking pathway for the facility. The ensemble solver is designed to accommodate the critical operating parameters and components to perform bottlenecking analysis by considering the return of investment, environmental and operation benefits and capability of the organisation.

3.3. Conclusion

Section 3.2 highlighted the development and application of the adaptive L&G model. The detailed development of the adaptive L&G model will be illustrated in the respective chapters. A case study will be presented in each chapter to demonstrate the application of the model. The industrialists shall be able to implement and benefit from the adaptive L&G model by referring to the methodology in each chapter.

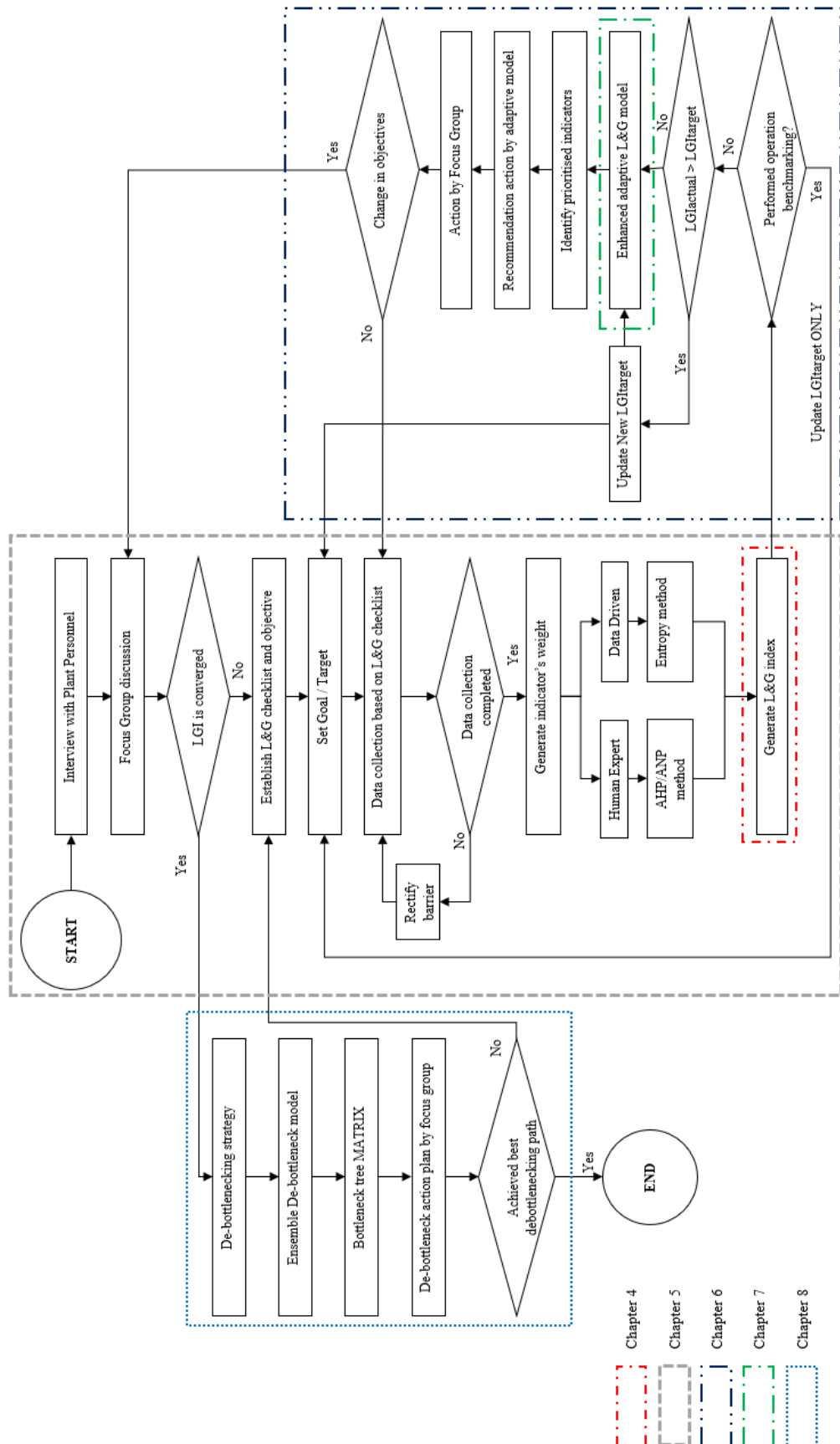


Figure 3-1: Enhanced adaptive lean and green framework

Chapter 4: Development of Lean and Green Index

4.1. Introduction

Based on the literature review in Section 2.3.1, the need to develop a systematic framework and analytic model is essential to enhance continuous process improvement. Before introducing the lean and green (L&G) framework (Chapter 5), an evaluation tool is required to monitor the progress of process improvement. Therefore, the lean and green index (LGI) is developed as the improvement benchmarking and process improvement monitoring tool. The benchmarking approach is a systematic assessment method to evaluate the performance of an organisation (Mangul *et al.*, 2019). In this chapter, the intention and development of LGI will be explained.

4.2. Basis of Lean and Green Index

This chapter focuses on the development of LGI with the consideration of both operational and environmental elements. The literature has reflected that the 5M model can be designed based on industries. For instance, 5Ms are known as manpower, money, material, machine and method in the management context (5ME, 2019). Septiawan and Beki (2016) highlighted that 5Ms is known as method, machine, material, measurement and manpower from a project management perspective. On the other hand, Knop and Mielczarek (2018) categorised 5Ms as material, method, machine, manpower and management in the visual inspection process. Liliana (2016) also demonstrated the use of 4M, 5M, 6M and 7M (i.e. machines, methods, manpower, materials, maintenance, mother nature – environment and management) using Ishikawa diagram. To

establish a sustainable benchmark and performance indicator, the element used to develop the LGI shall include both operation and environmental factor.

To ease the industrialist implementation and understanding, only the essential elements associate with operational and environmental aspect are selected for LGI. From an interview, the industrialist had feedbacked that the element of 5M should include the sustainability elements such as social, environmental and economic (Rajesh, personal communication, February 5, 2019). The selection of the 5M elements is based on the discussion output with the industry professionals from glove manufacturing, palm oil refinery, energy sector and chemical processing plant. The discussion output reflects the 5M representation into 5 main indicators such as manpower (MP), machine (MC), material (MT), money (MY) and environment (EV), also known as 4M1E.

4.2.1. Manpower

Manpower (MP) or talent is the backbone of any organisation. To strengthen the organisation's performance, a dedicated talent pool shall be nurtured. An organisation needs to consistently realign its human resource strategy with the fast-changing environment (Nasir, 2017). The continuous development of MP will not only improve their competitiveness but also prepare them to strive for innovation (Leong et al., 2018). However, Kar (2018) highlighted that the manufacturing workforce is shrinking due to the misconception by younger generations (i.e. lack of competitive wages, innovation, incompetence in safety). To overcome the challenges, the management commitment in establishing company policy to enhance safety and production performances is critical (Fairris and Tohyama, 2002). For the case of personnel safety,

the sugar industry in India has demonstrated effective management system to improve personnel safety based on training, competence and reporting (Sasidhar, Nandan and Sharma, 2015). Oedewald et al. (2015) highlighted that the implementation of safety culture has to undergo a proper assessment to prove the employee's competency under strict management procedures. Not to forget that unequal power-sharing among employee can cause deterioration in L&G approach especially within the same hierarchy (Sim et al., 2015). Thus, the MP indicator is used to reflect the MP performance with the consideration including a total number of employees, key performance index, competency rate, safety indicator and time management of the employee.

4.2.2. *Machine*

In the manufacturing context, machine (MC) is the core equipment that processes raw material to a final product. Roosevelt (2011) highlighted that technology advancement in machinery has led an extensive growth in production capacity and efficiency. This reflects the importance of machinery in a processing facility. Schmidt (2000) reviewed the importance and challenges of dealing with machine availability within processing facilities. Equipment and system performance efficiency are critical as it directly affects the commercial value of the product (Braglia, Frosolini and Zammori, 2008). These performance efficiencies can be improved using effective metrics and simulation analysis (Huang *et al.*, 2003). Another sub-indicator of MC is the quality of production. Ghosh (2014) has shown that quality control has been critical for the

manufacturing of cement products. For the case of oil refineries, Teng et al. (2019) demonstrated the simultaneous improvement of product quality efficiency and machine performance efficiency using novel machine learning methodologies, highlighting the importance of product quality with respect to solely throughput improvements.

The availability efficiency, performance efficiency and quality efficiency are the factors used to monitor the performance of MC which also reflected as the overall equipment effectiveness (OEE) (Singh *et al.*, 2013). The OEE is widely used to improve the machinery performance through minimizing breakdown, increase performance and quality of the product (Patel and Deshpande, 2016). The availability efficiency of the MC indicates the actual operation time of the production by monitoring equipment failure, and setup and adjustment time. As for performance efficiency, it indicates the production efficiency of the MC through idling and minor stoppage and reduced speed time. The quality efficiency shows the amount of defect that is being produced by monitoring defects in process and defects. This terminology is specifically used for LM, such as in the works of Gibbons (2006), where the study relates to OEE which consists of aspects such as equipment efficiency, downtime efficiency, performance efficiency.

4.2.3. *Material*

Material (MT) reflects on the number of resources that are being consumed and produced in the manufacturing process. The emphasize on responsible consumption and production from the SDG goal has

encouraged the industrialist to evaluate the production supply chain more critically (SDG, 2019). The SDG initiative has encouraged the industrialists to take consideration on recycling of production defects. On top of that, MT also associated with the material flow in and out of the process where total input, output, defects and recyclable units are considered. The inventory of MT is critical to ensure that the storage area is being utilized efficiently. Touš et al. (2015) demonstrated that variations in materials can be problematic in waste-to-energy industries then proposed a novel stochastic planning method to deal with the problem. Owen (2002) discussed the causes and challenges of material defects that can be detrimental in manufacturing facilities. In many conditions, the inventory needs to be continuously reviewed for stocks level and replenish when the stock level reaches the order limit (Silver, Peterson and Pyke., 1998). Chan et al. (2017) highlighted that many industrialists encounter challenges such as overproduction, out of stock and discrepancy of records with bad inventory management.

4.2.4. *Money*

The fourth indicator is known as money (MY). Christodoulou and Mcleay (2014) stated that the fundamental tools for evaluating a facility value is MY. Chong and Wong (2015) added that there are large literature interest on the effect of exchange rate arrangement on global trades. In many countries, the industrialists are often challenged financially in the global market due to the fluctuation of monetary policy. As the global monetary fluctuation is inevitable and

uncontrollable, industrialists are taking more pragmatic approach through in-house management. Research has shown that the average manufacturing facilities accumulate approximately 800 hours of downtime per annum (Daisyme, 2018). This highlights the huge self-improve gap that the organisation can improve within the battery limit of the operation. This is substantial as the sustainability of a manufacturing facility relies on a healthy balance sheet to maintain the human resource, operation, material and waste treatment expenses.

4.2.5. *Environment*

Moving on, the environment (EV) is the last indicator in the LGI where the global warming potential (GWP) is measured as the sub-indicator. The wastes are classified into three categories such as solid, water and air waste (Amasuomo and Baird, 2016). With the manufacturing sector being one of the main consumers in energy, effective energy management practice should be reviewed frequently. The GWP of energy generation can be reflected indirectly on the industrialist. Many industrialists focus on energy conservation and efficiency but neglect the environmental impact resulting from energy generation. Generally, IEA (2018) stated the average carbon intensity in electricity generation is around 475g CO₂/kWh of energy generation. Besides, the industrialist needs to be efficient and caution on water consumption behaviour to reduce the environmental impact and converse the sustainability of water supply (Ong *et al.*, 2015). Ng *et al.* (2014) added that environmental impact can be reduced with proper management and

reduction in the production of solid waste. Hong et al. (2016) emphasized on the importance of management commitment addressing environmental impacts challenges in the biomass industry.

Besides that, another emission such as air, solid and water waste should be treated according to environmental regulation before discharging into the environment. As the industry market continuous to spurs, the industrialists shall reduce and control excessive greenhouse gasses (GHG) emission into the environment.

The fundamental indicators (4M1E) have been discovered with the input from the literature review and industry input. These 5 main indicators will form the foundation for the formation of LGI. Figure 4-1 illustrates the information flow to form the LGI.

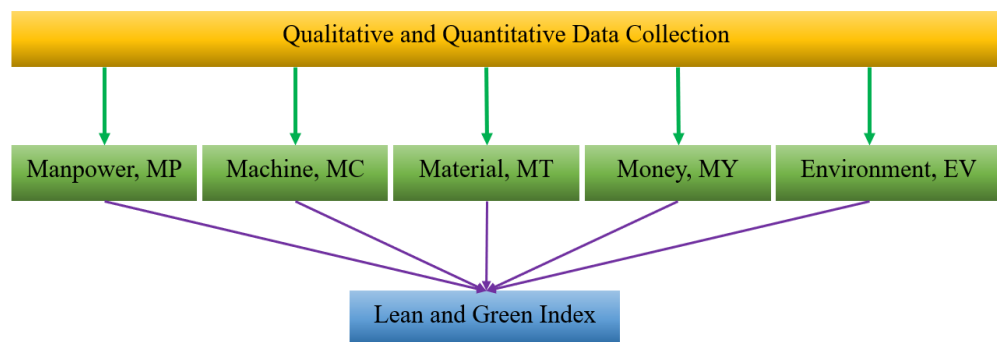


Figure 4-1: Information structure of lean and green (LGI)

4.3. Development of Lean and Green Index

The lean and green index (LGI) is developed to benchmark and evaluate operational performance. Based on the literature review, there are several indexes related to L&G have been developed by the researchers. Almeida (2014) developed lean index and green index to evaluate the company's

operation performance. In this chapter, the LGI is developed based on the elements of 4M1E (manpower, machine, material, money and environment) indicators. The L&G checklist will be discussed in the next section on the data required to be collected for LGI.

4.3.1. Lean and green checklist

Data collection and input from industry expert are critical in establishing the appropriate priorities for the specific industry. The L&G checklist demonstrated in Figure 4-2 serves as a generic checklist that comprises the analysis structure for the performance indicators for any processing facility. Additional indicators can be added into the general guideline of L&G checklist based on the industry sector as the sub-indicators can varies between industry sector.

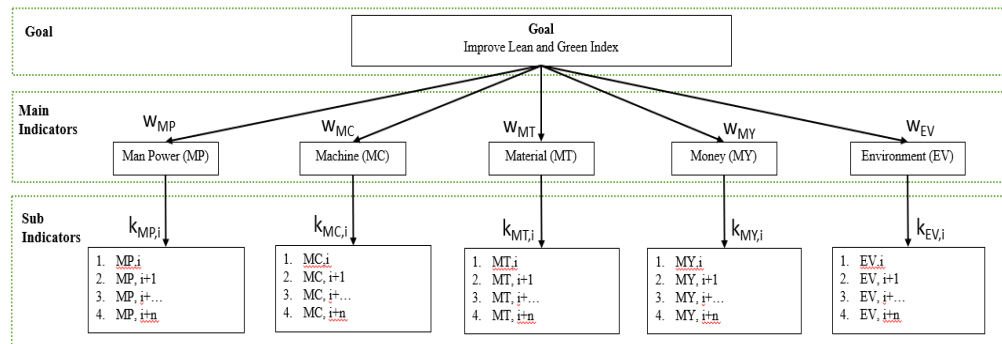


Figure 4-2: General guideline in L&G checklist and analysis

Figure 4-3 is developed through collaboration with industry expert and operators from palm oil refineries, glove manufacturing plant and power plant with the generic performance indicators.

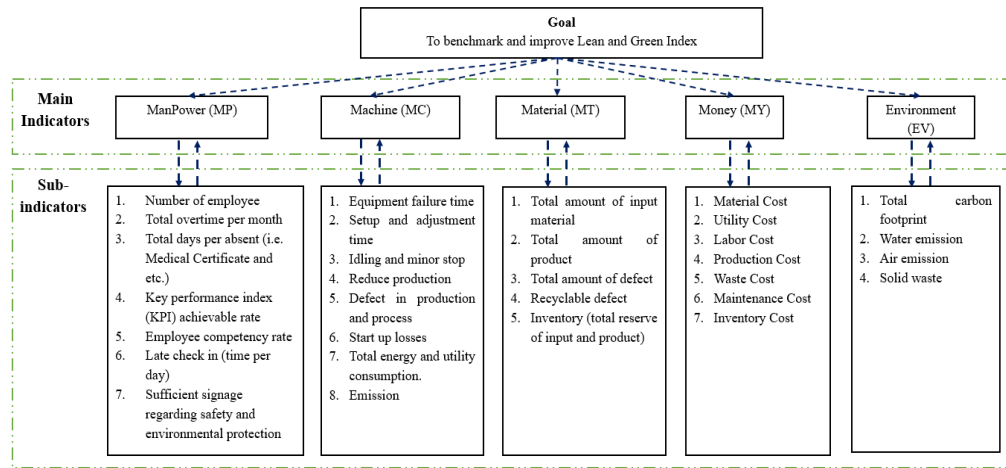


Figure 4-3: General conceptual lean and green checklist

With that, the L&G checklist can be extended into different industry sector by applying simple modification on the checklist based on operation requirement. Information or operation data that is deemed to be significant to the operation performance can be included under the appropriate 4M1E indicators. On top of that, non-related information can be removed from the checklist depending on the nature of the sector. For example, if the L&G checklist illustrated in Figure 4-3 is applied in a combine heat and power (CHP) plant. The CHP does not produce any solid waste from the process. Thus, the solid waste sub-indicator can be removed from the checklist.

As reflected in Figure 4-3, the information and data collected from the L&G checklist will be translated into LGI for performance benchmarking or monitoring purposes. Thus, the priority of indicators varies with the industry sector. The priority of the indicators will be evaluated with the multi-criteria decision-making tools (MCDM) that will be explained in detail in Chapter 5.3.

The LGI can be a benchmarking and monitoring tool for the manufacturing sector. LGI is contributed by 4M1E index in Eqn. 4-1. The w_{MP} , w_{MT} , w_{MC} , w_{MY} and w_{EV} represents the weights of the 5 main indicators obtained from L&G checklist through multi-criteria decision-making method (MCDM) (Figure 4-2). The MCDM methods will be discussed in Section 5.3.

$$LGI = w_{MP} \times MP + w_{MT} \times MT + w_{MC} \times MC + w_{MY} \times MY + w_{EV} \times EV \quad (4-1)$$

4.3.2. Manpower index, MP

In the manufacturing sector, manpower (MP) is the most valuable asset to any organisation. To implement the L&G approach successfully, the employee's attitude and ability to perform a specific task can be the key to better operation output. In an interview conducted on 20 January 2019, Cheng stated that an outstanding employee is a competent employee who is committed (maximum attendance rate) to fulfil his responsibility (i.e. KPI). The competency of an employee can be evaluated through a practical and theoretical test to ensure that the employee is competent in performing its duty. For instance, an employee must also be updated with the latest safety regulation within the manufacturing premises. This can be done through a short quiz after safety training to ensure the employee understands the safety response. Referring to Figure 4-2, the calculation for the sub-indicators for MP are illustrated (Eqn. 4-2 to 4-14) as below:

Total average overtime per employee per year, MP_{OTn} (hr/year)

Average OT per employee, $MP_{OTn} =$

$$\frac{\text{Total employee over time yearly}}{\text{Average number of employee working yearly}} \quad (4-2)$$

Normalise the indicator by comparing with total operation hours yearly:

$$\text{Total average overtime, } MP_{OT} = \frac{hr_{opt,year} - MP_{OTn}}{hr_{opt,year}} \quad (4-3)$$

Total absent day per employee per year, MP_{AB} (day/year)

Average total absent day, $MP_{ABn} =$

$$\frac{\text{Total employee absent day yearly}}{\text{Average number of employee working yearly}} \quad (4-4)$$

Normalise the indicator by comparing with total operation hours yearly:

$$\text{Total average absent day, } MP_{AB} = \frac{hr_{opt,year} - MP_{ABn}}{hr_{opt,year}} \quad (4-5)$$

Average KPI achievable per employee per year, MP_{KPI} (%/year)

Average KPI achievable, $MP_{KPI n} =$

$$\frac{\text{Total employee KPI achievable yearly}}{\text{Average number of employee working yearly}} \quad (4-6)$$

Normalise the indicator by 100 % achievable:

$$\text{Total average KPI achievable, } MP_{KPI} = \frac{MP_{KPI n}}{100} \quad (4-7)$$

Average employee competency rate per employee per year, MP_{CR} (%/year)

Average competency rate, $MP_{CRn} =$

$$\frac{\text{Total employee competency rate yearly}}{\text{Average number of employee working yearly}} \quad (4-8)$$

Normalise the indicator relative to the full rate:

$$\text{Total average achievable, } MP_{CR} = \frac{MP_{CRn}}{100} \quad (4-9)$$

Late check-in time per employee per year, MP_{LT} (hr/year)

Average late checkin time, MP_{LTn} =

$$\frac{\text{Total employee late check in time yearly}}{\text{Average number of employee working yearly}} \quad (4-10)$$

Normalise the indicator by comparing with total operation hours per annum:

$$\text{Total average late check in, } MP_{LT} = \frac{hr_{opt.year} - MP_{LTn}}{hr_{opt.year}} \quad (4-11)$$

The rate of safety competency per employee per year, MP_{SC} (%/year)

Average safety comp. rate, MP_{SCn} =

$$\frac{\text{Total rate of safety competency yearly}}{\text{Average number of employee working yearly}} \quad (4-12)$$

Normalise the indicator relative to full rate:

$$\text{Total average safety competency rate, } MP_{SC} = \frac{MP_{SCn}}{100} \quad (4-13)$$

The MP index is represented as below:

$$MP = k_{MP,OT} \times MP_{OT} + k_{MP,AB} \times MP_{AB} + k_{MP,KPI} \times MP_{KPI} + k_{MP,CR} \times MP_{CR} + k_{MP,LT} \times MP_{LT} + k_{MP,SC} \times MP_{SC} \quad (4-14)$$

where $k_{MP,OT}$, $k_{MP,AB}$, $k_{MP,KPI}$, $k_{MP,CR}$, $k_{MP,LT}$ and $k_{MP,SC}$ are the weightage of each sub-indicators. These sub-indicators are obtained from the MCDM method explained in Section 5.3.

4.3.3. Machine index, MC

The overall equipment effectiveness (OEE) is used to represent the machine (MC) index. OEE is developed by Nakajima (1988) which consists of three main indicators namely availability, performance and quality. Dadashnejad and Valmohammadi (2019) stated that OEE is a measurement of manufacturing performance that can be applied to different industry sector which allows simple comparison despite the dissimilarity in processes. The objective of OEE is to numerically indicate production efficiency through a simple and clear metric. It can pinpoint the bottleneck of the process through operation data analysis. The OEE consists of 6 main losses which are illustrated in Figure 4-4. The 6 main losses used to calculate the matrix for OEE are reflected in Table 4-1.

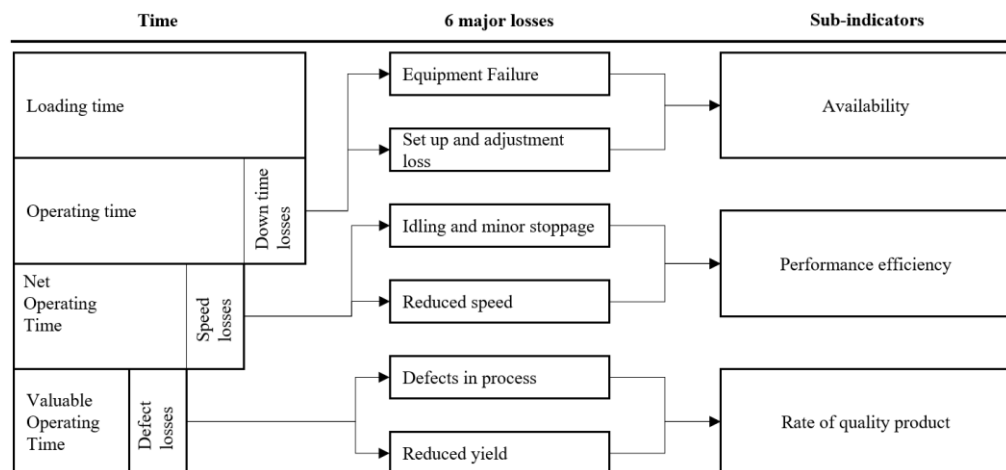


Figure 4-4: Relationship between 6 major losses of Overall Equipment Efficiency (OEE) (Modified from Parikh and Mahamuni (2015))

Table 4-1: 6 major losses of overall equipment effectiveness (OEE)

Major losses	Description	Source
Equipment failure	Losses due to equipment failure. Any activities that cause the unplanned production shutdown due to equipment faulty is deemed under this category.	Ahuja and Khamba (2008)
Set up and adjustment loss	These changes due to operation changeover such as a change in feed. Changes that do not related to equipment failure and planned shutdown shall be included in this section. For example, adjustment or fine-tuning of equipment or process parameter.	Ahuja and Khamba (2008)
Idling and minor stoppage	Idling and minor stoppage refer to temporary stop or idle of production due to sensor faulty. Many industrialists do not consider this loss as the total time contributes to idling and minor stoppage is very minimal during normal operation. This does not require shut down maintenance.	Herry et al. (2018)

Reduced speed	Reduced speed refers to production at a lower production rate. Not optimum condition.	Chikwendu and Chima (2018)
Defects in process	The amount of time or volume of defects that required to handle or re-processing on the product. This also includes financial expenses on re-processing and handling of defects.	Chandran (2015)
Start-up losses	Time loss during start-up, running in and stabilise before production can initiate.	Batumalay and Santhapparaj (2009)

Referring to Figure 4-4, the Availability (A) sub-indicator represents the actual operating schedule against the planned production schedule by accounting equipment failure and set up and adjustment loss. Thus, A is calculated as below:

$$A = \frac{\text{Planned opt. time} - (\text{equip. failure time} - \text{set up and adj. loss})}{\text{Planned opt. time}} \quad (4-15)$$

Performance efficiency (P) takes into consideration the total production rate against designed or maximum production rate. Idling and minor stoppage, and reduced speed operation will cause fluctuation on the total production rate. P indicator is shown below:

$$P = \frac{\text{Total processed amount} \times \text{Max production rate}}{\text{Actual operation time}} \quad (4-16)$$

The rate of quality product (Q) measured the total amount of quality product over the total produced amount. This will allow the industrialist to gauge the quality of their production. Q indicator is expressed as below:

$$Q = \frac{\text{Processed amount} - \text{Defect amount}}{\text{Processed amount}} \quad (4-17)$$

The OEE is calculated by obtaining the product of A, P and Q reflected in Eqn. 4-18. Huang et al. (2002) stated that OEE is widely accepted as a quantitative tool to measure manufacturing performance. According to Ahaju and Khamba (2008), the total productive maintenance (TPM) has a standard of 90 % of A, 95 % of P and 99 % of Q. An overall scoring of 85 % of OEE is considered a world-class performance.

$$OEE = A \times P \times Q \quad (4-18)$$

4.3.4. *Material index, MT*

In material (MT) indicator, it focuses on resources, products and inventory management. In lean practices, pull-based production is desired (Leong et al, 2019). The MT indicator assists the industrialist in identifying the optimum inventory capacity through its inventory storage data. Besides, the inventory data, qualified output, production defects and waste are considered to establish a comprehensive indication of resource performance. In any manufacturing condition, resource conversion is highly important as an indication of resource utilisation efficiency. Not to forget that the product quality shall meet the

specification requirement of the product. Besides that, the conversion of the resource to quality products is critical in contributing to the sustainable development goal (SDG) 12 which emphasize responsible consumption and production (SDG, 2019). Table 4-2 summarises the indicator used in MT.

Table 4-2: Sub-indicators for material (MT)

Sub-indicators	Description
The total amount of input material	The total amount of consumable resources (i.e. raw material, combustion fuel and steam) that required for production.
The total amount of product	The final product that the process product for sale.
The total amount of defect or waste	Waste or defect product that is being produced from the process.
Recyclable defect	The amount of defect that can be recycled back in the process for further processing.
Inventory	Information on existing inventory space and requirement. Inventory space can be optimised to improve space-use efficiency.

The sub-indicators defined in Table 4-2 provides a data collection guideline for the users. The relationship between each MT indicators are illustrated in the equation as below:

Resource consumption efficiency, MT_{RE} indicates the relationship for material consumption efficiency.

$$MT_{RE} = \frac{\text{Total amount of product}}{\text{Total amount of material input}} \quad (4-19)$$

Product to defect indicator, MT_{DI} is to evaluate the ratio of defects to total production. A healthy indicator will have the value of closer to 1.

$$MT_{DI} = \frac{\text{Total amount of product} - \text{Total product defects}}{\text{Total amount of product}} \quad (4-20)$$

The rate of recyclable defects, MT_{RD} can be important in some manufacturing sector (i.e. plastic or certain chemical processes). The MT_{RD} can impact directly on the financial report of the facilities. However, it is advisable to reduce the rate of recyclable good as it will increase the overall operation cost.

$$MT_{RD} = \frac{\text{Total amount of defects} - \text{Recyclable defects}}{\text{Total amount of defects}} \quad (4-21)$$

The inventory, MT_{IN} is also taken into consideration. The total inventory area required for the process can be calculated. Apart from using MT_{IN} , statistical process control (SPC) method can be applied to identify the optimum inventory storage required. However, the application of SPC will be highly dependent on the nature of the industry.

$$MT_{IN} = \frac{(\text{Minimum monthly material input} + \text{average monthly production})}{(\text{Average monthly input material} + \text{maximum monthly production})} \quad (4-22)$$

Finally, the MT index is generated to represent the performance of resource consumption where k_i represents the weightage of each sub-indicators obtained from MCDM method.

$$MT = k_{MT,RE} \times MT_{RE} + k_{MT,DI} \times MT_{DI} + k_{MT,RD} \times MT_{RD} + k_{MT,IN} \times MT_{IN} \quad (4-23)$$

4.3.5. Money index, MY

A process with a healthy return of investment (ROI) and operation capital (OpEx) is desirable. The money index (MY) reflects the financial performance of an organisation through two sub-indicators (i.e. total operation cost, MY_{OC} and total profit, MY_{TP}). The performance for both MY_{OC} and MY_{TP} are based on per unit of production.

In MY, MY_{OC} reflects the OpEx which covers the cost of input resources such as costs for material, utility, labour, production, waste, maintenance and inventory. In Eqn 4-24, the minimum operation cost is defined as the numerator while average operation cost is denoted as the denominator. This is to allow demonstrate a lower OpEx control will result in value nearer to 1. As such, the numerator will always benchmark against the lowest OpEx obtained in a facility while denominator will be actual OpEx for the actual period. To obtain optimise the performance of MY_{OC}, the cost of operation needs to be reduced to maximise profits.

$$MY_{OC} = \frac{\text{Minimum operation cost}}{\text{Average operation cost}} \quad (4-24)$$

The second indicator MY_{TP} reflects on the total profit performance from the operation. The product cost of sale is important to obtain higher accuracy of the analysis.

$$MY_{TP} = \frac{\text{Maximum profit cost}}{\text{Average profit cost}} \quad (4-25)$$

Therefore, MY index is contributed by the product of MY_{OC} and MY_{TP} as below:

$$MY = k_{MY,OC} \times MY_{OC} + k_{MY,TP} \times MY_{TP} \quad (4-26)$$

where k_i represents the weightage of each sub-indicators obtained from MCDM method.

4.3.6. Environment index, EV

Global warming potential (GWP) is the main sub-indicator contributing to the environment index (EV). Čuček et al., (2012) emphasized the need for including GWP as one of the environmental indicators. GWP is developed to compare the impact of different greenhouse gases (GHG). It measures the total energy for one ton of specific gas absorbs relatively to one ton of carbon dioxide (CO₂). The calculation in total carbon footprint is based on GWP value for common GHG is illustrated by Myhre et al. (2013). Larger GWP reflects higher heat-absorbing capacity compare to CO₂ (EPA, 2017). The emission of GHG from the production process should be recorded at all time. The EV targets

several sub-indicators such as water emission, air emission and solid waste. The total carbon footprint of the process will be calculated based on per unit of product produced.

For air emission, the flow rate and composition of the exhaust air are used to evaluate the carbon footprint (tCO₂/unit of product) of exhaust gas. The GWP can be obtained from EIA (2017).

$$CO_2 \text{ footprint}, EV_{CO_2} = \frac{\text{minimum monthly } CO_2 \text{ emission}}{\text{average monthly } CO_2 \text{ emission}} \quad (4-27)$$

For water emission, the flow rate of wastewater is required. Water-based emission and discharged are considered under the wastewater category. Eqn. 4-28 will reflect the performance of wastewater minimisation for a facility.

$$Wastewater, EV_{WW} = \frac{\text{minimum monthly wastewater emission}}{\text{average monthly wastewater emission}} \quad (4-28)$$

Solid waste generation varies with different industry. For example, palm oil mill generates empty fruit bunches as solid waste after extraction of oil. The empty fruit bunches are considered as waste if not converted to alternative products. Solid waste needs to be managed carefully to ensure the safety of the working environment.

$$Solid \text{ waste }, EV_{SW} = \frac{\text{minimum monthly generated solidwaste}}{\text{average monthly generated solidwaste}} \quad (4-29)$$

The EV index is very significant in the manufacturing context as it notifies the industrialist of the performance of EV. It reflects the performance of the EV of the facility.

$$EV = k_{EV,CO_2} \times EV_{CO_2} + k_{EV,WW} \times EV_{WW} + k_{EV,SW} \times EV_{SW} \quad (4-30)$$

where k_i represents the weightage of each sub-indicators obtained from MCDM method.

Generally, the 5 main indicators cover the fundamental operation aspect of the most industry. Modifications can be performed on the 5 main indicators and sub-indicators to suit each operation criteria.

4.4. Case Study

The application of LGI will be demonstrated with the case study in Chapter 5, Section 5.4.

4.5. Conclusion

In the L&G approach, the application of LGI plays an important role in establishing a baseline performance and act as a monitoring tool for the organisation performance. The development of LGI has covered the fundamental aspect of most operation including MP, MC, MY, MT and EV. With that, the LGI acts as a continuous performance monitoring tool for a specific operation by targeting specific indicator for evaluation or improvement. The LGI can be modified by adding in new indicator or sub-indicators according to user's process requirement. However, modification needs to be done by experienced personnel only to ensure the indicators are targeted appropriately. Referring to Section 3.2 (a) Chapter 3, the objective in developing the LGI has been achieved. With the development of LGI, it will be incorporated into the L&G framework that will be discussed in the next chapter.

Chapter 5: Development of Lean and Green Framework

5.1. Introduction

In this chapter, the lean and green (L&G) framework is developed to improve the operational performance in a systematic structure without compromising the environment.

The L&G framework consists of several analysis stages such as L&G interview, analysis and process optimisation. L&G framework will be broken down into several sections to explore ways and method to evaluate and improve operational performance. With the development of L&G checklist from Section 4.3.1., the need to define the relationship between the indicator and sub-indicators will be illustrated in Section 5.3. The multi-criteria decision making (MCDM) method will demonstrate the incorporation of human expert input into L&G framework especially in defining the relationship and priority of the indicators. The lean and green index (LGI) developed in Section 4.3 to act as a benchmarking and process improvement monitoring tool. This chapter aims to develop a systematic L&G framework to guide the industrialist in implementing L&G approach. The L&G framework is mainly split into 3 sections such as modification of L&G checklist, data collection and LGI. A combine heat and power (CHP) case study will demonstrate the feasibility of the L&G framework in Section 5.4.

5.2. Methodology

In this research project, the proposed L&G framework (Figure 5-1) is structured based on a few industry players' inputs (i.e. palm oil refinery, glove

manufacturing and cogeneration industry). The L&G framework intends to improve the sustainability of the organisation by improving the operation and environmental aspect. Several interviews have been conducted with industrialists to smoothen the implementation of L&G framework. One of the main concerns discussed on the development of L&G framework is the employee's adaptability of change. The feedbacks from several industrialists are taken into consideration to minimise operation interruption when implementing L&G approach.

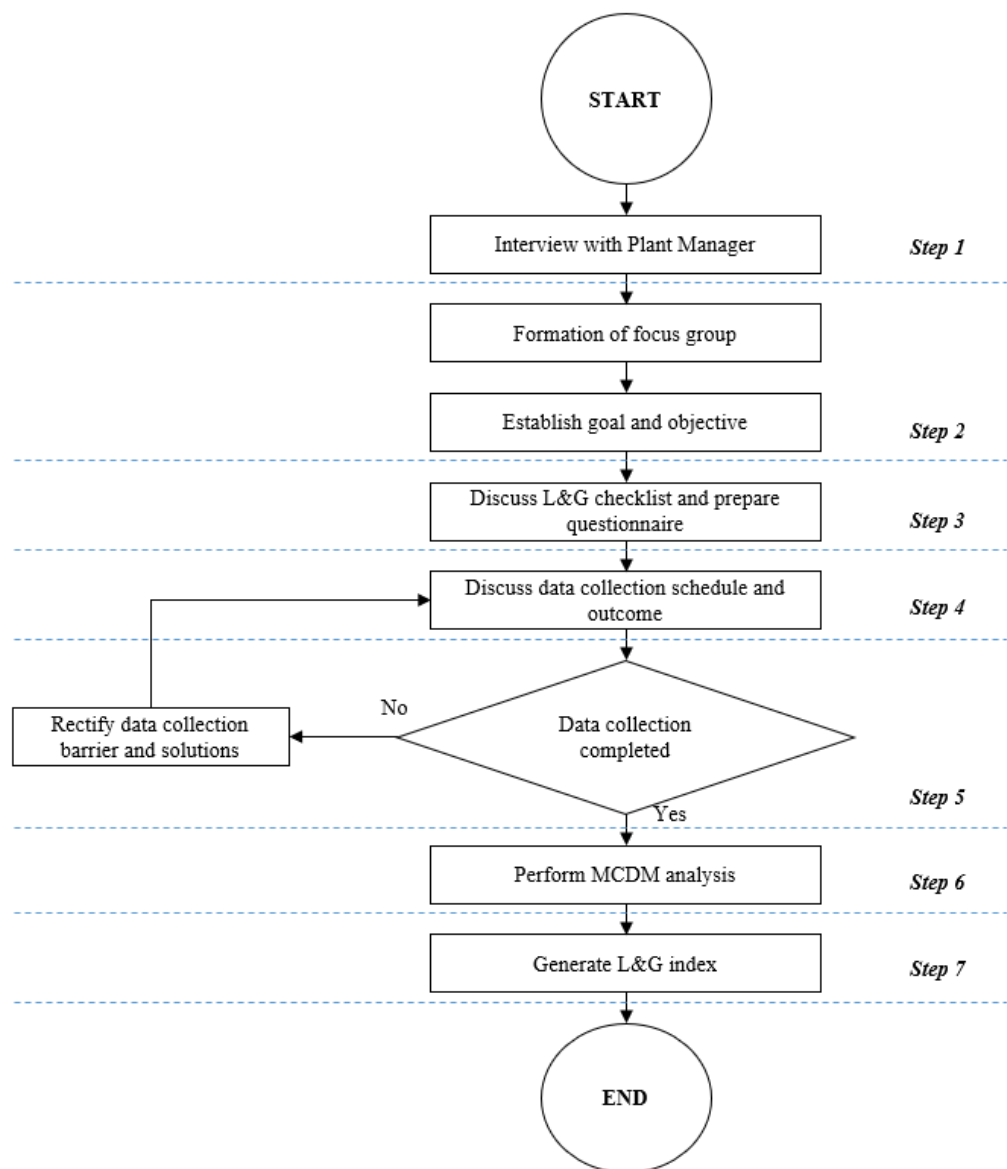


Figure 5-1: Lean and green (L&G) framework

Moving on, Figure 5-1 illustrate the step by step approach towards implementation of L&G framework. The methodology will demonstrate a macro approach to improve the performance of an organisation. The methodology of the L&G framework will follow as below:

1. Interview with plant manager/operation manager/maintenance manager/human resource manager to understand the standard operating procedure (SOP) and operation behaviour of the production facility. The interview session is utmost critical as to encourage and initiate the industrialist participation in implementing the L&G approach for continuous improvement.
2. Formation of a focus group to handle the implementation of L&G framework. This is to include an expert from a different department to contribute their ideas and commit to L&G implementation. Each department will nominate an experienced person to handle the L&G implementation. The nominated person shall have authority to execute an action plan according to the outcome of a focus group. The initial target and objective of the L&G implementation will be discussed and established by the focus group.
3. The generic L&G checklist developed in Section 4.3.1. will be discussed among the focus group members. The 5 main indicator and sub-indicators shall be discussed and finalised by the focus group member before data collection. Once the L&G checklist is finalised, L&G questionnaires will be developed and distributed to operation management teams to gain their input on their decision-making hierarchy.

4. Next, the respective person from each department shall need to collect operation data for analysis. Data collection shall be over six months or one operation year. Facilities with data collection function through supervisory control and data acquisition (SCADA) or distributed control system (DCS) will ease data collection. Apart from that, an event such as unscheduled and scheduled shutdown should be taken into consideration during analysis. Data can be digitally or manually collected from process logbook. In case of interruption occurs during data collection, inform the focus-group and re-arrange for data collection schedule.

5. Once the data collection is done, the collected data shall be reviewed before performing analysis. Review collected data before performing the analysis. If data dispute is found, inform coordination team to discuss for action plan and solutions. Based on the collected data sample, abnormal event (i.e. events that does not occur during normal operation) shall be taken into consideration during analysis.

6. The questionnaire feedback from the focus group will be compiled and analysed with the analytical hierarchy process (AHP) method. The selection of AHP is illustrated in Section 2.5.1. AHP is a least complicated method to convert qualitative decision making into quantitative scoring. The weights of every sub-indicators are converted from the questionnaires. The detail calculation method of AHP is explained in section 5.3.1. The data collected from the process indicators are evaluated and calculated as illustrated in chapter 4, section 4.3.1. to section 4.3.6.

7. The lean and green index (LGI) is generated with Eqn. 4-1 as demonstrated in chapter 4, section 4.3.1. The first LGI generated for each factory is known as the benchmarking index. The LGI will act as a performance tracking tool to monitor the progress of improvement.

5.3. Multi-Criteria Decision-Making (MCDM) Selection

In respect to the application of L&G framework, the involvement of industry expert in giving professional input in the L&G approach can be very helpful. With the L&G checklist, the sub-indicators for 4M1E can be identified. It is important to involve the industry expert to identify the sub-indicators for the L&G model. However, human input can be qualitative and need to be translated into qualitative data.

In this section, the multi-criteria decision-making (MCDM) analysis is used to add value to the human expert's opinion by translating it into quantitative output. By establishing the relationship between the sub-components, the organisation can have a better understanding of both the indicators and sub-indicators that affect the operation performance. As Chapter 2, section 2.4 covers the review on MCDM, this section focusses on the method of MCDM approach.

5.3.1. Analytic Hierarchy Process (AHP) method

The analytical hierarchy process (AHP) has been selected as the MCDM tool in this research due to several reasons (i.e. ease to use, hierarchy structure can be adjusted, require expert input and can be applied in

various industries). AHP method developed by Thomas Saaty (1980) is most frequently used among researcher and industry players. The AHP is an effective MCDM tool that is widely applied in the research arena as well as business applications over the past decades (How and Lam, 2017). It is a relative measurement that transforms both qualitative judgments as well as quantitative values into an objective measure (Ngan *et al.*, 2018). The AHP method reduces the complexity of the decision-making process into a series of pairwise comparison. It allows the decision-maker to model a complex problem which associates with multiple criteria and alternatives in a hierarchy structure to derive the final solution in a simple and systematic manner (Skibniewski and Chao, 2007). The mathematical simplicity of AHP has allowed the method to be applied in business, engineering, health care, environmental science and various other fields. It adopts the concept of relativity to compare the element in pairs to determine its dominance relationship, which could be importance, preference, influence, dependence. The judgements of the pairwise comparison questions are mainly based on personal experience, expertise, situation and state of mind of the respondent (Yadav and Jayswal, 2013). This is different from most statistical tools which require significantly larger sample groups. AHP only required small sample size (i.e. 2 - 20) which have deep understanding and expertise on the subject matter (Baby, 2013). In terms of the applications in operation strategy, AHP has been adopted to evaluate fuel cell engines performance based on the properties of different stages (i.e., steady-state, start-up, dynamic, safety) (Hou et al.,

2011). Govindan et al. (2014) applied the AHP model to evaluate and identify the key barriers for the green supply chain management. The model defined five main barriers and 47 specific barriers into a hierarchical model to study the key factors that hinder the achievement of green supply chains. AHP is also used to develop systems for building refurbishment assessment scheme to prioritize factors such as energy, waste, economics, social and cultural and others for the reduction of energy consumption and CO₂ emission building in Malaysia (Kamaruzzaman et al., 2018).

In this work, the AHP model is established after the interview and discussion with industry experts. The AHP methodology is as below:

1. Referring to Figure 5-1, Step 3, the L&G checklist will be finalised after the discussion with the members from the focus group. The indicator and sub-indicators of the processing facility shall be identified. The questionnaire (refer to Appendix I) will be developed to collect the quantitative input of the industry expert.
2. The decision-making structure, as illustrated in Figure 4-2, of the process including the main indicator and sub-indicator will illustrate the relationship between the indicators. The first level of the hierarchy model is the goal of this paper which is to benchmark and improve the LGI. The second level represents the 5 main components (i.e. 4M1E) that contribute to the final goal. The third level reflects the sub-indicators that affect and contribute to the significance of 4M1E. The

downward arrow, which connects the upper level to lower level another, indicates that dependency of the lower level group to the upper level.

3. Questionnaires are being developed and distributed to experts in the industry to gain their input. Industry experts of the subject are required to evaluate the dominance relationship of the indicators within the same level. Ngan et al. (2018) highlighted that the prioritisation of AHP based on individual or group of people do not necessarily require a large sample size. The number of participants required are between 5-10 individuals. At this stage, Saaty's pairwise comparison scale is adopted to represent the intensity of the relationship between the pairing (Saaty, 2008). The 9-point fundamental scale is described in Table 5-1.

Table 5-1: Saaty pairwise comparison scale (Saaty, 2008)

Verbal Judgement	Numeric Value
Extremely Important	9
	8
Very Strongly more Important	7
	6
Strongly more Important	5
	4
Moderate more Important	3
	2
Equally Important	1

4. The industry experts' input will serve as the input for the development of the pairwise comparison matrix. The eigenvalue of the components and indicators will be calculated to form local priority matrices. Eqn. 5-1 demonstrated the input from the experts are used to fill the upper right part of the matrix (i.e. w_{12}) while the lower left is the inverse of upper-right value (i.e. $1/w_{12}$). Ngan et al. (2018) stated that the geometric mean method is used for multiple inputs. The matrix is then normalised to produce the normalized eigenvector as the weight of the components.

$$m = \begin{matrix} & \begin{matrix} C_1 & C_2 & C_{...} & C_n \end{matrix} \\ \begin{matrix} C_1 \\ C_2 \\ C_{...} \\ C_n \end{matrix} & \begin{bmatrix} 1 & w_{12} & w_{1...} & w_{1n} \\ 1/w_{12} & 1 & w_{2...} & w_{2n} \\ 1/w_{1...} & 1/w_{2...} & 1 & w_{...n} \\ 1/w_{1n} & 1/w_{2n} & 1/w_{...n} & 1 \end{bmatrix} \end{matrix} \quad (5-1)$$

The matrix is then normalised to produce the normalized eigenvector as the weight of the components. Saaty (2008) emphasized that $CI \geq 0$ indicates the m is consistent. The consistency ratio (CR) (Eqn. 5-3) can be calculated to estimate the consistency of the expert's input. Generally, it is considered acceptable if the $CR < 0.1$. The Consistency Index (CI) is illustrated in Eqn. 5-2 while the random index (RI) can be obtained in Table 5-2 below:

$$CI = (\lambda_{max} - n)/(n - 1) \quad (5-2)$$

Table 5-2: Random index (RI) (Saaty, 2008)

<i>n</i>	2	3	4	5	6	7	8
<i>RI</i>	-	0.52	0.89	1.11	1.25	1.35	1.40
<i>n</i>	9	10	11	12	13	14	15
<i>RI</i>	1.45	1.49	1.52	1.54	1.56	1.58	1.59

The CR of the matrix can be obtained as below:

$$CR = \frac{CI}{RI}, CR < 0.1 \quad (5-3)$$

5.4. Case study

An industry case study was used to demonstrate the proposed L&G framework. Figure 5-2 illustrates a combined heat and power (CHP) process consists of a gas turbine with a heat recovery steam generator (HRSG). A CHP or cogeneration plant is considered a thermodynamically efficient way of converting energy (Ferreira et al., 2014). The gas turbine acts as the prime mover in the CHP plant by rotating the alternator to generate electricity and releasing high-temperature exhaust air with only consuming a single fuel source. The high-temperature exhaust air will be recovered by HRSG as steam.

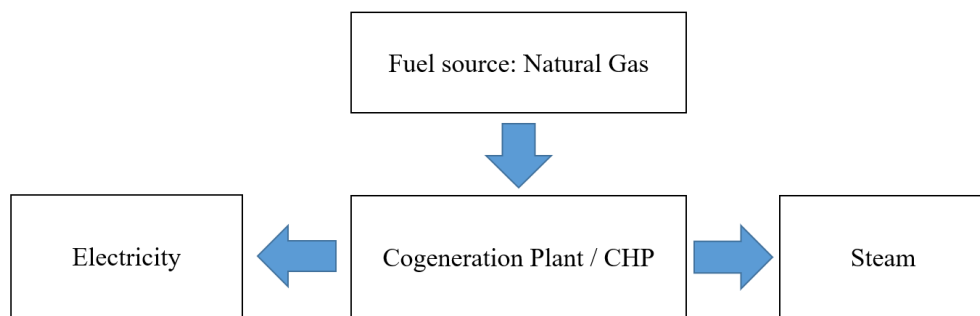


Figure 5-2: Flow Diagram of case study

The CHP case study was obtained from a manufacturing facility located in North of Malaysia. The CHP plant started operation in the year 2015 with island mode where it operates independently without synchronising with the national grid. The specification of the CHP plant is shown below:

- a. Main fuel source : Natural Gas (NG)
- b. Max. electricity generation : 6.5MW @ 32degC

- c. Max. steam recovery : 16 tonnes / hour @ 10barG saturated steam

An interview was conducted with the plant manager before visiting the CHP plant. The CHP was operated as an independent facility that supplies electricity and steam. The boundary of this case study is limited to the CHP operation as shown in Figure 5-3. The case study covers the 4M1E indicators in the operation. The supply of electricity and steam from the CHP plant is dependent on the demand requirement. Figure 5-4 illustrates the indicators modified L&G checklist finalised by the focus group member for L&G implementation. Figure 5-4 is modified accordingly to the needs of the case study.

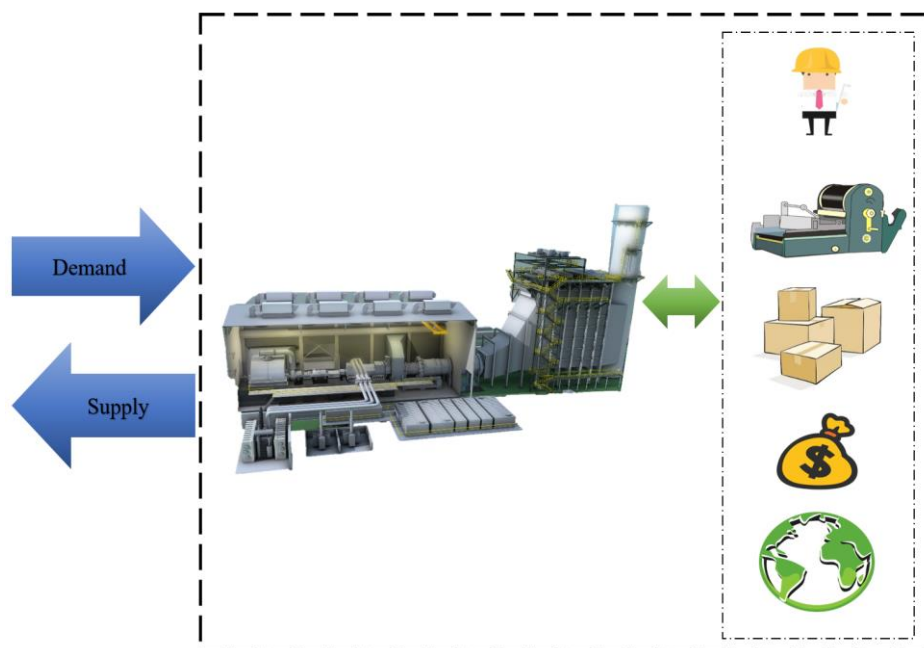


Figure 5-3: Boundary limit of CHP case study

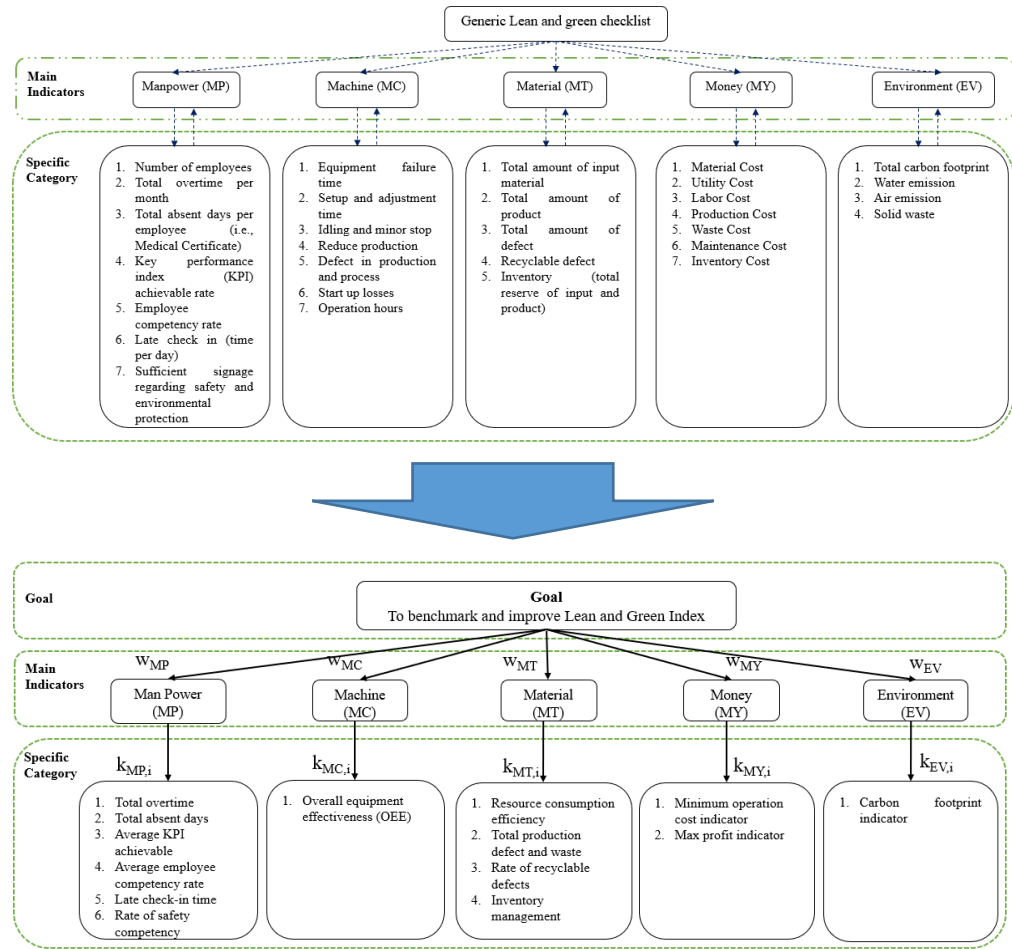


Figure 5-4: Modification of L&G checklist

5.4.1. Data collection

Before data collection, the L&G framework (Figure 5-1) and L&G checklist (Figure 5-4) are explained to the operation team. The importance of the indicators and sub-indicators, as well as the intention of data collection, are explained in detail to ensure the employee who participates in the L&G program can execute the process smoothly. In this case study, four years of CHP operation data are being collected since the year 2015 to the year 2018.

Table 5-3 shows the fluctuation of natural as per million British thermal unit (Btu) and generation cost per tonne of steam. Additional data furnished by the plant manager as below:

- a) Total operation days : 351 days
- b) Total operation hours : 8424 hours
- c) Annual shutdown days : 14 days

Table 5-3: Cost of natural gas and steam generation. (Data obtained from Energy Commission Malaysia (2017))

	RM/M MBtu	RM/Ton of steam		RM/M MBtu	RM/Ton of steam
2015 - Jan	19.77	59	2017 – Jan	26.31	78
2015 - Jul	21.80	65	2017 – Jul	26.46	79
2016 – Jan	25.53	76	2018 – Jan	32.52	96
2016 - Jul	27.05	80	2018 - Jul	32.69	97

5.4.2. Analysis and Discussion

This case study is supported by industry data obtained from the year 2015 to 2018. Figure 5-4 demonstrated the modification of L&G checklist based on industry expert's input. The plant manager responded

that some of the indicators in level three do not apply for the CHP process such as rate of recyclable defects and inventory management. The rate of recyclable defects can be excluded as the supply of electricity and steam are connected to the process stream once the supply is stabilised. Besides, the supply of NG is obtained directly from the pipeline supply. The plant manager added that the gas turbine manufacturer has been rewarded with the maintenance contract who will be responsible for the maintenance of the gas turbine. Therefore, no inventory is required.

5.4.3. Analytic Hierarchy Process (AHP) analysis

Based on the AHP analysis, the distribution of weight based on main indicators (i.e. 4M1E) are presented in Table 5-4. According to the feedback from the respondents, money (MY) is ranked first in improving the LGI of the cogeneration plant with 26.10 %, followed by the environment (21.54 %), manpower (18.70 %), machine (18.28 %) and material (15.38 %).

Table 5-4: Consolidated pairwise comparison matrix of 4M1E with respect to the goal

	MP	MC	MT	MY	EV	Eigenvector	Ranking
MP	1.00	1.00	1.17	0.70	1.04	0.1870	3
MC	1.00	1.00	1.43	0.67	0.80	0.1828	4
MT	0.85	0.70	1.00	0.41	1.11	0.1539	5
MY	1.42	1.50	2.46	1.00	0.76	0.2610	1

EV	0.96	1.25	0.90	1.32	1.00	0.2154	2
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CR: 0.0283

MY was ranked first in the analysis due to technology limitation and profitability. The dependency on foreign exposes the local industrialist to several risks (i.e. monetary risk, geopolitical risk and local maintenance support) (Leong et al., 2019). Besides, MY is the main indicator that reflects the profitability of the organisation. The EV indicator has rated as the second most significant component by the experts. The Malaysia government has the intention to reduce 45 % of its greenhouse gas (GHG) emission intensity of GDP by 2030 relative to 2005 (MITI, 2017). Based on the ranking, the industrialists are committed to contributing to the national goal. Also, the facility has a stringent EV policy to ensure environmental emission is minimised complying to the regulation imposed by the Department of Environment Malaysia including air and water emission limits.

In operation of the CHP plant, human resource is important to ensure smooth operation and troubleshooting. The lack of experienced talent in the CHP plant increased the challenge of the employee in retaining the talent. On the machine aspect, the reliability of prime mover (i.e. gas turbine or gas engine) technology has relief the industrialist from many operation concerns. However, the performance of the technology may vary due to climate difference. Lastly, as Malaysia is a natural gas (NG) production country, industry players can enjoy a consistent supply of high-quality NG supply.

Table 5-5 demonstrates the priorities of manpower (MP) sub-indicators. It is observed that employee safety, MP_{SC} is the utmost priority in MP (24.17 %), followed by an absent day, MP_{AB} (23.40 %), employee competency rate, MP_{CR} (18.37 %), key performance index (KPI) achievable rate, MP_{KPI} (13.59 %), late check-in time, MP_{LC} (10.84 %) and lastly overtime, MP_{OT} (9.63 %) respectively. From the MP perspective, the plant manager indicates that the facility has stringent compliance on Occupational Safety and Health (OSH) Act 1994. From the priority distribution, the employer seems to have the employee's safety and health condition as the priority before the capability to perform. As CHP plant involves the generation of electricity and heat energy, the health and working condition of the employee are ranked as the utmost priority. The MP_{AB} reflects the days when an employee takes medical or accident leave. The ranking also indicates that the organisation emphasizes the availability of the employee to be at the site. The plant manager added that the competency of the employee can only be improved when the employee is available to perform its duty at work safely.

Apart from MP, Table 5-6 shows the dominance of profit indicators over operation cost for money (MY) components. This can be explained that the manufacturer has established a maintenance contract with the owner of the plant. Therefore, the profit of CHP output is prioritised as the maintenance cost is fixed by contract.

Table 5-5: Pairwise comparison matrix of Manpower (MP) indicators

	MP_{OT}	MP_{AB}	MP_{KPI}	MP_{CR}	MP_{LC}	MP_{SC}	Eigen- vector	Rank
MP_{OT}	1.00	0.36	0.91	0.54	0.78	0.51	0.0963	6
MP_{AB}	2.79	1.00	3.47	1.72	1.12	0.44	0.2340	2
MP_{KPI}	1.10	0.29	1.00	0.67	2.05	0.80	0.1359	4
MP_{CR}	1.85	0.58	1.50	1.00	2.35	0.83	0.1837	3
MP_{LC}	1.28	0.89	0.49	0.43	1.00	0.47	0.1084	5
MP_{SC}	1.97	2.27	1.25	1.20	2.11	1.00	0.2417	1

CR= 0.063

Table 5-6: Pairwise comparison matrix for Money (MY) indicators

	MY_{OC}	MY_{PT}	Eigenvector	Ranking
MY_{OC}	1.00	0.58	0.3678	2
MY_{PT}	1.72	1.00	0.6322	1

5.4.4. Lean and green index (LGI)

Figure 5-5 presented the historical performance record of MP indicator. The MP indicator is calculated with Eqn. 4-14. The average MP_{KPI} and MP_{CR} need to be improved to increase the MP index. In the year 2015, the MP_{KPI} and MP_{CR} have shown lower performance rate. Extensive training and guidance are required to develop a competent team to manage the new facility (C.K. Cheng, personal communication, January 20, 2019). However, Figure 5-5 reflects that the average MP_{SC} is above 90 % which reflects the priority of employee safety in the facility. This

illustrates that the information provided by the experts are in-line with the operation behaviour.

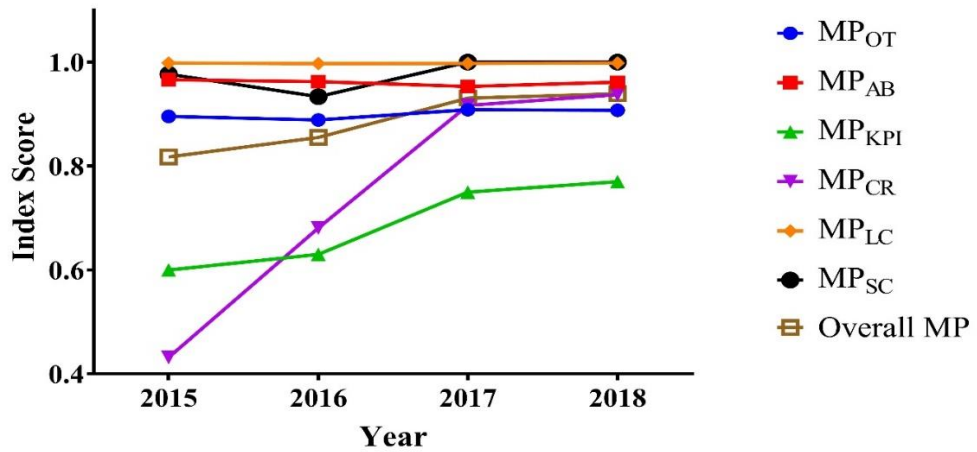


Figure 5-5: Manpower (MP) indicators

Figure 5-6 shows the performance of MC indicator. The improvement of MC index increased substantially in the year 2017 as the CHP loading has been maximised. The CHP was operating at a lower loading rate in the year 2015 and 2016 due to lack of energy demand. MC index achieves outstanding performance in the year 2017 as it achieves higher than 85 % of overall equipment effectiveness (OEE) achieving world-class performance. Besides that, as the competency of the employee increases, the MC index can be further improved.

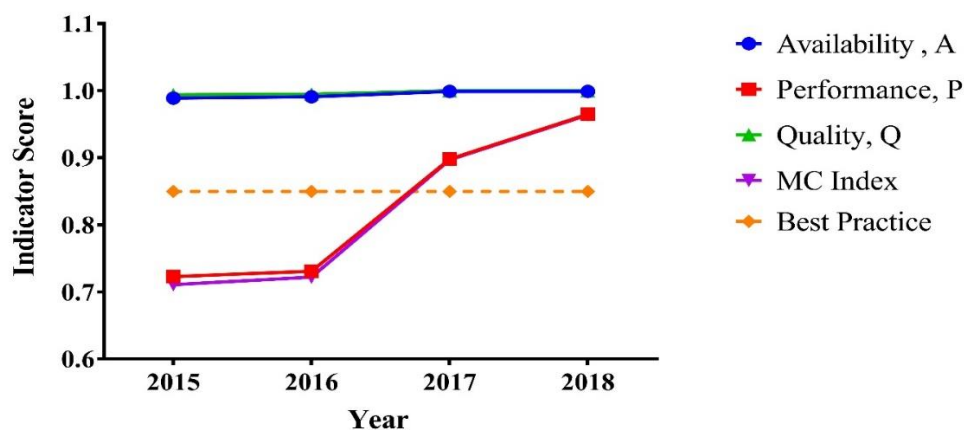


Figure 5-6: Machine (MC) performance indicators

Figure 5-7 illustrated the input resource and output product performance of the CHP plant. The MT index reflects directly on energy demand. However, the gas turbine requires a minimum amount of fuel to sustain the rotation motion when idle. Therefore, the MT index tends to be lower due to reduced demand loading and frequency of idling in the year 2015 and 2016. In CHP plant, there is no storage or inventory requires as the natural gas is supplied directly from the main gas supply pipeline.

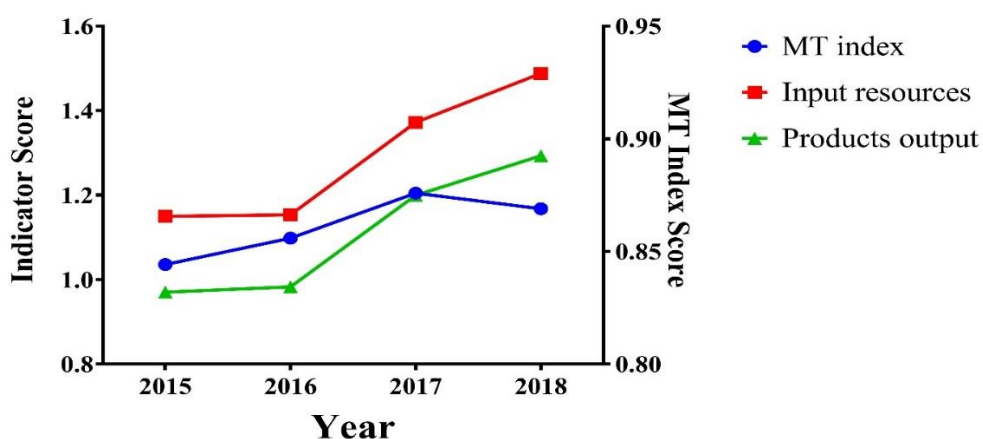


Figure 5-7: Material (MT) performance indicator

MY index is evaluated based by comparing the minimum operation cost with the average operation cost and maximum profit with average profit. In the year 2015, Figure 5-8 showed profit rating is relatively low compared to operation. According to the plant manager, lack of experience in operating the plant has brought down the profit index for the year 2015. Besides that, the lack of consistent demand in the year 2015 and the year 2016 has also contributed to lower MY index.

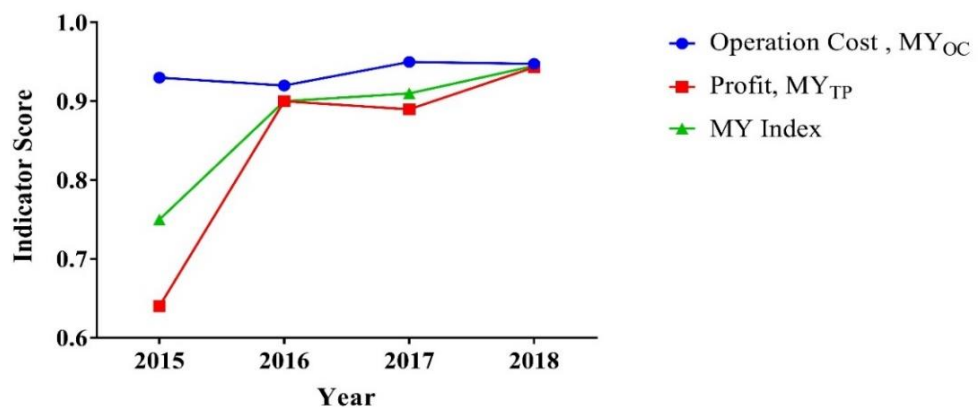


Figure 5-8: Money (MY) performance indicator

EV indicator is relatively important especially dealing with the environmental regulatory and emission. Referring to Figure 5-9, the carbon footprint emission has improved with the increase in production and competent employee. Based on gas turbine operation, the dry low emission (DLE) mode activates when the gas turbine operates above the desired load demand (i.e. 50% depending on model) to sustain low NO_x emission. Therefore, the increase in load demand in the year 2017 onwards has reduced the environmental emission.

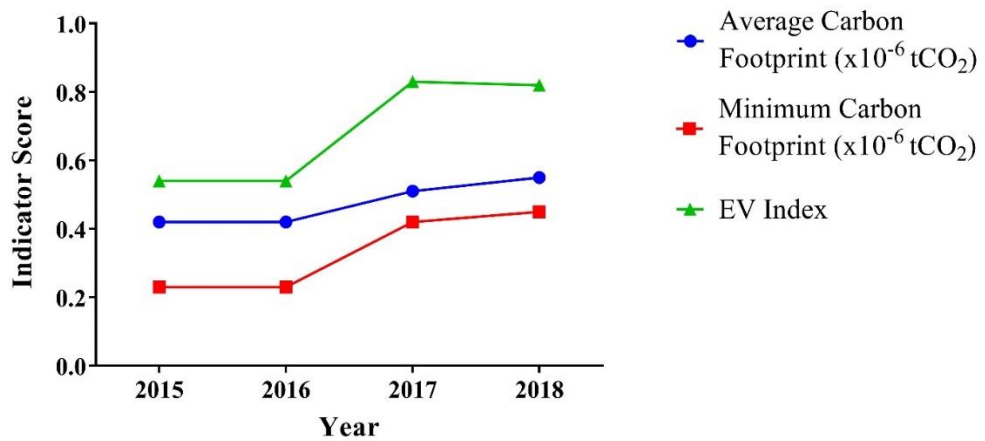


Figure 5-9: Environment (EV) performance indicator

Figure 5-10 and Table 5-7 summarises the L&G outcome of the CHP case study. The LGI has reflected a consistent improvement since the year 2015.

Table 5-7: Summary of L&G Index

	MP	MC	MT	MY	EV	LGI
2015 Index	0.8173	0.7108	0.8442	0.7456	0.5439	0.7244
2016 Index	0.8551	0.7219	0.8559	0.9045	0.5439	0.7767
2017 Index	0.9306	0.8967	0.8758	0.9138	0.8276	0.8894
2018 Index	0.9390	0.9640	0.8689	0.9448	0.8162	0.9078

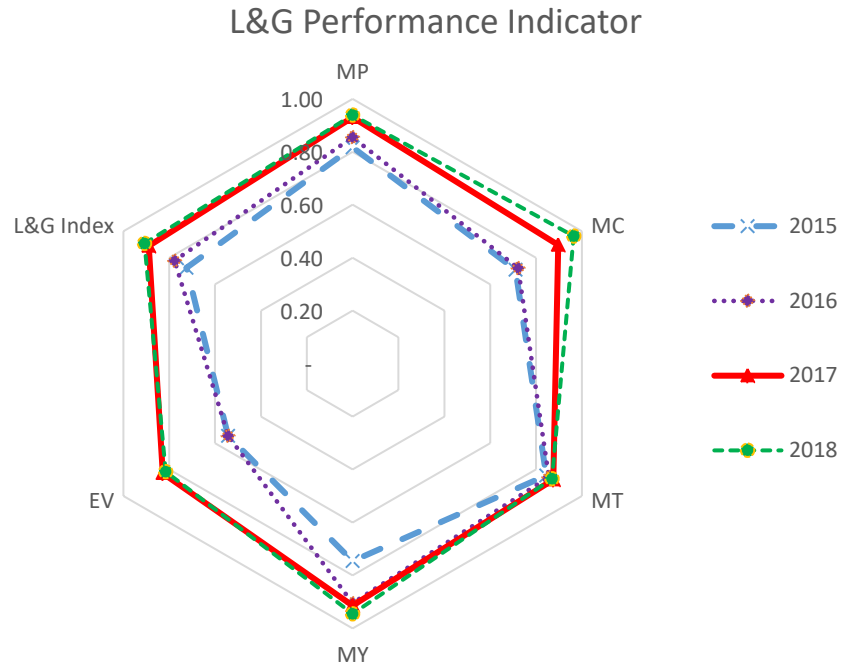


Figure 5-10: Progress of L&G performance index

5.5. Conclusion

The implementation of L&G framework with LGI and AHP have been validated and demonstrated in the industry case study in Section 5.4. The L&G framework comprises LGI from Chapter 4 that demonstrate the operation benchmarking in this case study. With the implementation of L&G approach, the industrialist reflected that the L&G checklist is a good performance tracking tool for improvement. It helps the focus group to keep track of their operation priority. Therefore, the objectives in developing the systematic L&G framework has been achieved as referred to section 3.2 (b). In the next chapter, the L&G framework will be extended with the adaptive analytical approach that analyses the operation and environmental performance with a machine learning approach.

Chapter 6: Adaptive Analytical Lean and Green approach

6.1. Introduction

With the availability of operation data from the industry, the data-driven model can be useful to improve operational performance. In many industries, process data that is recorded can be used for many analysis (i.e. statistical prediction, process optimisation, etc). A static analytical model can be exceptionally good at value prediction but is unable to cope with changes with the dynamic changes in the real world. Extended from Chapter 5, the adaptive analytical approach is incorporated into the L&G framework to perform continuous process improvement. The adaptive analytical approach is proposed to respond to real-time problems by adopting machine learning (ML) concept such as backpropagation method. This chapter will explain the integration and advantages of the adaptive analytical approach in L&G framework.

6.2. Analytical Adaptive Approach

The backpropagation (BP) is an algorithm that was fully based on the reverse mode of differentiation, the idea was first presented by Seppo Linnainmaa (Griewank, 2012). The method was then popularized with an application on neural networks to learn representations by Rumelhart et al. (1986). Lecun (1988) further demonstrated the formalization of BP in network frameworks. BP has also shown to have optimal convergence by works such as Gori and Maggini (1996). The significant differences between the proposed analytical approach with the BP method, when compared with the computational approach, are error prediction by analytical methodologies and slower update frequency. Figure 6-1 demonstrate a simple neural network structure by indicating the feed-

forward and back-propagation direction. In this chapter, BP is incorporated into the lean and green (L&G) analytical framework for continuous improvement.

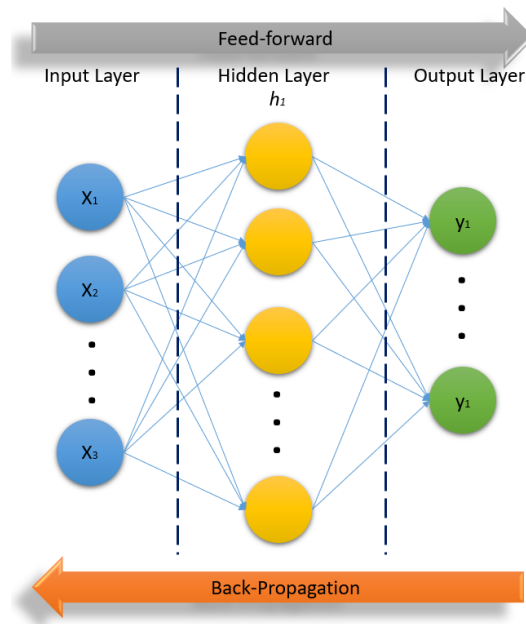


Figure 6-1: Simple neural network structure

Continuous improvement of the adaptive analytical approach must be carried out with an updating algorithm with time. Figure 6-2 explains the concept of a high-level adaptive analytical approach for L&G implementation. In the adaptive model, the “human expert” input is important as it contributes to the initial weight of all indicators in the operation. It is important to note that the priorities of main and sub-indicators vary with the different industry sector. The adaptive model reflects the actual output from the *Process Plant* by comparing it with the *Expected Improvement* value. The adaptive model will then adjust the improvement priority of the main and sub-indicators from the L&G checklist with the BP approach as illustrated in the *AHP structure*. With the outcome from the adaptive model, the industrialists need to make *Improvement Decision* and action for process improvement.

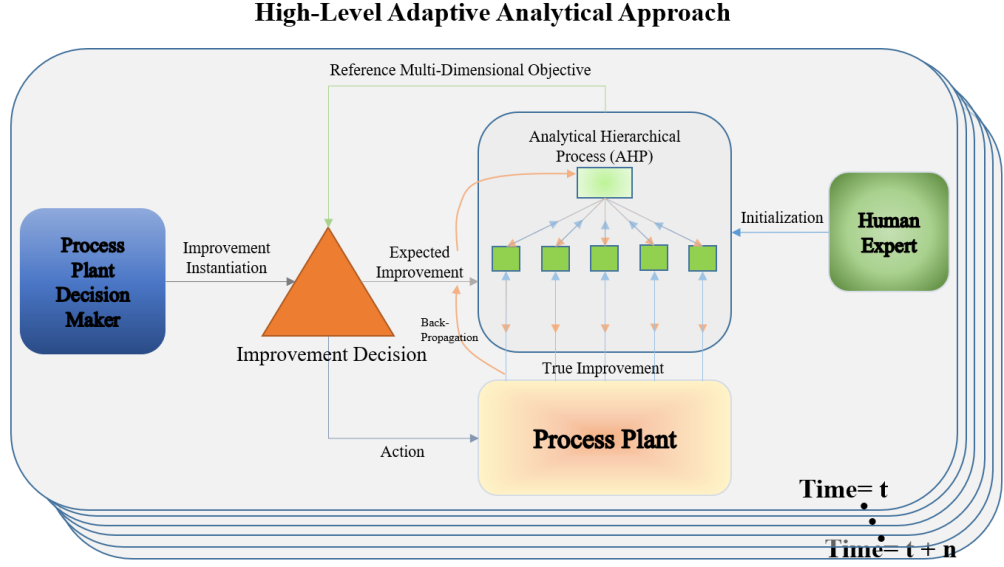


Figure 6-2: High-Level Adaptive analytical approach

In analytical L&G management, the lean and green index (LGI) vary over time. There is a constant requirement of correcting the target LGI (LGI_{target}) with respect to the actual LGI (LGI_{actual}). The BP algorithm is used as the update rule for this purpose. The error in the analytical hierarchical process is backpropagated within the network model. The error used is the mean squared error which is defined as the following:

$$E = \frac{1}{2} (LGI_{actual} - LGI_{target})^2 \quad (6-1)$$

where E is the error, LGI is the lean and green index which can be an LGI_{actual} or LGI_{target} . The LGI_{target} can be quantified when an improvement is planned, but not implemented. On the other hand, the LGI_{actual} is measured after the improvement has been implemented and computed using actual data. The updating of the main indicator's weight is computed using the following equation:

$$w_{i+1} = w_i - \eta \frac{E_i - E_{i-1}}{w_i - w_{i-1}} \quad (6-2)$$

w_i is the weight for the 5 main indicators (4M1E) on the current month, w_{i+1} is the new weight for the next time step (next month in this case study), w_{i-1} is the weights for the last time step, while E is the error having subscripts of the same notation. The learning rate η is a proportional constant that is used to update the weights. Learning rate is a hyperparameter that controls the changing gradient of the model in response to the estimated error each time when the model weights are updated (Brownlee, 2019). Small learning rate may result in a long learning process while big learning rate will result in an unstable training process where the fluctuation of the result can have big variance. A heuristic learning rate of 0.05 is used since the predicted maximal change of the LGI is unlikely to be more than 5 % per month. In every case, the learning rate of 0.05 has the smallest error, indicating that is the fastest learning rate in terms of reduction in total sum square (TSS) error (Wilson and Martinez, 2002).

As the decision-making structure moves further downwards from the main indicator to sub-indicator, the sub-indicators are calculated with the equation below:

$$k_{i+1} = k_i - \eta \frac{E_i - E_{i-1}}{w_i - w_{i-1}} \times \frac{w_i - w_{i-1}}{k_i - k_{i-1}} \quad (6-3)$$

k_i is the weights for the sub-indicators under the main-indicators, where i is the time-step. The error is passed down the analytical model using the chain rule and updated for each time step.

The adaptive analytical approach is extended from the L&G framework presented in Chapter 5, Figure 5-1. Figure 6-3 shows the integration of L&G framework with the adaptive model. The detailed step by step procedure will be explained as below:



Figure 6-3: L&G framework with adaptive analytic model

1. The initial LGI is generated will be the benchmarking LGI of the process.
Update and record the LGI as the present LGI.
2. Compare the LGI_{target} and LGI_{actual} . If LGI_{actual} is higher than LGI_{target} , the higher LGI_{target} will be updated as the new LGI_{target} of the new improvement cycle.
3. Perform BP analysis with Eqn. 6-1 to 6-3 to get the improvement weight for a new improvement cycle. The improvement cycle can be weekly, biweekly or monthly.
4. With the outcome from BP analysis, the weight of each sub-indicator will be recalculated to reflect the effectiveness of process improvement action. The priority of the indicators will be updated.
5. The member of the focus group will make the final decision based on the recommendation reflected by the adaptive model. Data collection continues after a new process improvement action is implemented. If there are any changes in goal or indicators, the L&G framework shall be restarted through focus group discussion.

6.4. Case study

The adaptive L&G approach is illustrated with the case study in chapter 5, section 5.4. The adaptive approach is extended after the LGI is established. The BP analysis is introduced in July 2018 where the facility is requested to establish a monthly target. Extending from Chapter 5, the facility has achieved the highest target as 0.96. Therefore, the industrialist has decided to set the LGI target at 0.96. As the facility is operating at a stable condition in the year 2018, Figure 6-4 illustrates the changes after implementation of the BP optimiser. It reflects fluctuation of monthly LGI in July as the BP optimiser provides feedback on

changes in main indicators' and sub-indicators' weight for improvement. Starting from August 2018, the monthly LGI showed an oscillation pattern as the BP optimiser feedback to the industrialist for improvement.

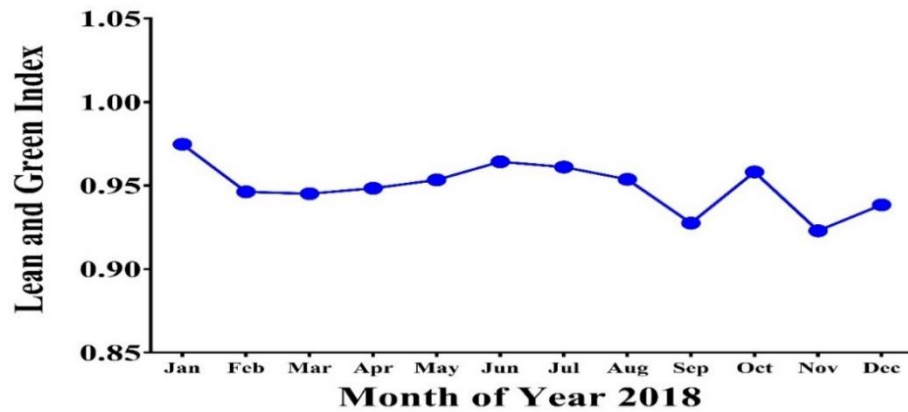


Figure 6-4: Monthly LGI update (BP optimisation initiated in July)

Figure 6-5, 6-6 and 6-7 demonstrate the weight update of 4M1E main indicator, MP and MY based-on BP optimisation respectively. All three figures show a similar pattern as the BP optimise the L&G model. In September 2018 and October 2018, BP explores some potential improvement area by using the previous data points. Based on the continuous feedback from the BP model and the industrialist, data from November 2018 and December 2018 showed sign of data converged. The convergence of the indicators demonstrates that the BP model, which is based on gradient descend optimiser has found a maximum point. The converged values are very close to their initial weight, and this validates that the expert has provided useful insights. These results from the BP model is dependent on the input from the historical process parameter. The average deviation of the targeted LGI after the implementation of BP is calculated to be 1.3 %. As compared to before implementation of the BP method, the average deviation is calculated to be 1.4 %. The BP model has only

implemented for 7 months in the operation. The accumulation of operation data will enhance the adaptivity of the optimisation model to improve the efficiency of the operation. Therefore, BP optimisation can support the industrialist in continuous process improvement.

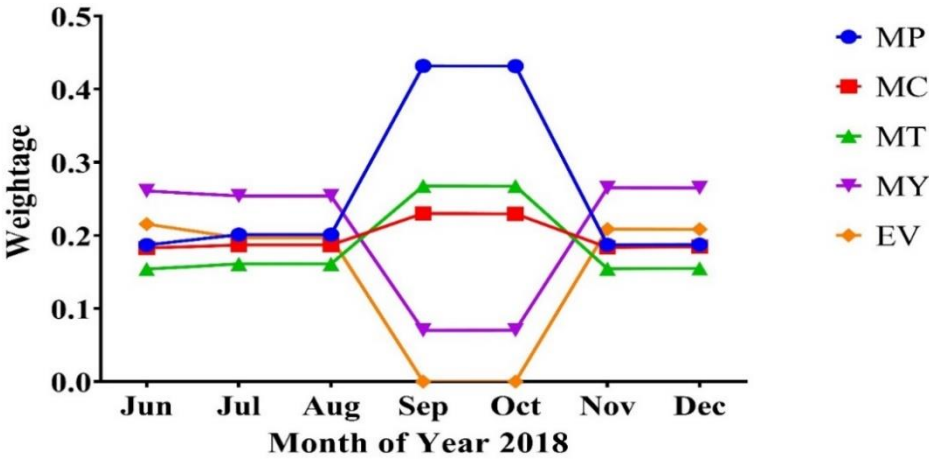


Figure 6-5: Backpropagation optimisation on 4M1E main indicators

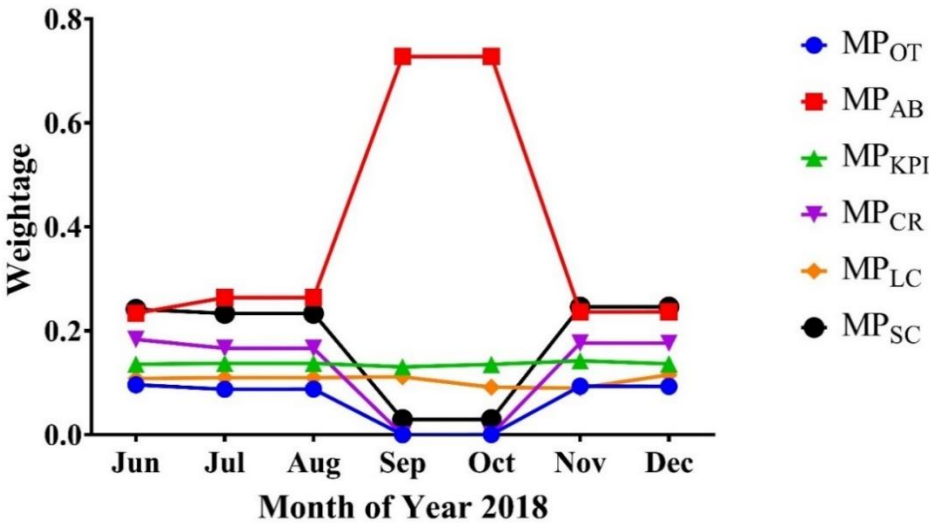


Figure 6-6: Backpropagation optimisation on MP indicator

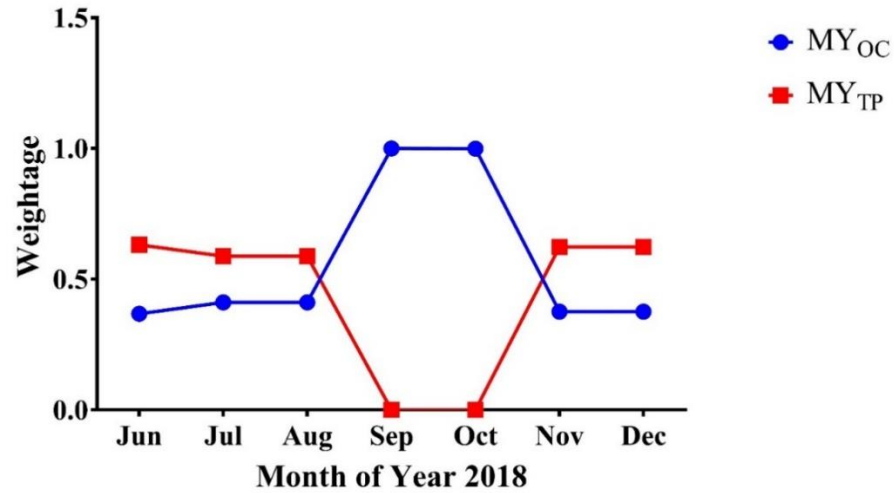


Figure 6-7: Backpropagation optimisation on MY indicator

6.5. Conclusion

The process improvement can be observed from the case study with the average deviation between the benchmarking LGI and adaptive LGI are showing a positive outcome. However, the deviation has not indicated massive improvement based on the comparison of the deviation. The industrialists have feedbacked that the adaptive model is providing a systematic process improvement strategy to the operation. The consistent review of the LGI has alerted the operators to be always mindful with their task. Overall, the adaptive analytical approach has provided a comprehensive analysis by including both data-driven and human expert input in analysing the process improvement strategy. Therefore, referring to section 3.4 (c), the development of the adaptive model has demonstrated the functionality in adapting to dynamic condition occur in the industry. The complexity of the adaptive analytical approach can be enhanced where the decision-making strategy and adaptive model can be further improved for better performance. The enhancement of the adaptive model will be extended in Chapter 7.

Chapter 7: Development of Ensemble Solver for Complex Adaptive Analytical Lean and Green Approach

7.1. Introduction

To extend the application of the adaptive analytical approach in a complex operation, the adaptive model needs to be enhanced by taking into consideration of the relationship between all indicators. The development of ensemble solver is proposed in this chapter to improve the functionality of the adaptive model to cope with higher complexity operation. This chapter focuses on enhancing the complexity of multi-criteria decision making (MCDM) method and the integration of ensemble solver to improve the performance of the adaptive model. The reliability of the model will be demonstrated with a case study in this chapter.

7.1.1. Development of Ensemble Solver

Several gradient descent optimisers can be used to enhance the performance of backpropagation (BP) model such as adaptive gradient (Adagrad), stochastic gradient descent (SGD) and adaptive moment estimation (Adam). Adagrad is developed by Duchi et al. (2011) to integrate the geometry of data observed in the earlier iteration to perform more informative gradient-based learning. The Adagrad method allocates a low learning rate to frequently occurring feature while the least occurring feature will be assigned with a higher learning rate. This act as an “alert” indicator for the learner to take note of the least occurring feature or abnormality. On the other hand, the SGD operates by randomly pick data to estimate the gradient. As the SGD does not

require to remember the selected data set for the previous iteration, it can be used to optimise the data directly (Bottou, 2010). The convergence of SGD is highly dependant on the noise approximation in the dataset. Moving on, Adam was introduced by Kingma and Lei Ba (2015) with adaptive learning rates for different parameters from estimates of first and second moments of the gradient. These 3 enhanced algorithms will form an ensemble solver for performance improvement. The best outcome from the algorithms will be used for the next improvement cycle.

7.1.2. *Integration of multi-criteria decision-making methods*

The lean and green (L&G) framework established in Chapter 5 has utilised the analytical hierarchy process (AHP) as the MCDM tools. To improve the MCDM approach, the “human expert” and data-driven input are considered in MCDM strategy. The combination of both MCDM approach shall result in an un-bias outcome.

In this section, the analytic network process (ANP) method is adopted to evaluate quantitative data (i.e. input from employee). The ANP is a general form of AHP to study the structural dependency of multiple criteria or level for decision making. AHP analyses the issue/problem that can be structured in a hierarchy structure (i.e., top-down). As most real case studies do not only involve the unidirectional dependence, ANP overcomes the constraint of AHP to include the inter-, inner- and feedback dependency of criteria of the problem. The supermatrix enables ANP to take in consideration of multiple

relationships to propose the final criteria weights to achieve the goal (Saaty, 2001). With the ANP approach, human expertise and experience which hardly can be quantified can be evaluated, prioritized and selected for process improvement.

On the other hand, the entropy method is applied to determine the weight of the performance indicator based on quantitative input. The entropy concept was first introduced by Rudolph Clausius in 1865 to measure the thermodynamics of the unavailability of a system's energy by measuring the disorder (Daub, 1970). The concept of information entropy was first introduced by Shannon (1948) to measure the uncertainty in information formulated in terms of probability theory. Entropy method can measure the amount of useful information with the given dataset (Işık and Adalı, 2017). The smaller the indicator's entropy, the higher the entropy weight which reflects the indicator provides more useful information and impactful for decision making (Cui, Zhang and Wang, 2009). The application of entropy was used widely in many applications such as finance (Zhou, Cai and Tong, 2013), engineering (Marvizadeh, 2013) and economy.

The combination of ANP and entropy approach has been used utilised in many areas. As ANP collects subjective inputs from a human expert, the weight of the indicators can have bias. The biases of ANP will be compensated by the entropy method where the weight of the indicators is b data-dependent. Many researchers have applied the combination of ANP and entropy in their work such as supply chain management (Liu et al., 2018), investment risk management (Yuan et

al., 2019), policymaking in renewable energy (Yang et al., 2018), production management (Mei et al., 2016), etc.

7.2. Methodology

The application of ensemble solver aims to deal with higher complexity problems. This involves the analysis of a higher volume of data with higher complexity between the inter-relationship of performance indicators. The improvements in the complexity of the adaptive model are illustrated in Figure 7-1 as below:

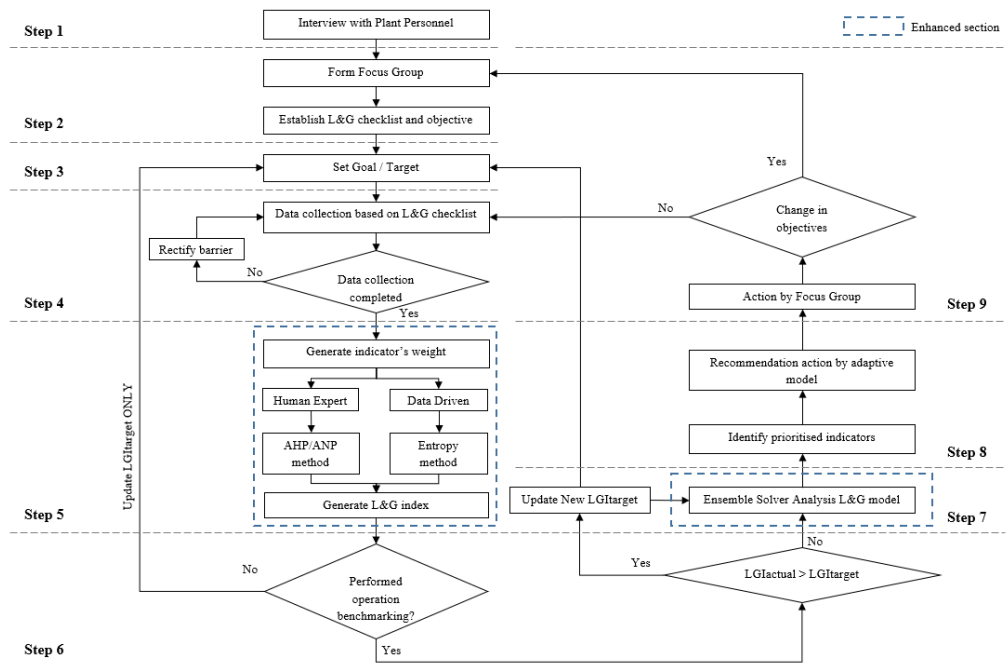


Figure 7-1: Adaptive analytical L&G framework with ensemble solver

The adaptive L&G model with ensemble solver shall be detailed in 9 steps as below:

Step 1: Establish contact with the plant manager and team to understand the organizational structure. To establish agreement and commitment with the organisation to implement L&G strategy.

Step 2: Establish a focus group to execute the L&G strategy. Review and understand the production/operation condition of the organisation. At this stage, the critical equipment and process control strategy shall be identified. The L&G checklist shall be finalised at this stage to develop the questionnaire. Figure 7-2 demonstrates the generic ANP structure that shows the relationship between the indicators. e represents the sub-indicator. The ANP structure is important in aiding the focus group to identify the relationship between the indicators for ANP analysis at a later stage.

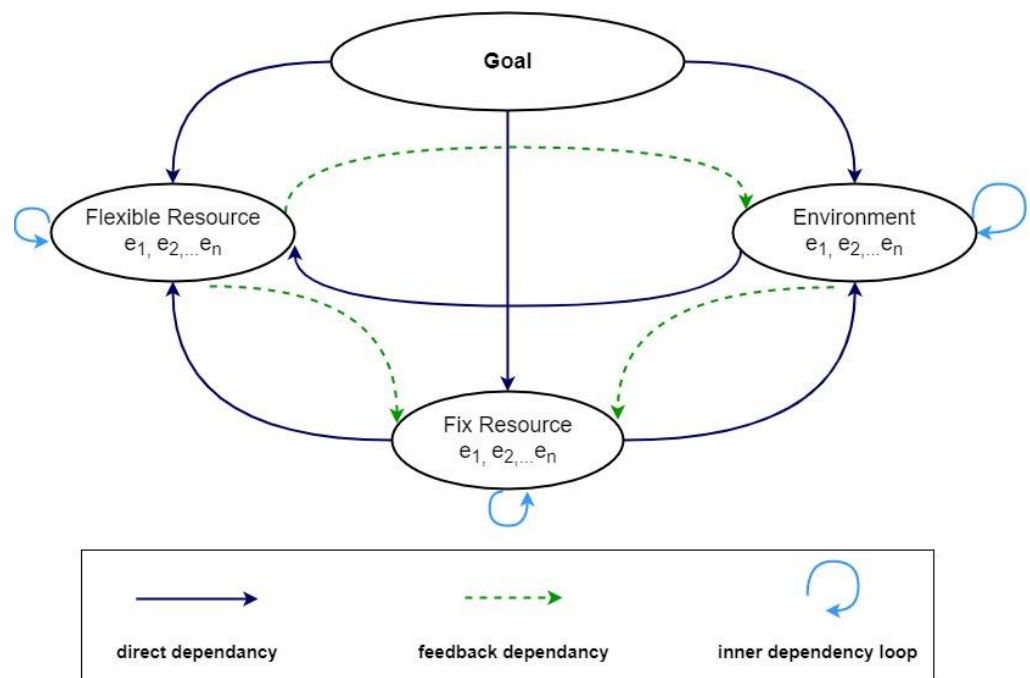


Figure 7-2: Example of the analytic network process (ANP) structure

User may refer to the generic L&G checklist (Section 4.3.1.) as the guideline to finalise the performance indicators. For instance, manufacturers who do not produce schedule waste, the scheduled waste indicator in the EV indicator can be removed from the checklist. The flexibility of the L&G checklist allows the industry players to modify

the checklist based on their organisation operation behaviour. It is important to note that only experienced and competent personnel who are familiar with the operation and process can perform modification on the generic L&G checklist. Any misinterpretation on the L&G checklist may result in wastage of additional resources and loss in productivity.

Step 3: When the industrialist first implemented L&G strategy, it is not required to establish an LGI target (LGI_{target}). User can skip this step for the first time. The first actual LGI (LGI_{actual}) acts as the benchmarking index is updated from Step 6, the focus group can now establish the improvement target (LGI_{target}). The improvement target will be within the range of 0 to 1.0, the user can establish 0.75 as the LGI_{target} as the initial target.

Step 4: With the questionnaire developed in Step 2, the questionnaire will be distributed to the plant manager and team to obtain their input. Ngan et al. (2018) highlighted that the prioritisation of ANP based on individual or group of people do not necessarily require a large sample size. The industry expert will need to input based on Saaty's pairwise comparison scale to represent the intensity of the relationship between the pairing as illustrated in Table 5-2 (Saaty, 2008).

The operation data shall be collected based on the L&G checklist concurrently. Any barrier in collecting the operation data shall be investigated and reported to ensure data collection can be done smoothly.

Step 5: The questionnaire and operation data collected in Step 4 will be analysed with ANP and entropy method to determine the weight of the performance indicators respectively.

Analytic Network Process (ANP)

The matrix, M_{ANP} in Eqn. 7-1 is formed by the pairwise comparison input of each C_n criteria reflected in the questionnaire and ANP structure. Edit (2008) stated that the collected data obtained from a group of expert will be combined with the geometric mean method.

$$M_{ANP} = \begin{matrix} & \begin{matrix} C_1 & C_2 & C_{...} & C_n \end{matrix} \\ \begin{matrix} C_1 \\ C_2 \\ C_{...} \\ C_n \end{matrix} & \begin{bmatrix} 1 & w_{12} & w_{1...} & w_{1n} \\ 1/w_{12} & 1 & w_{2...} & w_{2n} \\ 1/w_{1...} & 1/w_{2...} & 1 & w_{...n} \\ 1/w_{1n} & 1/w_{2n} & 1/w_{...n} & 1 \end{bmatrix} \end{matrix} \quad (7-1)$$

The M_{ANP} is then normalised to produce the normalized eigenvector as the weight of the components. Despite obtaining the weight of each matrix, it is important to note that the quality of ANP output is dependent on the consistency of the pairwise comparison.

Saaty (2008) emphasized that $CI \geq 0$ indicates the M_{ANP} is consistent. The consistency ratio (CR) (Eqn. 7-2) can be calculated to estimate the consistency of the expert's input as below:

$$CR = \frac{CI}{RI}, \quad CR < 0.1 \quad (7-3)$$

Generally, it is considered acceptable if the $CR < 0.1$. The Consistency Index (CI) is illustrated in Eqn. 7-3 while the random index (RI) can be obtained in Table 5-2:

$$CI = (\lambda_{max} - n)/(n - 1) \quad (7-3)$$

Figure 7-3 shows the steps in achieving the final weight for each performance indicator. Referring to Step 1 in Figure 7-3, all the collected questionnaires are evaluated, the pairwise comparison outcome is

combined to form an unweighted supermatrix. The combination of a matrix in the supermatrix is termed as cluster *A*, *B* and *C* in the unweighted supermatrix. The unweighted supermatrix is then normalized into weighted supermatrix by normalizing the column values in the supermatrix into the total sum of 1 to obtain the normalised eigenvector in Step 2. Next, in Step 3, the weighted supermatrix is then raised to the power until it is established to form the limit matrix. The limit matrix is said to be established until all the columns in the matrix have the same value as illustrated in Step 4.

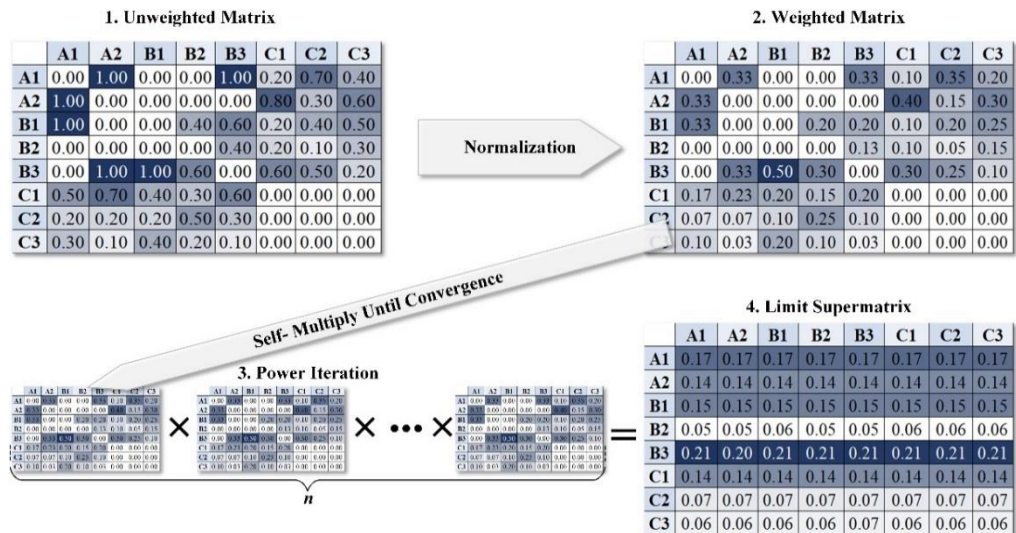


Figure 7-3: ANP supermatrix convergence steps

Entropy

The entropy weight is used to measure the weight of the data of the variables or indicators. Similar to ANP, the indicator and alternative of the MCDM problems will be expressed in a matrix structure.

$$p_{entropy} = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} C_1 & C_2 & C_{...} & C_n \\ w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{bmatrix} \quad (7-4)$$

The A_1 , A_2 , and A_m are the available alternatives that can be used for MCDM selection while C_1 , C_2 , and C_n are the indicators or criteria that are available to evaluate the alternatives. The methods of formulating the entropy weight are demonstrated below:

Calculation of weight, P_{ij} for i th alternative and j th indicator

$$P_{ij} = \frac{a_{ij}}{\sum_{i=1}^m a_{ij}^2}, (1 \leq i \leq m, 1 \leq j \leq n) \quad (7-5)$$

The output entropy e_j of j th indicator

$$e_j = -k \sum_{i=1}^m (P_{ij} \log P_{ij}), (1 \leq j \leq n) \quad (7-6)$$

$$k = 1/(\ln m) \quad (7-7)$$

Calculation of variation coefficient of j th indicator g_j

$$g_j = |1 - e_j|, (1 \leq j \leq n) \quad (7-8)$$

Calculation of weight of entropy, w_j

$$w_j = \frac{g_j}{\sum_{i=1}^m g_j}, (1 \leq j \leq n) \quad (7-9)$$

Combination of ANP + entropy

The evaluation of the weight of the main and sub-indicators are based on ANP and entropy method illustrated above. The combination of ANP and entropy creates a combined weight, w_c that consist of subjective and objective weight that strike a balance between human expert and data-

driven approach. Cui et al. (2009) have demonstrated a method to establish the combined weight as below:

$$w_c^i = \frac{w_{ANP}^i \times w_{entropy}^i}{\sum_{i=1}^n w_{ANP}^i \times w_{entropy}^i} \quad (7-10)$$

The LGI is then calculated before proceeding to the next step. The development of LGI is explained in Section 4.2.

Step 6: The first LGI generated from Step 5 will be updated in Step 3 as the benchmarking LGI and use to establish the LGI_{target} . Once the LGI has been benchmarked, compare the LGI_{actual} with LGI_{target} . Whenever the LGI_{actual} is larger than the LGI_{target} , an LGI that is larger than LGI_{actual} will be automatically updated as the new LGI_{target} .

Step 7: The adaptive L&G model with ensemble solver evaluates the operation performance by comparing LGI_{actual} with LGI_{target} with BP approach. The improved L&G model has incorporated a novel ensemble optimisation model which consists of 3 gradient descent optimisers to analyse the performance indicators for maximum operation improvement. The purpose of using an ensemble solver as to a single solver is due to the nature of the problem. As solving and computational time is not a constraint for adaptive process optimisation, using an ensemble of solvers would provide more efficient optimisation. This translates to lesser search step to achieve an optimal point. The mathematical formulation for the ensemble solver is explained in Table 7-1 below:

Table 7-1: Backpropagation optimiser

Mathematical formulation	
Adaptive gradient algorithm (Adagrad)	Adagrad is a gradient descent optimisation algorithm that adapts the learning rate according to parameters (Duchi et al., 2011). It allocates a smaller learning rate for frequently occurring events while assigning a higher learning rate for lesser occurring events. The general gradient descent algorithm is defined as below: $w_{t+1} = w_t - \eta \frac{\partial L}{\partial w}(t) \quad (7-11)$ where w_{t+1} is the weight needs to be updated, w_t is the previous wight, η is the initial learning rate as 0.01 (Ruder, 2017), $\frac{\partial L}{\partial w}(t)$ is the gradient in time step, t. For Adagrad optimiser, the learning rate is expressed as below: $w_{t+1} = w_t - \frac{\eta}{\sqrt{G_i(t) + \epsilon}} \frac{\partial L}{\partial w_t} \quad (7-12)$ $G_i(t)$ is an important element in Adagrad where it is defined as the squared gradient over time, t. $\epsilon, (1 \times 10^{-8})$ is a smoothing factor (to avoid the function dividing with zero.

The gradient, also known as loss function, can be expressed as below:

$$\frac{\partial L}{\partial w_i} = \frac{E_i - E_{i-1}}{w_i - w_{i-1}} \quad (7-13)$$

$$G_i(t) = G_i(t-1) + \left(\frac{\partial L}{\partial w_i}\right)^2 \quad (7-14)$$

**Stochastic
gradient
descent (SGD)**

SGD operates by randomly select the indicator's weight for BP optimisation (Bottou, 2010). Referring to Eqn. 7-15, the SGD is expressed as below:

$$w_{t+1} = w_t - \eta \frac{\partial L_R}{\partial w_R}(t) \quad (7-15)$$

where η is the learning rate of 0.05, $\frac{\partial L_R}{\partial w_R}(t)$ is the gradient calculated with a random value from the data set which is expressed as below:

$$\frac{\partial L_R}{\partial w_R} = \frac{E_i - E_R}{w_i - w_R} \quad (7-16)$$

where E_R is the random error while w_R is a random weight of a component.

**Adaptive
moment
estimation
(Adam)**

Adam is an adaptive learning rate optimisation algorithm (Kingma and Lei Ba, 2015). It has the advantage to deal with the magnitude of parameters updates that are invariant to a rescaling of gradients. Adam optimiser is expressed as below:

$$w_{t+1} = w_t - \frac{\eta \cdot \hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \quad (7-17)$$

where η is the learning rate as 0.001 (Kingma and Lei Ba, 2015), $\widehat{m}_t$ as the compute bias-corrected first moment estimate, $\widehat{v}_t$ as the compute bias-corrected second raw moment estimate and ϵ is 1×10^{-8} , a very small number to prevent division by zero.

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad (7-18)$$

$$\widehat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (7-19)$$

where m_t is the update biased first-moment estimate, v_t is the update biased second raw moment estimate, β_1 and β_2 are defaulted as 0.9 and 0.999 respectively. β_1^t and β_2^t are β_1 and β_2 to the power of t .

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t \quad (7-20)$$

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2 \quad (7-21)$$

where g_t is known as the loss function $\frac{\partial L}{\partial w_i} = \frac{E_i - E_{i-1}}{w_i - w_{i-1}}$.

The ensemble model (i.e. Adagrad, SGD and Adam) is initiated based on each time step. The outcome of the optimiser with the highest LGI output will be used for performance improvement. Kindly refer to Appendix II (a) for the mathematical proof.

The architecture of the ensemble solver is presented in Figure 7-4. The strategy represents the process improvement method and pathway. As the time step progress, the error reflects the gap between

the LGI_{actual} and LGI_{target} . With this error feed into the ensemble, the value of the solver with maximum LGI_{actual} will be utilised for the next time step. This will accelerate the improvement process as the ensemble solver will always select the best pathway for process improvement. As an outcome exceeds the target LGI, the highest achieved LGI will be updated as the new target LGI. The novelty of the ensemble architecture is the flexibility of the solver to cope with the dynamic condition in a production facility.

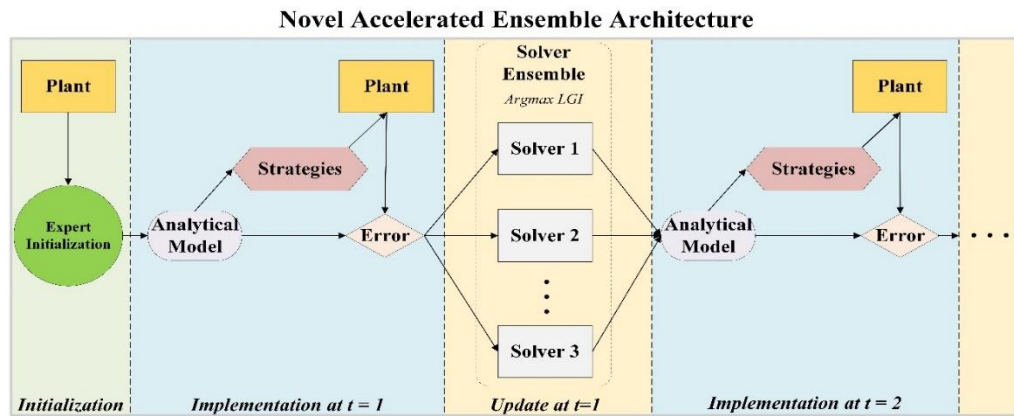


Figure 7-4: Novel accelerated ensemble architecture

Step 8: The outcome from adaptive L&G model will highlight potential improvement indicators. This will be reflected through the weight of the performance indicators.

Step 9: The focus group member can take action based on the recommendation by the adaptive model. However, the final decision is to be made by the group members. Once the improvement process is in place, the organisation can return to Step 4 for data collection. If the improvement objectives need to be amended, proceed to Step 2.

The optimisation is considered converged and achieved the optimum point when the final output of the LGI_{actual} is very close to the LGI_{target} for several cycles. At this junction, the focus group can move to Step 2 to establish a new target for performance improvement.

7.3. Case study

The case study presented a combined heat and power (CHP) plant with the capacity of 20MW electricity generation and 50 ton/hr of steam at 10bar. The configuration consists of 3 unit of gas turbines (GT) with a generation capacity of 6.7MW each. Each GT will be couple with heat recovery steam generator (HRSG) to recover the waste heat to steam. The facilities hold a big responsibility to ensure a constant supply of energy utility is met. The CHP plant configuration is illustrated in Figure 7-5.

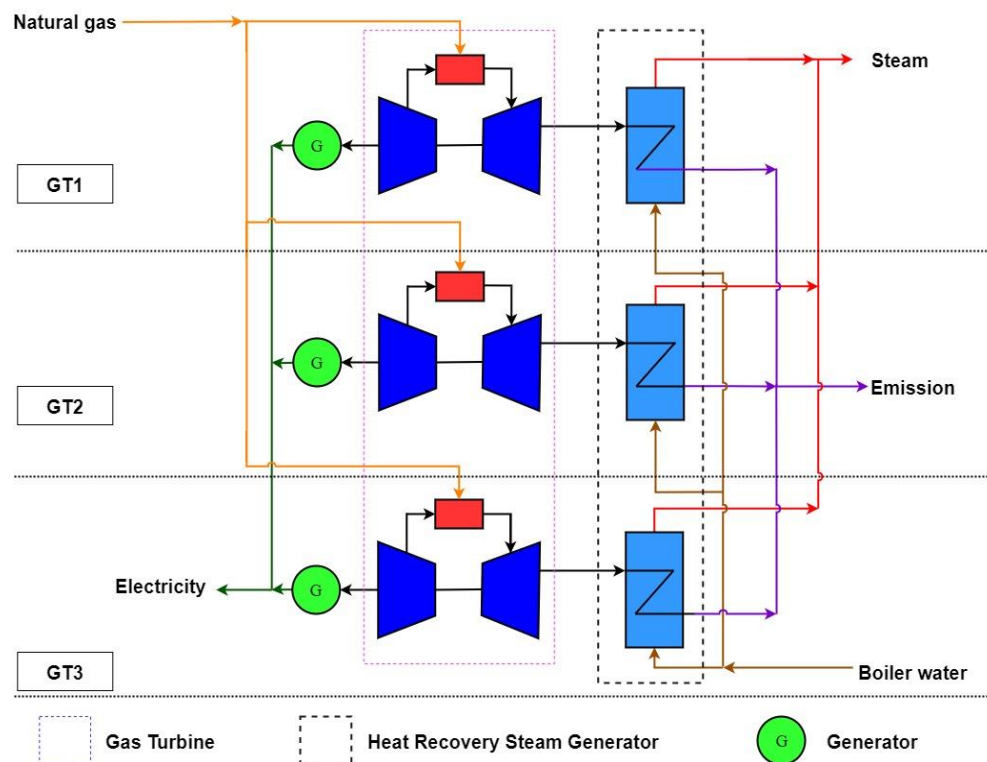


Figure 7-5: process flow diagram of combined heat and power plant

According to the enhanced L&G framework, a focus group is established after the interview with the plant management (*Step 1*). A simple focus group organisation structure (Figure 7-6) is formed to ensure the L&G strategy can be implemented and coordinated smoothly (*Step 2*). The organisation structure of the focus group includes a member with higher decision-making authority to ensure the smoothness of the L&G strategy implementation process. In this case, the focus group was led by the operation manager of the organisation with the assistant of representatives from production, utility, human resource and maintenance team.

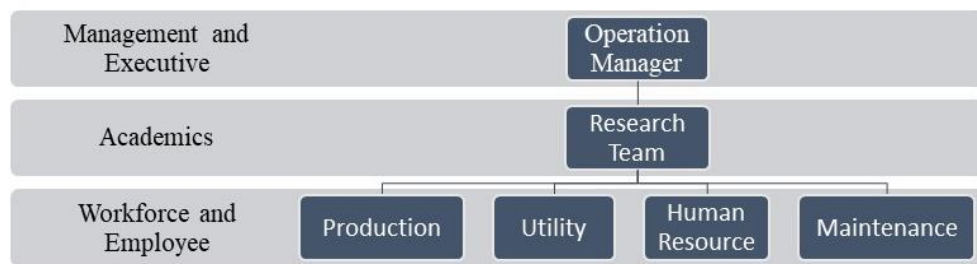


Figure 7-6: L&G strategy focus group team structure

Referring to the general L&G checklist (Figure 4-2) as the guideline, the performance indicators have been identified by the focus group. Figure 7-7 presents the ANP decision-making structure contributed by the focus group member.

As compared to the general L&G checklist, Table 7-2 was modified according to the operational needs (*Step 3*). However, the structure still covers the fundamentals of operation which includes manpower, machine, money, material and environment aspects.

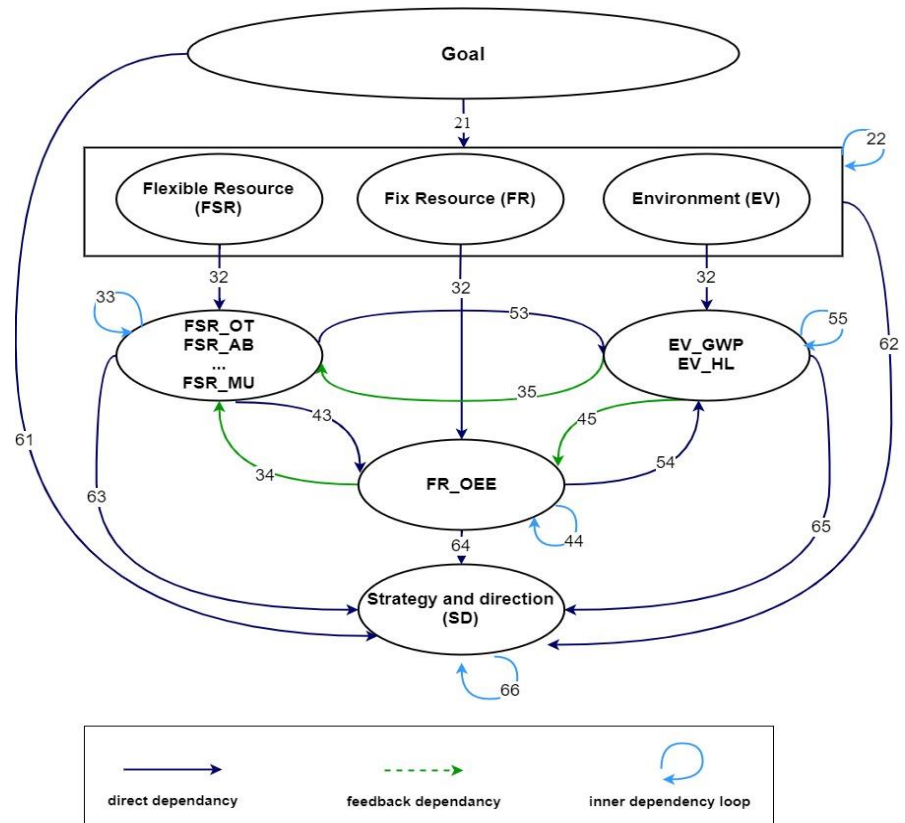


Figure 7-7: ANP structure for case study

Table 7-2: Identified performance indicators for CHP plant.

Main indicators	Sub-indicators	Factor determination method
Fix Resources (FR)	Overall	Determined based on a process data logger
	FR_OEE	
	Equipment Effectiveness	
Flexible Resources (FSR)	FSR_OT	Determined based on the human resource record
	Employee Overtime	
	FSR_AB	Determined based on the human resource record
	Employee Absent	

	FSR_KPI	Employee KPI	Determined based on an actual performance indicator
	FSR_CS	Employee Competency rate	Determined based on actual performance output and expert evaluation
	FSR_SA	Employee Safety competency	Determine based on training records, safety test and on-site evaluation
	FSR_OPE X	Operation Cost	Determined based on actual operation data collection
	FSR_TP	Operation Profit	Based on the difference of operation cost and contract selling price
	FSR_PP	Total product produced	Based on total production output
	FSR_MU	Total material used	Based on total production consumption
Environment (EV)	EV_GWP	Carbon Emission	Based on carbon emission output

	EV_HL	Heat Loss	Based on outlet temperature sensors
Strategy			
and	EE	Employee	Based on expert input
direction		empowerment	
(SD)			
		Improve	
	ENV	Working	Based on expert input
		Environment	
	ER	Employee	Based on expert input
		rewards	
	ET	Employee	Based on expert input
		training	
	ME	Machinery	Based on expert input
		enhancement	
	RD	Operation R&D	Based on expert input

A common decision-making strategy (SD) is added to the ANP structure to have a better understanding of the decision-making strategy. A set of questionnaires are then prepared based on the L&G checklist (Table 7-2) to collect qualitative input from the industry expert. To achieve a balanced weight, entropy and ANP analysis method are used. However, some performance indicator may not be able to present quantitative data. Therefore, Figure 7-8 has highlighted the performance indicators that contribute to the weight of the performance indicator with both analysis methods.

	GO	FSR	FR	EV	FSR_OT	FSR_AB	FSR_KPI	FSR_CS	FSR_SA	FSR_OPEX	FSR_TP	FSR_PP	FSR_MU	FR_OEE	EV_GWP	EV_HL	EE	ENV	ER	ET	ME	RD
GO	11	12		13										14	15		16					
FSR	21	22		23										24	25		26					
FR																						
EV																						
FSR_OT	31	32		33										34	35		36					
FSR_AB																						
FSR_KPI																						
FSR_CS																						
FSR_SA																						
FSR_OPEX																						
FSR_TP																						
FSR_PP																						
FSR_MU																						
FR_OEE	41	42		43										44	45		46					
EV_GWP	51	52		53										54	55		56					
EV_HL																						
EE	61	62		63										64	65		66					
ENV																						
ER																						
ET																						
ME																						
RD																						

ANP Weights with Entropy

ANP Weights Only

Figure 7-8: Supermatrix structure with the weight determination method

Referring to the L&G checklist (Table 7-2), the LGI is calculated from the weight of flexible resource (w_{fsr}), fix resource (w_{fs}) and environment (w_{EV}) as below:

$$LGI = (w_{fsr} \times FSR) + (w_{fs} \times FS) + (w_{EV} \times EV) \quad (7-22)$$

To ease presentation and understanding to the industry user, the LGI can be presented on the scale of 1 as illustrated in Figure 7-9.



Figure 7-9: Performance scale with lean and green index

Moving on, the calculation of sub-indicators are presented in Table 7-3 below:

Table 7-3: Lean and green index calculation for sub-indicators

Main indicators	Sub-indicators	Explanations
Flexible resources (FR)	Overall equipment effectiveness	The OEE is widely accepted as a quantitative tool to measure manufacturing performance. It is established from the availability (A), performance efficiency (P) and rate of product quality (Q). An OEE score of more

of machinery than 85% is considered world-class
(FR_OEE) performance.

$$A = \frac{\text{Planned opt. time} - (\text{equip. failure time} - \text{set up and adj. loss})}{\text{Planned opt. time}}$$

(7-23)

$$P =$$

$$\frac{\text{Total processed amount} \times \text{Ideal production rate}}{\text{Actual operation time}}$$

(7-24)

$$Q = \frac{\text{Processed amount} - \text{Defect amount}}{\text{Processed amount}} \quad (7-25)$$

$$OEE = A \times P \times Q \quad (7-26)$$

Fix resources (FSR)	Employee's overtime (FSR_OT)	The total time obtained from employee's OT can be averaged and normalised with the total working hours per month. Where $hr_{opt,month}$ is the total working hours per month and OT_{avg} is the average employee OT obtained per employee.
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$$OT_{avg} = \frac{\text{Total employee over time monthly}}{\text{Avg. no. of employee working monthly}}$$

(7-27)

$$OT = \frac{hr_{opt,month} - OT_{avg}}{hr_{opt,month}} \quad (7-28)$$

Employee's absent from	Employee's absent day from work can cause inconvenience to the operation performance. As one of the indicators in LGI, the total
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work record (FSR_AB)	absent day from the employees can be averaged and normalised with the total working days per month. The absent day includes an emergency day off, a medical day off and any unplanned day off. Where AB_{avg} is the average absent day per employee monthly while the $day_{opt.month}$ is the total working day per employee.
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$$AB_{avg} = \frac{\text{Total employee absent day monthly}}{\text{Avg. no. of employee working monthly}} \quad (7-29)$$

$$AB = \frac{day_{opt.month} - MP_{ABi}}{day_{opt.month}} \quad (7-30)$$

Employee's key performance index (FSR_KPI)	The KPI is used to evaluate the performance of an employee. It is to note that the KPI establishment shall be reasonable and based on specific, measurable, attainable, relevant and time-based (SMART) criteria. KPI is evaluated by the achievable percentage which can be normalised to scale of 1 in Eqn. 20. The KPI_{avg} is the average KPI achievable per employee monthly.
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$$KPI_{avg} = \frac{\text{Total employee KPI achievable monthly}}{\text{Avg. no. of employee working monthly}} \quad (7-31)$$

$$KPI = \frac{KPI_{avg}}{100} \quad (7-32)$$

Employee's competent skill evaluation (FSR_CS)	Employee competent skills evaluation can be done through training record and knowledge assessment program. The assessment can be done monthly to ensure that the employee is fit and competent to perform the task. This also so safeguards the quality of work and continuously improve the skills of the workers to improve work performance. MP_{avg} is termed as the average employee competency rate per employee monthly.
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$$SC_{avg} = \frac{\text{Total employee competency rate monthly}}{\text{Avg. no. of employee working monthly}} \quad (7-33)$$

$$SC = \frac{MP_{avg}}{100} \quad (7-34)$$

Employee's safety awareness (FSR_SA)	Employee safety is recognised as one of the critical factors in an organisation. The SC_{avg} evaluates the safety awareness rate of the employee through safety assessment and training by rating the safety competency of every employee. This evaluation can be done by safety officer based on the worker's
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	awareness of safety when performing their task at the site. $SC_{avg} = \frac{\text{Total rate of safety competency monthly}}{\text{Avg. no. of employee working monthly}} \quad (7-35)$ $SC = \frac{SC_{avg}}{100} \quad (7-36)$
Total operation cost expenditure (FSR_OPEX)	FSR_OPEX is always an important indicator in all industry. The benchmarking is performed on the production cost with respect to per unit of product. As minimum FSR_OPEX is favourable, the FSR_OPEX indicator is evaluated as below: $FSR_OPEX = \frac{\text{Min.opt. cost / unit of product}}{\text{Avg. opt. cost/unit of product}} \quad (7-37)$
Total production profit (FSR_TP)	Apart from FSR_OPEX, TP is also an important indicator. As maximum profit is desired, the TP is evaluated as below: $TP = \frac{\text{Avg. profit / unit of product}}{\text{Max. profit /unit of product}} \quad (7-38)$
Total material use (FSR_MU)	The total material used is evaluated as an indicator of resource consumption efficiency. This is also used as a statistical process control instrument to assist the operators to monitor the material

consumption. Material monitoring is through continuous monitoring of material consumption efficiency. When a new operation optimum is achieved, the new optimum point will be used as the new process benchmark.

$$MU = \frac{\text{Total min.material use for per product}}{\text{Monthly material used per product}}$$

(7-39)

Production consistency (FSR_PP)	The total production is evaluated as an indicator to monitor the consistency and production quantity and quality. It measures the total production including main product and by-product.
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$$PP = \frac{\text{Monthly production output}}{\text{Monthly material used for production}}$$

(7-40)

Environment (EV)	Total global warming potential (EV_GWP)	The GWP of the organisation is measured in terms of carbon dioxide (CO ₂) emission. Shindell et al. (2013) have listed out the GWP conversion factor based on a series of greenhouse gases (GHG). The GWP indicator is to benchmark the GWP to control it at the minimum.
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$$GWP = \frac{\text{minimum monthly GWP}}{\text{average monthly GWP}} \quad (7-41)$$

Total heat loss (EV_HL) In this case study, another important indicator is the total HL. As a control indicator, the HL is valued by comparing the average HL with the minimum HL of the operation. This is to ensure that the HL will always be at the minimum.

$$HL = \frac{\text{Ideal energy prod.} - \text{loss of heat prod.}}{\text{ideal heat prod.}}$$

(7-42)

The initial weight of the main and sub-indicators are demonstrated in Figure 7-10 (Step 4). Figure 7-10 summarises the input from industry expert and data collected from the facility. It shows that the FSR (52.91%) rated highest followed by FR (28.66%) and EV (18.43%).

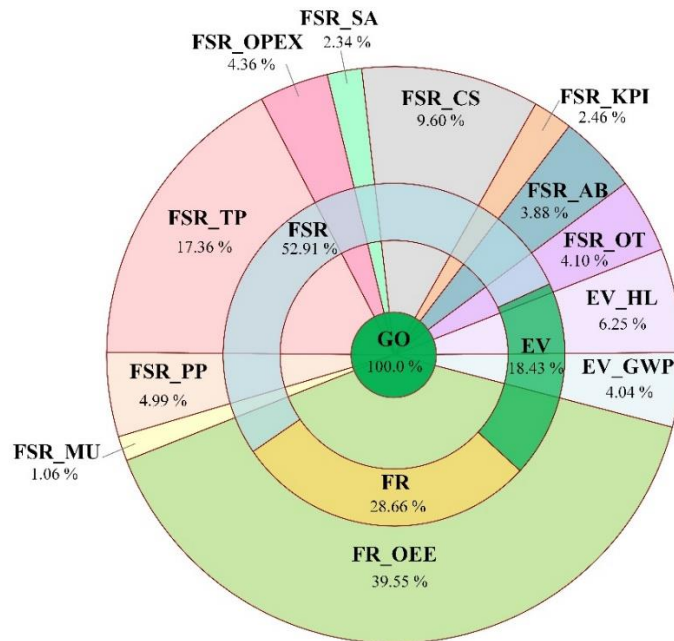


Figure 7-10: Consolidated weight for performance indicators.

By focusing on the sub-indicators, it can be observed from Figure 7-11 that FR_OEE (39.55%) was the top priority in the organisation followed by FSR_TP (17.36%), FSR_CS (9.60%), EV_HL (6.25), FSR_PP (4.99%) and FSR_OPEX (4.36%). The focus group member explained that FR_OEE is the top priority of the organisation due to the nature of the organisation business model as a utility provider. As the supply of utilities (electricity and steam) are legally contracted, the organisation will want to avoid failure in meeting the utility demand which will cause them a higher penalty. Moving on, FSR_TP and FSR_OPEX are both performance indicator for financial performance. As for human resource matter, the competency of the employee is among the top priority due to the lack of competent and experienced GT personal available in the labour market. The focus group also highlighted that the organisation is focusing on building up a strong workforce to maintain the operation of the business. Moving forward, EV_HL representing the importance of heat loss in the CHP plant. From the operation feasibility study, EV_HL is one of the main factors in ensuring the profitability of the organisation. Waste heat from CHP plant is normally recovered as steam or hot water. Conventionally, industry players generate heat from the boiler with natural gas where the additional cost will be incurred on FSR_OPEX. On the other hand, the total material usage in the facility has the lowest priority among the indicators due to the requirement to fulfil the utility supply contract.

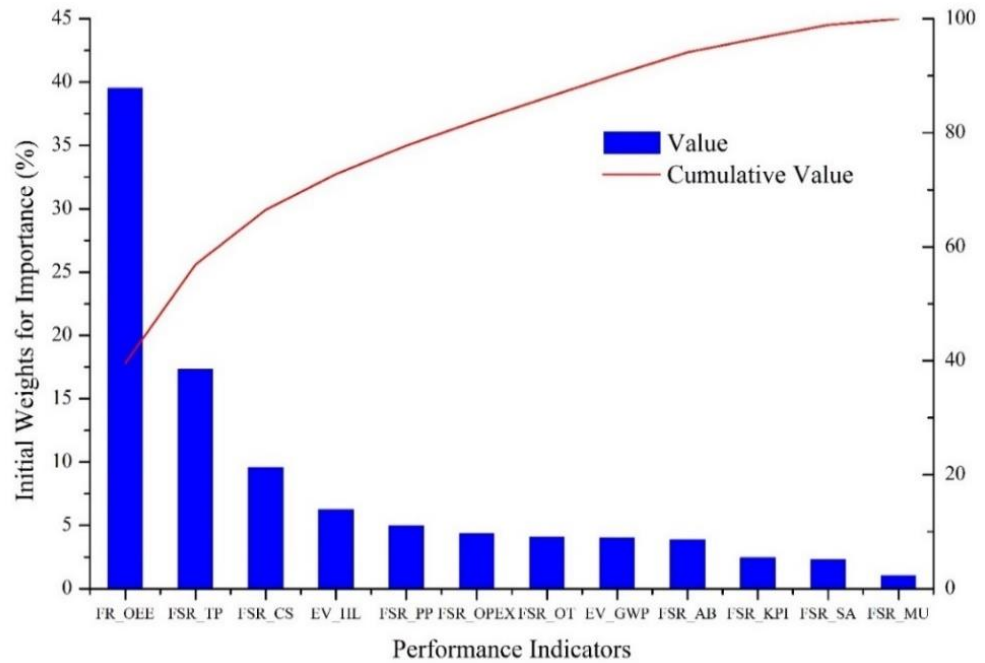


Figure 7-11: Pareto chart of all performance indicators

In normal operation management, the organisation imposed several critical strategies for process improvement, especially on the employee. Figure 7-12 illustrates the importance of the strategy that the organisation uses to motivate the employee for process improvement and enhancement. The list of strategies are illustrated in Table 7-2. Based on the input from the focus group, it can be observed that employee reward (28.16%), employee training (19.95%) and machinery enhancement (14.15%) are among the top priority for process improvement.

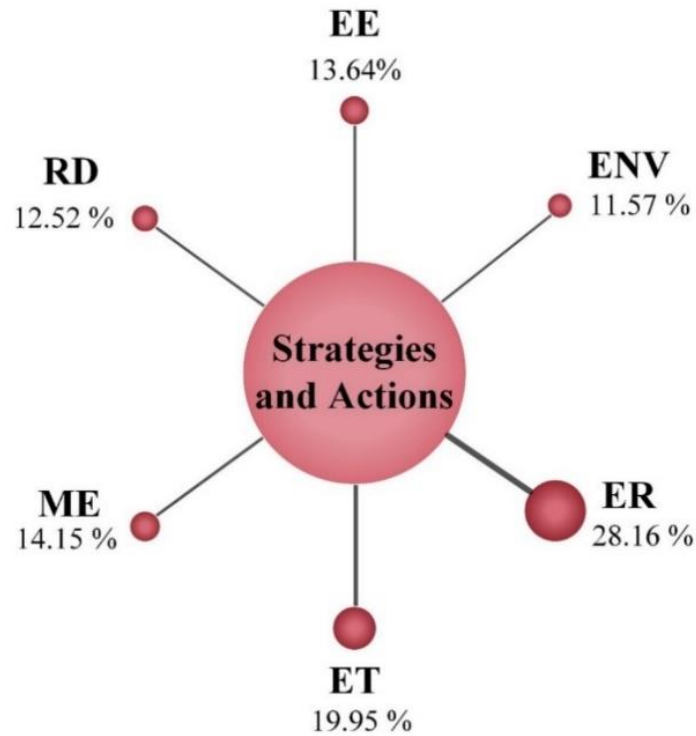


Figure 7-12: Process improvement strategy and direction (SD)

The management further explained the adoption of a performance-based approach to reward the employee with respect to the plant performance. This will motivate the employee to strive for maximum reward by achieving the organisation goal. To achieve the goal, on-job training is provided to ensure that the employees can execute their daily task. The management has also revealed that most of the employees are reward-driven which can be one of the main reasons resulting in consistent performance improvement. The organisation has also expressed the concern of losing experience personal. The competition of talent recruitment and retainment has been a tough challenge among the same sector. Due to the lack of experienced and competent GT engineers and operators in the market, employers always have the risk of losing their employee to the competitor. Due to human resources concern in the industry, the adoption of the analytic model can be an alternative to improve plant operation.

7.3.1. Gas turbine configuration

The case study was provided with the operation data from the year 2017 to the year 2019. Despite the adaptive L&G strategy is implemented in the facility from January 2019, the LGI of the year 2017 and year 2018 were also analysed with the L&G model as illustrated in Figure 7-13 (b). As for the data collected for the year 2017 and 2018, the management maintains the same operation philosophy and behaviour as indicated by the operation expert through the focus group discussion. As explained by the industrialist, the facility's operation relied on the GT availability to cope with energy demand. Therefore, a high priority is imposed on the equipment.

The LGI is calculated for the first time in the CHP plant using Eqn.7-22 (*Step 5*). Based on Figure 7-13, despite the total GT energy generation increased with time, LGI has not reflected a consistent improvement with time. In May 2018, a spike drop in LGI is observed as the demand for energy reduced. Through data analysis, the drop in LGI in the circle area is mainly due to the demand distribution to each GT unit. Referring to Figure 7-13 (a), the energy generation capacity for all the GT is not evenly spread. Therefore, the operation setup has enabled GT3 to operate at lower equipment efficiency which leads to lower LGI. GT operates at lower energy demand will consume more fuel which results in higher operation expenditure (OpEx) and waste. As the energy demand increases in January 2018, the configuration of GT remains the same where GT1 and GT2 as the main prime mover while

GT3 act as the backup unit. The LGI has also increased accordingly showing better performance. This is mainly due to the increase in equipment efficiency of the GT. Generally, it is best to operate the GT at a higher energy demand to increase the production efficiency while bringing down the operation cost per kWh of energy produced. At this point of time, despite the GT3 is operating at lower energy demand, the performance of GT1 and GT2 can compensate the performance of GT3 in terms of OpEx and fuel consumption which leads to higher LGI. In October 2018, a sudden drop of LGI is due to scheduled maintenance of GT1. The drop in LGI is mainly caused by the FSR_TP factor.

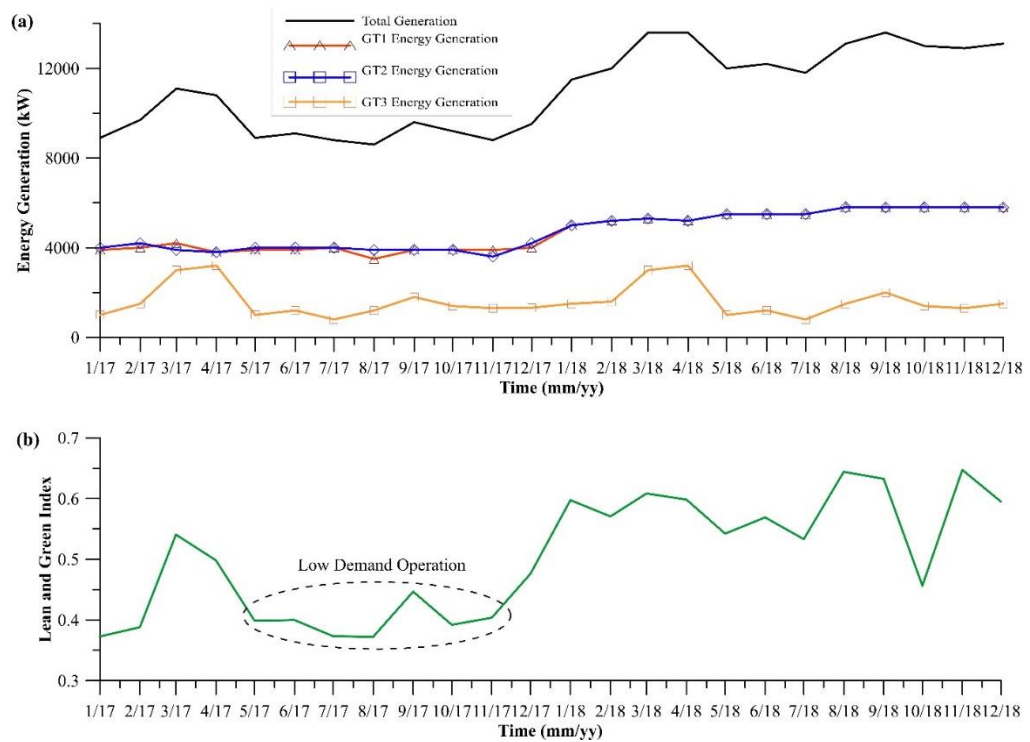


Figure 7-13: (a) GT configuration with load demand and (b) LGI for the year 2017 and 2018

7.3.2. *Adaptive lean and green approach with ensemble solver*

The implementation of the enhanced adaptive L&G model in the CHP facility started in January 2019. The recommended action from the ensemble model was discussed among the focus group members before implementation. Before process optimisation started, the process is benchmarked for its initial performance. The initial LGI is evaluated to be 0.59. Then, the focus group decided to establish the LGI_{target} at 0.75 (*Step 6*). With the input from the industry expert and operation data, the ensemble solver was used to optimise the process. The ensemble solver has been implemented since January 2019 to August 2019. Figure 7-14 shows the performance of ensemble solver with respect to LGI_{target} . In April 2019, the LGI_{target} at 0.75 is achieved where the ensemble solver obtained the LGI_{actual} at 0.76. Therefore, a new LGI_{target} is automatically updated at 0.77 (*Step 7*). The reason to update the LGI_{target} higher than the newly achieved LGI is to avoid 0 at the loss function. In Jun 2019, the ensemble solver managed to break-through the LGI_{target} at 0.77 with a new LGI at 0.81. Again, a new LGI_{target} is updated with 0.82 in the ensemble solver. Generally, the CHP plant performance was improved by 18.25% since the implementation of adaptive L&G model. With the auto-update LGI_{target} function, the enhanced adaptability of the analytic model can be useful in a dynamic process condition.

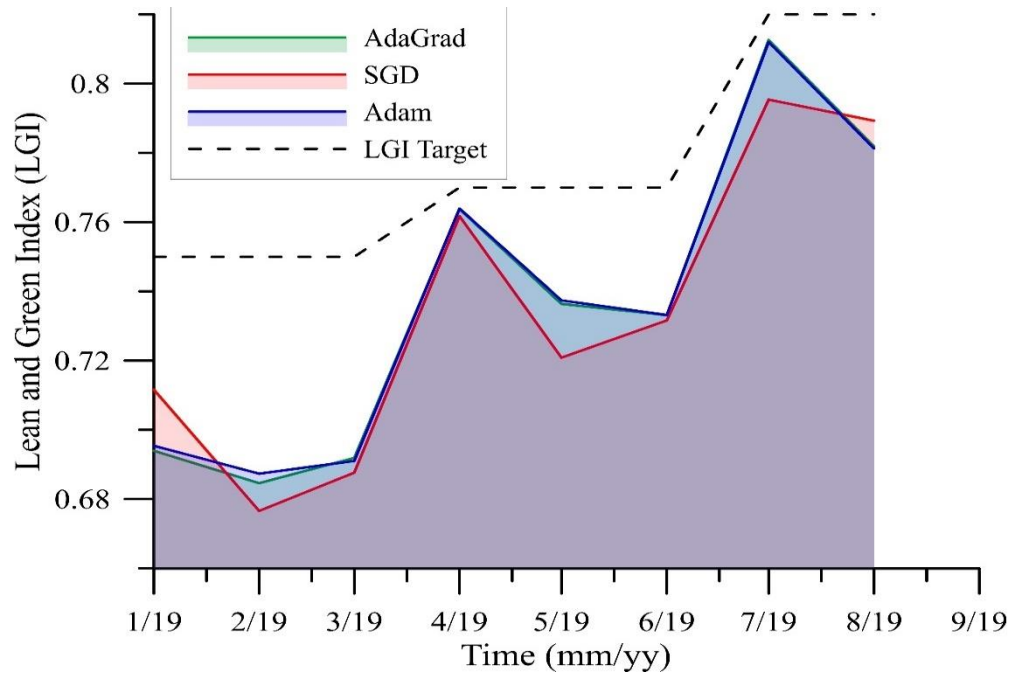


Figure 7-14: LGI resulting from ensemble solver

Figure 7-15 shows the weight changing trend of the performance indicators resulting from the ensemble solver. Based on Figure 7-15(a), the outcome from the ensemble solver indicates that the influence of EV is gradually decreasing in the operation. This illustrates that EV does not contribute extensively to this facility. FSR is indicating a gradual increase in weight while FR shows a consistent weight.

Next, the FSR indicates gradual decrease followed by an increase in LGI in August 2019 as illustrated in Figure 7-15(b). It is within the expectation that the FSR will have more fluctuation as it consists of the performance indicators of human resource, financial and material consumption. 4 performance indicators in FSR has shown a consistent increase in weight (i.e. FSR_KPI, FSR_OPEX, FSR_OT and FSR_SA). Both FSR_TP and FSR_MU have shown a gradual decrease

in weight with time while the remaining indicators indicate relative consistent weight.

Moving on to FR (Figure 7-15(c)), both FR and FR_OEE have relatively stable and consistent weight outcome. The FR_OEE is often influenced by the availability of equipment, product quality and production capacity. It is important to note that FR_OEE is constrained by the machinery limitation. Due to the operation limitation of GT configuration, the fluctuation of FR_OEE is mainly affected by the energy demand and maintenance schedule that leads to the energy generation efficiency.

In Figure 7-15(d), EV_HL shows a gradual increase in weight reflecting the effort in increasing heat recovery for steam. However, EV_GWP is reflecting a gradual decrease in weight. Based on the support from the operation data, the EV_GWP has achieved the current operation optimum point. Therefore, the EV_GWP emission is considered achieving the steady-state where it will not have a large effect on the facility's performance.

The increase in weight of the performance indicator indicates that more attention is required. FSR_KPI, FSR_OT and FSR_SA are related to human resource management. It can be translated as the KPI performance of the employee does not meet the expectation of the organisation, the overtime claims exceed the limits and the safety competency of the employee at work respectively. Referring to Figure 7-11, despite these indicators does not reflect high weight in process improvement, it should not be neglected as it may affect the overall

performance of the organisation. Not to forget FSR_OPEX, the main factor that causes fluctuation of the OpEx is the fluctuation of natural gas price. In Malaysia's natural gas supply chain, the natural gas price will be adjusted on a 6 months basis.

The FSR_TP and FSR_MU have demonstrated a decrease in weight throughout process improvement. FSR_TP reflects the profit gained while FSR_MU represent the total material used in the CHP facility. Based on the operation condition, it can be interpreted as the FSR_TP and FSR_MU have reached a point where the profit and material use has reached the optimum condition.

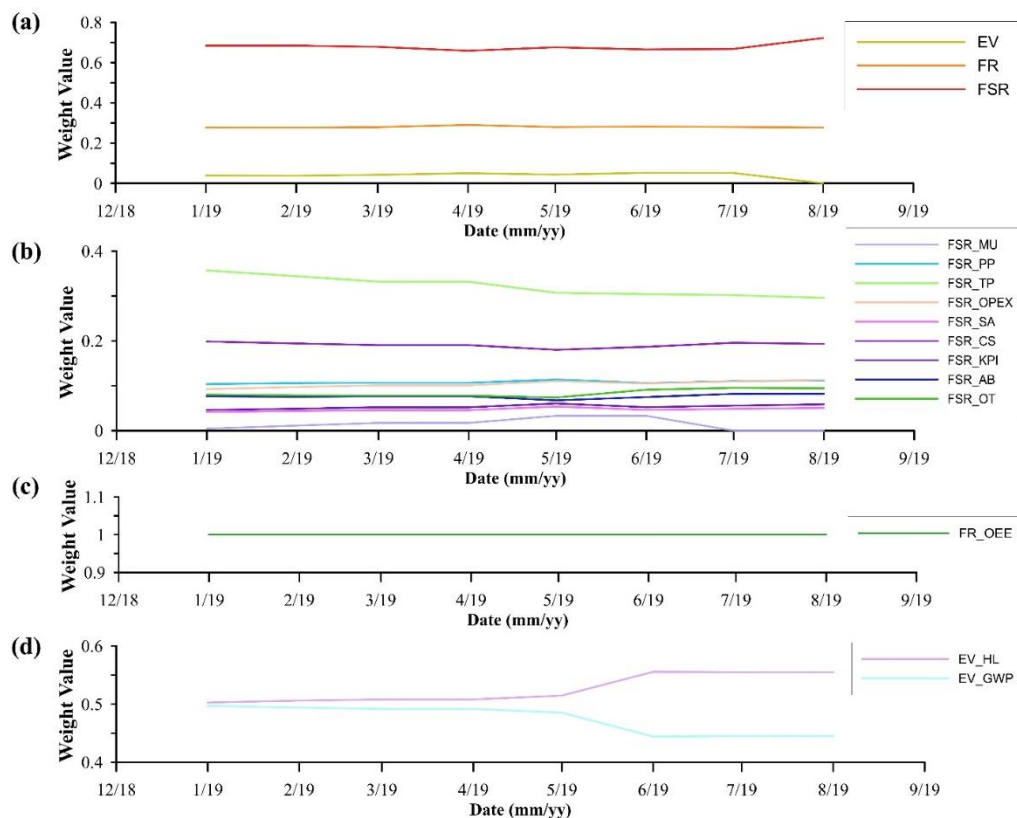


Figure 7-15: weight trend of (a) main components, (b) FSR indicator, (c) FR indicator and (d) EV indicator

7.4. Conclusion

The enhanced adaptive model has been incorporated with the combined analytical network process (ANP) and the entropy method to achieve an un-bias decision outcome. The enhanced model has also improved the optimisation model with an ensemble model where the best improvement path is always selected for process improvement. With the enhancement made, the enhanced adaptive model can deal with higher sophisticated challenges more effectively. The adaptability of the model has performed LGI_{target} updates from 0.75 to 0.82. With the improvement on LGI_{target} , the weight of the indicators have also reflected the effectiveness of the adaptive model in identifying the important operating indicators that can improve the LGI in real-time. The LGI performance has been improved by 18.25% since the implementation of the adaptive model as illustrated in the case study. The enhanced adaptive L&G model can lighten the burden of the industrialist by indicating the area for improvement that can maximise the performance of the organisation. As a result, the objectives of chapter 7 has achieved. In the next chapter, an L&G debottlenecking strategy will be explored to improve the expansion pathway of the organisation.

Chapter 8: Debottlenecking Strategy with Ensemble Neural Network Approach

8.1. Introduction

The ensemble neural network approach has been incorporated in the debottlenecking strategy to identify the potential debottlenecking pathway of a process. The debottlenecking strategy will be demonstrated with a combine heat and power (CHP) system. Based on the literature, the bottleneck associated with the CHP system focuses on the macro perspective including CHP as a distributed power plant for the local community (Martin Pehnt *et al.*, 2006), reducing transmission and energy loss (L.D. Danny, 2012), and sufficient supply of energy for city consumption (DFIC, 2016). Dr. Fromme International Consulting (DFIC) (2016) added that CHP systems can be a debottleneck solution to energy solution. However, the debottlenecking of the CHP system on micro-scale has not received much attention. As the prime mover of the CHP system is normally designed with International Standard Organisation (ISO) conditions, the debottlenecking strategy in the CHP system can increase the total energy output by targeting the small component in the system.

A collaboration has been established with a CHP owner for data collection and model validation.

8.2. Methodology

The process systems are modelled using an ensemble of neural networks with mass and energy balance. In this section, the ensemble model is used to simulate the actual brain function. The ensemble model consists of several optimisers to

reflect the complexity of human brain in making analysis. Firstly, the ensemble model is modelled with a supervised strategy with uncertainty and variable data as input and critical process data as output. The uncertainty and variable of data are normally obtained from the technology provider, performance data sheet and historical operational data. Critical process data are operation variables that illustrate non-linear behaviour and are critical toward assessment of the full operation such as operation resources consumption, environmental impacts, and economics. This allows the data-driven model to take into consideration of uncertainty and variable data on the full process as demonstrated in Figure 8-1.

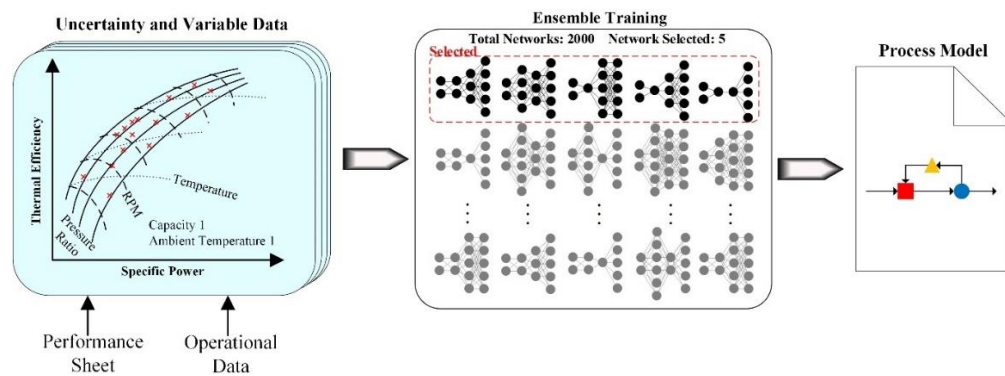


Figure 8-1: Overall method for data-driven modelling with neural network ensemble

This chapter presents an ensemble training algorithm by utilising random sampling to select 5 neural networks with top validation accuracy. Each neural network is individually trained using the gradient descent algorithm, Adam (Kingma and Lei Ba, 2015) and cross-validated using separate datasets. The computational cost is bounded with the maximum number of evaluated neural networks (set to 2000 in our case). The activation functions for the ensemble neural networks can be selected from multiple activation functions

including sigmoid, exponential (Exp), logarithmic (Log), linear, identity, radial basis function (RBF). The number of neurons within each layer can be selected from between integers of 1 to 200 which allows for many combinations of neural architectures.

8.2.1. Enhanced bottlenecking tree analysis (BOTA)

The ensemble prediction is obtained from the ensemble averaging method (Naftaly, Intrator and Horn, 1997). The bottlenecking tree analysis (BOTA) was first developed by Teng et al. (2020) will be enhanced to deal with multi-dimensional debottlenecking challenges. Referring to Figure 8-2, the method for enhanced multi-dimension BOTA illustrated in 7 steps.

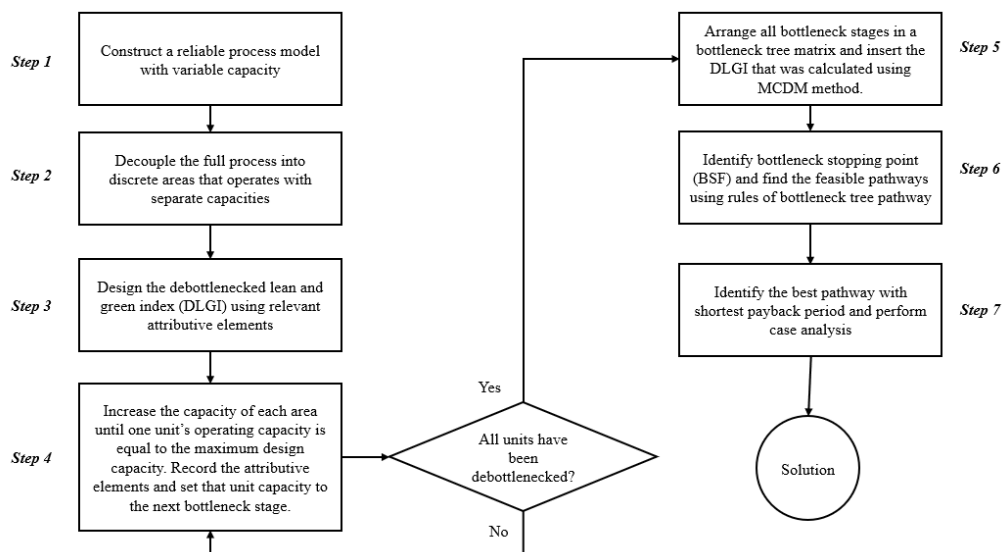


Figure 8-2: Flow diagram for the enhanced bottleneck tree analysis (BOTA) approach

Step 1: Construct a reliable process model. Commercial process simulator such as SuperPro Designer or Aspen software can be used of process

modelling. Ge (2017) stated that systems with higher variability require data-driven approaches to produce higher reliable process model. Therefore, operation data of each equipment shall be recorded as much as possible to form the big-data set.

Step 2: The full operation process should be classified into different segment that separates different operational capacities while having minimal performance dependencies between each other. This can exist for areas that are in sequential or parallel configuration within the process.

Step 3: A debottlenecking lean and green index (DLGI) will be generated to evaluate the process performance (similar to the LGI in the adaptive model proposed in Chapter 4). In the debottlenecking context, the DLGI represents different attributes that focus on the macro perspective including economic, operation and environment aspect of an organisation. A systematic approach to select relevant attributive elements is necessary for a specific case study.

Step 4: In the simulation, the capacity of each segment is increased until one of the units operating capacity is at its maximum design capacity. This is identified as the bottleneck capacity. Record all the attributive elements at this stage. Then, set the capacity of this unit to the next bottleneck capacity and continue to increase the area capacity. In actual practice, the bottlenecked equipment will be retrofitted or improved to provide higher output. For computational simplification, a utilisation factor is used (Eqn. 8-1). The utilisation factor reflects as 1 when the current operating capacity is equal to maximum design capacity.

$$Utilization\ factor = \frac{Current\ Operating\ Capacity}{Maximum\ Design\ Capacity} \quad (8-1)$$

Step 5: The bottleneck stages are arranged in a d -dimensional bottleneck tree matrix (Figure 8-3) in an ascending manner (where d is the number of areas). The bottleneck tree matrix will contain a cell (state) for each combination of bottleneck capacity.

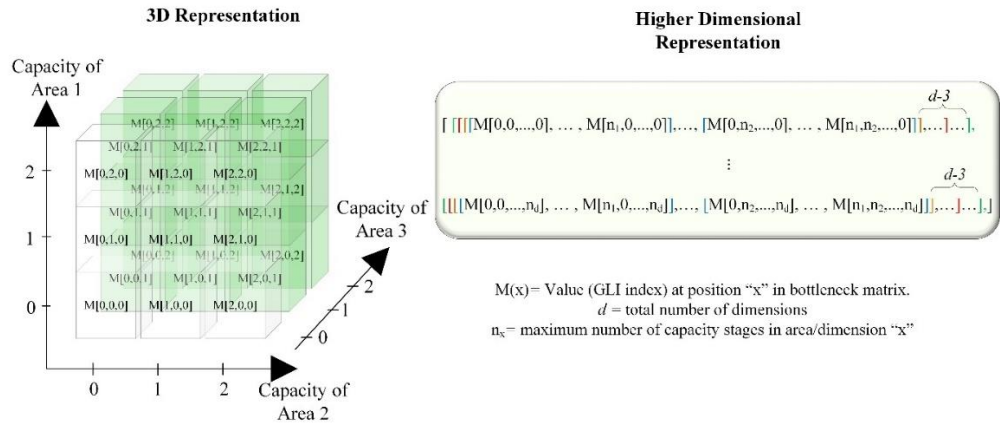


Figure 8-3: Three-dimension (3D) representation for bottleneck matrix and higher dimensions

Step 6: From the attributive elements of each state, the DLGI can be computed using MCDM algorithm. The global maximum of DLGI within the matrix is set as the bottleneck stopping point (BSP), where this is the state of the process which gives the highest benefit for long-term sustainability. To identify feasible pathways from the origin towards the BSP, the model needs to abide by the bottleneck tree pathway rules:

Rule 1: The bottleneck pathway shall start from origin and end at BSP.

Rule 2: The bottleneck pathway can only move from low capacity to high capacity.

Rule 3: The bottleneck pathway can only move from low DLGI to high DLGI.

Rule 4: Jumping through a cell is allowed, however always take the longest possible pathway (it is possible to have multiple longest pathways).

Rule 5: If there is more than one longest pathway, only accept pathways that pass through the cell highest DLGI within 1 step of the origin.

The multi-dimensional bottleneck tree pathway rules can be expressed in the mathematical formulation in Eqn. 8-2 to 8-6.

$$\max S \quad (8-2)$$

$$x_{n+1} = x_n + [\Delta x_{n,1}, \dots, \Delta x_{n,d}] \quad \forall n \in [0, s], \Delta x \in N = \{0, 1, 2, \dots\} \quad (8-3)$$

$$M(x_{n+1}) > M(x_n) \quad (8-4)$$

$$x_0 = [0, \dots, 0] \text{ and } x_s = u^* \text{ where } M(u^*) = BSP \quad (8-5)$$

$$\text{if } \text{count}(\text{argmax}(S)) > 1 \text{ then } p^* = p_d \text{ where } x_1 = \max(x_0 + q) \in p_d \quad (8-6)$$

where S is the number of steps taken in project stages, x_n is the position of the cell in the matrix in the “ n ” project stage, $M(x_n)$ is the DLGI at the cell position of x_n and q is a d -dimensional vector with binary value in any dimension.

Step 7: In the pathway rules, there is a possibility of having multiple feasible pathways, the secondary objective is to compare the payback period (PP) of each bottlenecking pathway. All the feasible pathways and their schedules are then compared and the pathway with the minimal PP is selected. The calculation for the time and state dependant net present value (NPV) is presented as in Eqn. 8-7 and the pathway dependant PP can be represented in Eqn. 8-8 or solved graphically.

$$NPV(x, t) = II + \sum_t NP(x, t) - \sum_t IC(x, t) \quad (8-7)$$

$$PP(p) = T \text{ where } NPV(x_s, T) = II + \sum_t NP(0, t) \quad (8-8)$$

where II is the initial investment, NP is the state and time-dependent net profit, IC represents the state and time-dependant investment cost.

In considering process variance, the enhanced BOTA model performs case study analysis for worst- and best-case scenarios by reapplying the enhanced BOTA approach to evaluate the bottlenecking pathway. By doing so, the model also reflects the condition of the project schedule under difference process variance. The pseudocode for neural network ensemble training and inference can be found in Appendix II (b).

8.2.2. Debottlenecking index – Lean and green index (DLGI)

The debottlenecking lean and green index (DLGI), a composite index, is developed to evaluate the long-term sustainability of a facility under different stages of bottleneck levels. The index is constructed using multi-criteria decision-making (MCDM) methods. Similar to LGI

developed in chapter 4, the DLGI ranges from 0 to 1. The larger value indicates better expected long-term sustainability of the facility. With the DLGI, the enhanced BOTTA model performs de-bottlenecking until the maximum BSP point is achieved. With the DLGI, the efficient pathways are then planned and scheduled to achieve the BSP. The consideration of DLGI can depend on many factors such as data source, supply chain, geographical location, and other aspects (Zhou *et al.*, 2012). However, Omer (2008) stated that the most important attributive elements for any system would include aspects of energy, environment, and economics. The details of developing the attributes will be demonstrated in Table 8-1.

Table 8-1: Mathematical formulation for critical attributes

Attribute	Explanation / Formulation
Energy	With consideration of the energy aspect, two forms of energy (i.e. total energy and total heat energy generated) are calculated from the facility. The mathematical formula is shown below: $A_E = \sum_{i=1}^n E_i \quad (8-9)$ $A_H = \sum_{i=1}^n H_i \quad (8-10)$ where A_E is the attributive element for electrical power generated (MW), A_H is the attributive

	element for heat energy produced (MW), n is the number of sources.
Environment	In many industries, carbon emission is considered as an indicator to measure environmental emission. Other emissions can be converted to carbon dioxide equivalent with respect to the global warming potential (GWP) factor. $A_C = \sum_{i=1}^n F_{C,i} C_i \quad (8-11)$ where A_C is the attributive element for carbon emission (CO₂-eq tonnes/h), F_C is the flow rate of carbon dioxide containing stream (flue gas in this case), and C is the mass fraction of carbon dioxide within the stream.
Economic	The economic attributive includes two elements including capital expenditures (CapEx) and operating expenditures (OpEx). For debottlenecking purposes, the attributive element for CapEx, A_{Capex} is a direct quotation of equipment and installation that were procured from a technology provider. Alternatively, an investment cost estimation methods from Peters et

al. (2003) or Sinnott and Towler (2013) can be referred for front-end studies.

The income includes sales of power and heat energy while expenditure consists of natural gas and maintenance costs. The OpEx is calculated as the following:

$$A_{Opex} = \sum_{i=1}^n F_{E,i} \cdot P_E + \sum_{i=1}^n F_{H,i} \cdot P_H - \sum_{i=1}^n F_{N,i} \cdot P_N - M \sum_{i=1}^n F_{N,i} \quad (8-12)$$

where A_{Opex} is the attributive element for operating expenditures (m.u./year), F_E is the generation rate of electrical energy (MW), P_E is the price of electrical energy per year (m.u./MW year), F_H is the production rate of steam (ton/h), P_H is the price of heat energy per year (m.u. h/ton year), F_N is the flowrate of natural gas that is being consumed (MMSCFD), P_N is the price of natural gas (m.u./MMSCFD year), M is the estimation of maintenance cost per year correlated to the feed capacity (m.u./MMSCFD year). Note that m.u. is the monetary unit that depends on the currency of the country.

These attributive elements will be combined into DLGI using the GRA-based TOPSIS multi-criteria decision-making algorithm (Refer to

Section 2.4.3. for the literature review). Figure 8-4 presents the overall concept of the GRA-based TOPSIS.

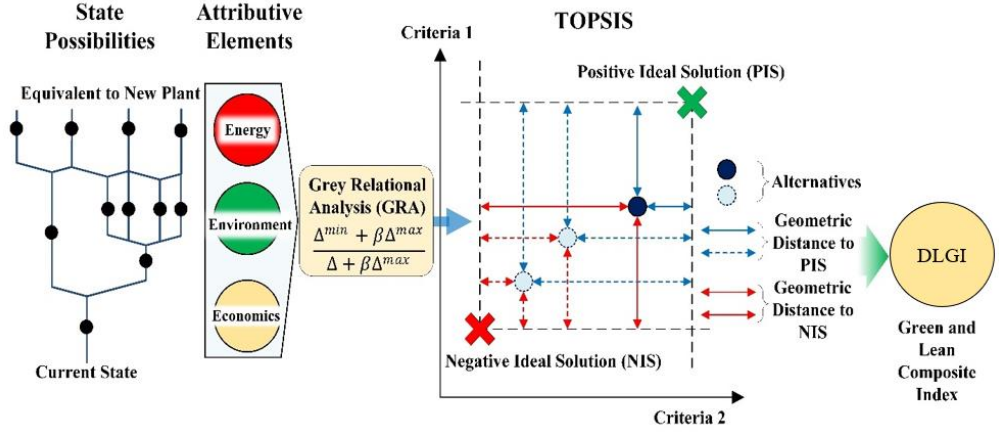


Figure 8-4: Illustration for the concept of GRA-based TOPSIS

Under GRA-based TOPSIS, the closeness between each alternative is defined using grey relational coefficient (GRC) instead of being expressed in the form of geometric distance (Qibing and Anhua, 2010). The closeness between the given alternative i to the respective PIS and NIS in terms of criteria j (i.e., ξ_{ij}^+ and ξ_{ij}^- respectively) can be mathematically expressed as:

$$\xi_{ij}^+ = \frac{\Delta_{ij}^{+min} + \beta \Delta_{ij}^{+max}}{\Delta_{ij}^+ + \beta \Delta_{ij}^{+max}} \quad \forall i \in I, \forall j \in J \quad (8-13)$$

$$\xi_{ij}^- = \frac{\Delta_{ij}^{-min} + \beta \Delta_{ij}^{-max}}{\Delta_{ij}^- + \beta \Delta_{ij}^{-max}} \quad \forall i \in I, \forall j \in J \quad (8-14)$$

where Δ_{ij}^{+max} and Δ_{ij}^{+min} denote the upper and lower limit of Δ_{ij}^+ ; the maximum and minimum value of Δ_{ij}^- are referred to as Δ_{ij}^{-max} and Δ_{ij}^{-min} respectively; while β indicates the distinguish coefficient which used to control the resolution scale of the problem. In this work, the

parameter is commonly set to be 0.5 to give a balanced result between PIS and NIS (Zhang and Li, 2006; Sylajakumari, Ramakrishnasamy and Palaniappan, 2018). Δ_{ij}^+ and Δ_{ij}^- are expressed as below:

$$\Delta_{ij}^+ = |x_j^{Best} - x_{ij}| \quad \forall i \in I, \forall j \in J \quad (8-15)$$

$$\Delta_{ij}^- = |x_j^{Worst} - x_{ij}| \quad \forall i \in I, \forall j \in J \quad (8-16)$$

x_j^{Best} and x_j^{Worst} refer to the performance of PIS and NIS in terms of criteria j respectively. The relative closeness for each alternative, i (C_i) is determined by Eqn. 8-17, where n denotes the total number of criteria, while γ_i^+ and γ_i^- are computed using Eqn. 8-18 and 8-19. Please note that C_i is used as an indicator to rank all the alternatives where greater C_i is preferable.

$$C_i = \frac{\gamma_i^-}{\gamma_i^+ + \gamma_i^-} \quad \forall i \in I \quad (8-17)$$

$$\gamma_i^+ = \frac{1}{n} \sum_{j=1}^n \xi_{ij}^+ \quad \forall i \in I \quad (8-18)$$

$$\gamma_i^- = \frac{1}{n} \sum_{j=1}^n \xi_{ij}^- \quad \forall i \in I \quad (8-19)$$

8.3. Case study

In this case study, the ensemble neural network model is used to predict the process variables with high variability and input-output models for equipment with static nature.

This case study demonstrates the proposed enhanced BOTA on CHP system. The case study adopted from a CHP facility in Malaysia has a series of CHP systems as illustrated in Figure 8-5. The multiple-train setup of the CHP system consists of 2 identical CHP systems (i.e. Train 1, T1 and Train 2, T2) and a lower capacity CHP system (i.e. Train 3, T3). Each CHP system operates independently to produce electricity and steam energy. The CHP system is classified into 4 main areas such as the prime mover (i.e. gas turbine section), generator (i.e. electricity generation), supplementary firing and heat recovery steam generator (HRSG). Table 8-2 demonstrates the important operation parameter of a CHP system that will affect the operation performance.

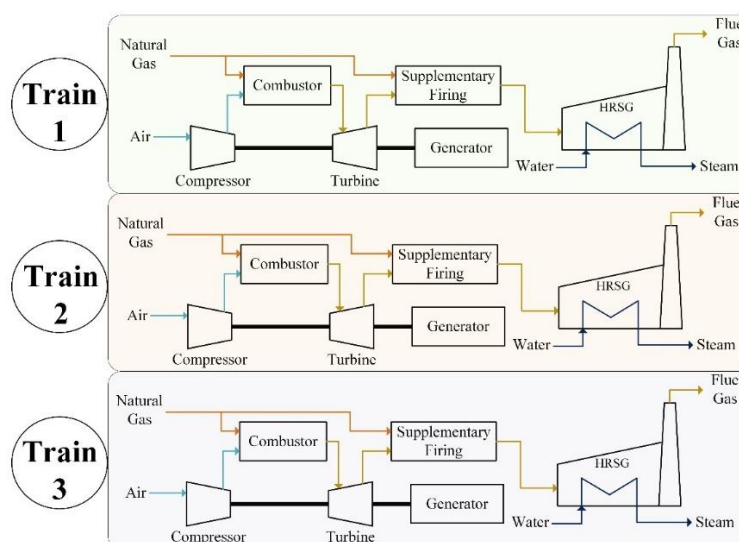


Figure 8-5: Simplified process flow diagram of a multi-train cogeneration plant.

Table 8-2: Operation parameter for CHP system

Operation parameter	Descriptions	Source
Ambient temperature	The ambient temperature affects the prime mover's performance, especially for gas turbines. The inlet air flow rate is dependent on the ambient temperature and elevation that can influence the air density. The average ambient temperature profile in Malaysia is illustrated in Figure 8-6(a). The maximum and minimum temperatures are 31.3 °C and 22.1 °C respectively (Figure 8-6(b)).	Fang and Lahdelma (2016), and Arthur L. and Richard B. (1997).
Fuel selection	The fuel selection and consumption are also important to determine the efficiency of the CHP system. Typically, the fuel for CHP includes natural gas, light fuel oil, biogas and syngas.	Abbasi et al. (2015)
Energy output	The total energy output including electricity and thermal energy reflects the primary performance parameter for the CHP system.	Bhatia (2014)
Exhaust gas temperature	The exhaust gas temperature and flow determine the total recoverable waste heat	Nolan (2017)

from the prime mover. The typical exhaust gas profile ranged between 200 °C to 700 °C.

Carbon To reflect the environmental impact, GWP Siddiqui and footprint of the CHP system, carbon dioxide footprint Dincer (2019) is required to be measured.

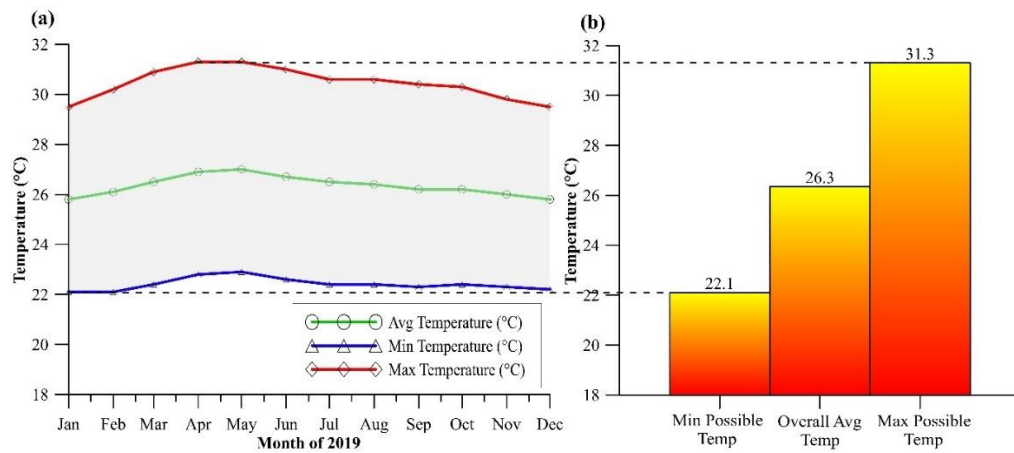


Figure 8-6: Temperature in case study location, Malaysia: (a) monthly temperature trend (b) Minimum possible temperature, overall average temperature and maximum possible temperature. (data source: OpenWeatherMap Database (OpenWeatherMap, 2020))

8.3.1. Ensemble neural network model

The CHP performance data obtained from the industry was modelled using an ensemble of neural networks. The inputs for the neural network are ambient temperature and fuel capacity while power output, intake airflow, exhaust gas temperature, exhaust gas flow rate and carbon emission were predicted. The model is provided with a total of 241

datasets from the technology provider and operational data with a split of 70 % training data, 15 % testing data and 15 % validation data. This allows for a data-driven model for process performances with variation in ambient temperature and fuel capacity. Using the ensemble training method as described in Section 8.2, top five of the best selected neural networks have hidden layers of [112, 5], [107, 5], [105,5], [113,5], [46,5] with neuron of [Exp, Exp], [Sigmoid, Linear], [Sigmoid, Exp], [Exp, Exp], [Sigmoid, Exp] respectively. Interestingly, the second hidden layer was found to be optimal at 5 hidden neurons for this case study. The prediction values from these best-performing neural networks were pooled to give an average combined prediction which gave a test result of 0.0154 root mean square error (RMSE) ($R^2=0.9978$) (Figure 8-7(a)). The ensemble prediction model was then validated with a separate dataset (Figure 8-7(b)) and found to obtain a similar output of 0.0170 RMSE ($R^2=0.9970$). This confirms the validity of the training procedure. These predicted values will serve as the basis for mass and energy balance analysis to ultimately compute the attributive elements (i.e. energy, environment, and economics) of the organisation.

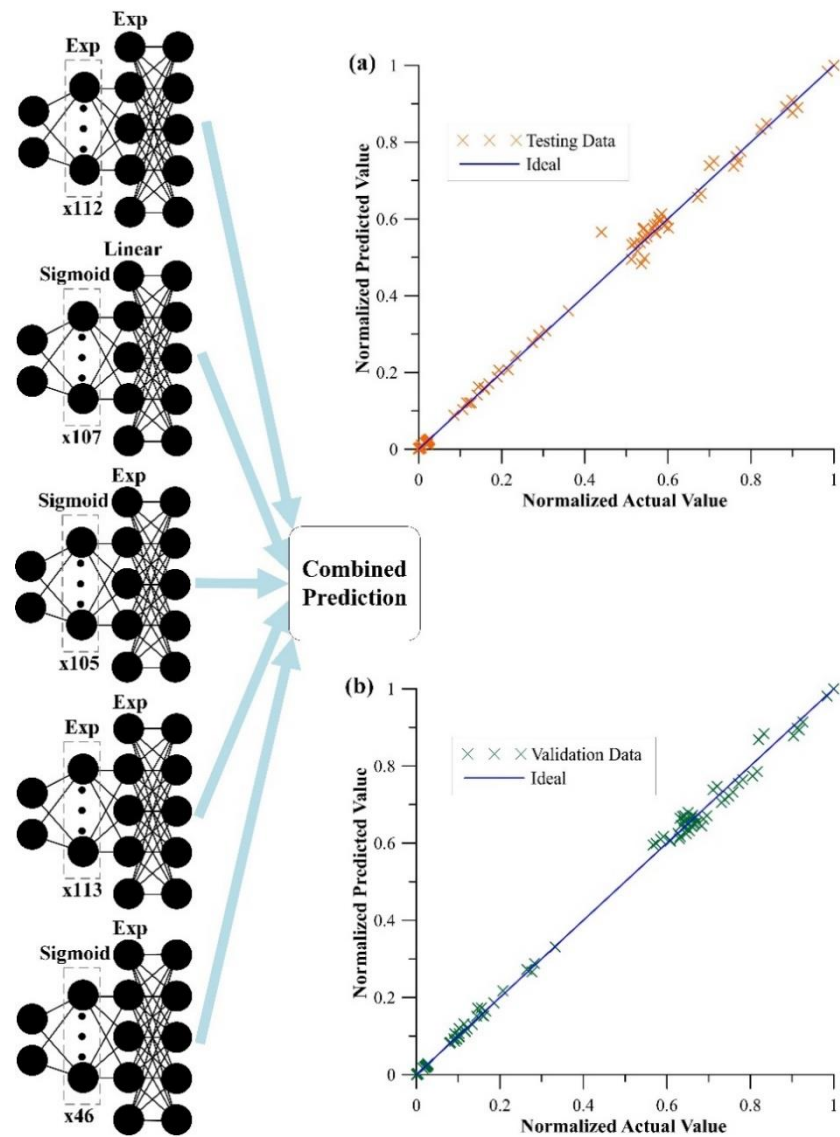


Figure 8-7: Architecture of neural network ensemble and performance
for (a) testing dataset (b) validation dataset

Figure 8-8 illustrates the 3-dimensional bottleneck tree matrix, where the three axes show the capacities of the three cogeneration trains. There are a total of 125 cells in the bottleneck tree matrix based on the five capacity levels of each cogeneration train (5 x 5 x 5). Using the capacity level of cogeneration train 3 as a basis, the tree matrix is decomposed into 5 layers (see Figure 8-8). Each cell is assigned with a DLGI value which is computed by using the GRA-based TOPSIS

approach shown in Eqn. 8-2 to 8-8. Based on Figure 8-8, the bottom leftmost cell in the first layer (DLGI = 0.056) is the original state where the debottlenecking process is not carried out. Its adjacent cells, on the other hand, refer to the state when the corresponding cogeneration unit is operated under its maximum capacity (e.g., the cell located above the origin cell showed a DLGI value of 0.302, this is the DLGI can be obtained when cogeneration unit 1 is operated at its maximum capacity). Further along the axis, each cell indicates the replacement of a larger-capacity CHP unit.

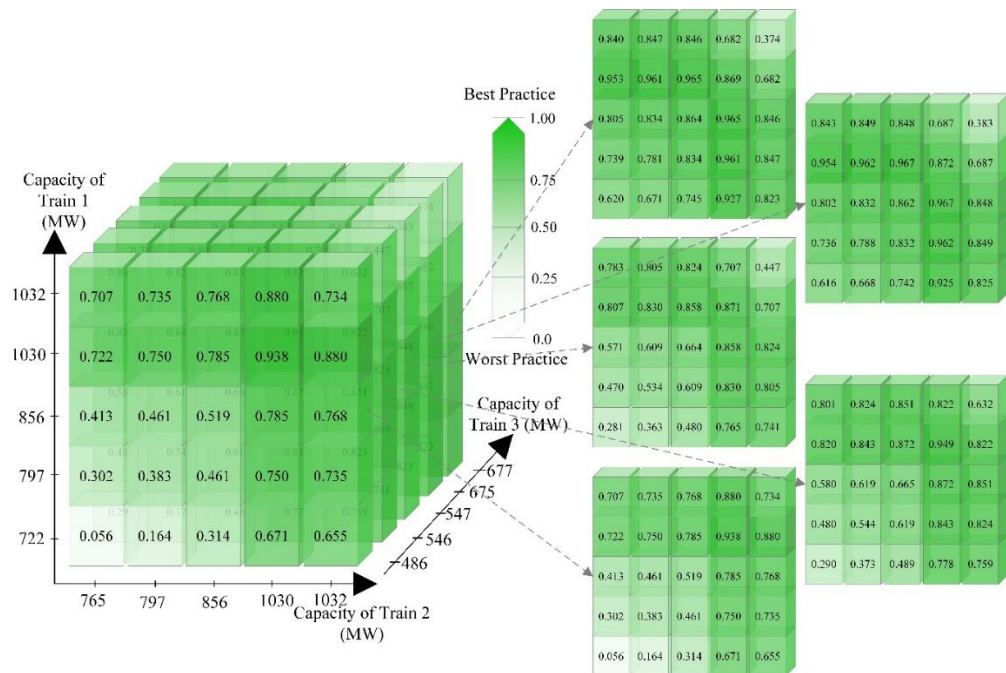


Figure 8-8: 3-dimensional bottleneck tree matrix for the presented case study

Referring to Figure 8-9, it can be observed that the greatest achievable DLGI appears at the fourth layer indicating 0.967. These cells are considered as the BSPs for this case study. In other words, the

debottlenecking process should start from the origin cell, progress gradually to another cell which provides higher DLGI until it reaches one of the BSP. It is worth noting that the existence of two BSPs in this case study is mainly due to the use of two identical sets of CHP units. This creates two superimposable options that provide a similar DLGI value. For instance, the performance of using a 1030 MW overall input capacity of first CHP train and an 856 MW of that in the second CHP train, is the same as the performance of using an 856 MW overall input capacity of first CHP train and a 1030 MW of that in second CHP train.

By following the five rules presented in Section 8.2.1., Step 6, the feasible pathways are outlined in Figure 8-9. The first bottleneck stage shows a leap from the original cell to a layer-two cell which provides a DLGI of 0.544 (i.e., the sustainability performance when all three cogeneration units are operated under the existing maximum capacities). This is the common first debottlenecking action that should be conducted without the need for changing the existing process design (Hodge, 2018). Moving on, the debottlenecking process will be carried out by replacing the CHP unit with a larger capacity. Based on the second and third rule, one should avoid replacing the existing unit with a smaller unit and making changes that lead to lower DLGI. Moving on, further increase in the capacity scale of CHP T2 from 1030 MW input capacity to 1032 MW is not preferable as a lower DLGI will be obtained. The drop of DLGI is mainly due to the lower cost-effectiveness of these changes where the increase in energy generation is relatively insignificant. Thus, not worth the high investment.

With these rules, all combinatorial feasible bottleneck paths can be formed. However, only the longest pathways are considered, this case study assumes the decision-makers are “aggressive players” who will opt to improve the system whenever there is an opportunity (i.e., not saving up money, but to invest for improvement whenever it is possible). By complying to the rules stated in Step 6, Section 8.2.1., all paths that take five bottleneck stages are considered as the longest paths. For the ease of the reader, all these feasible paths are extracted and presented in the tree representation diagram in Figure 8-9.

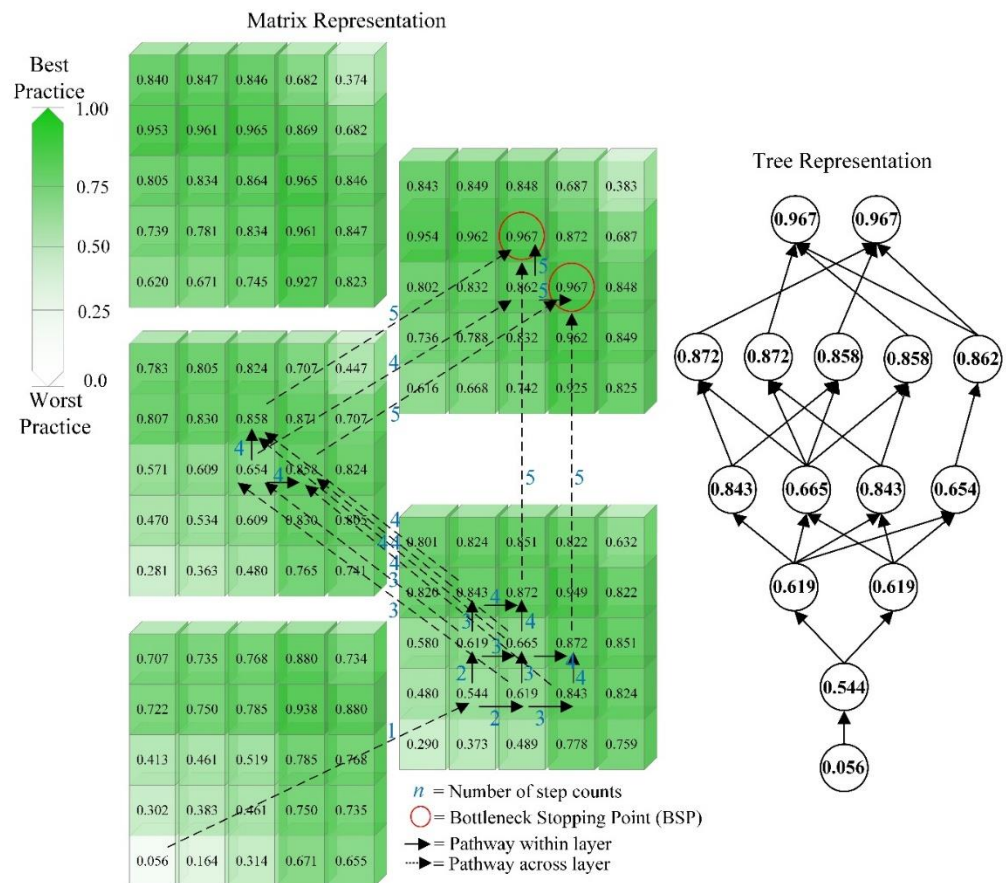


Figure 8-9: Identification of feasible pathways using the bottleneck tree matrix by obeying the pathway rules.

As mentioned, as the CHP T1 and T2 are identical units, there are pathways which are equivalent to each other. It is important to note that fully utilising the CHP T1 and T2 are two different strategies but both pathways impose the same DLGI improvement. Therefore, before analysing the feasible paths, these equivalent paths which provide similar DLGI improvement (i.e., the “faded” paths in Figure 8-10), can be removed. The remaining paths are known as the “effective feasible pathways”. The effective feasible pathways can be further decoupled into five individual pathway strategies (i.e., the “possible pathway solution” listed in Figure 8-10). Despite all five strategies lead to the same BSP state (i.e., $DLGI = 0.967$), the different sequences of the bottleneck path will lead to different economic performance in terms of PP (Figure 8-12).

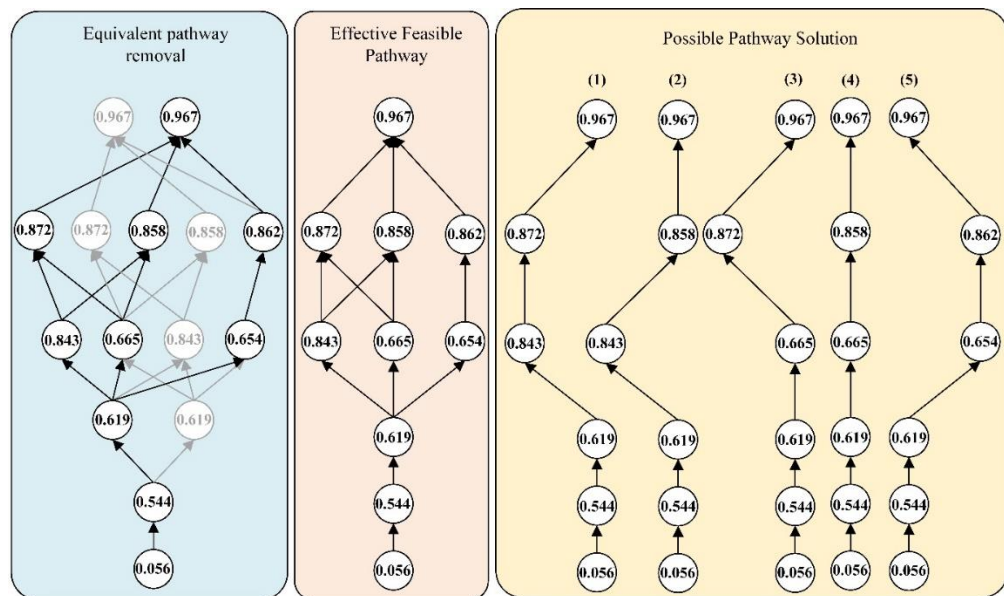


Figure 8-10: Equivalent pathway removal and decomposition of individual pathway solution

8.3.2. Possible bottlenecking pathway with investment analysis

Figure 8-11 summarised a detailed illustration of the de-bottleneck pathway for the case study. The current state of the case study has the DLGI at 0.056 and best BSP is at 0.967. Again, it is reminded that the aim of the bottlenecking analysis strategy focuses on maximising the operation, commercial and environmental potential. As the configuration of the case study has 2 identical CHP system (i.e. T1 and T2) and smaller capacity CHP system (i.e. T3), the debottleneck of T1 and T2 are identical and improvement on either unit will produce identical results.

The recommended de-bottleneck actions for all debottlenecking pathways are the same for the first 3 steps. The current state (Step 1) reflects a DLGI of 0.056 can be improved to 0.544 by maximising the capacity of all the CHP systems (Step 2). The pathway has also indicated that upgrading the generator capacity from maximum capacity to 321MW for T1 (both are identical units) can improve the DLGI to 0.619 (Step 3).

Pathway 1 recommended the turbine set of T1 to be upgraded in Step 4 with fuel consumption of 1030 MW with further enhancement of the generator to 397 MW. Such improvement can elevate the DLGI from 0.619 to 0.843. In Step 5, the generator of T2 is improved to accommodate 321MW electric generation that leads to a DLGI of 0.872. Lastly, the enhancement of T3 CHP system in Step 6 to improve the capacity of the turbine set with 676 MW fuel consumption, up to 249

MW electricity generation, supplementary firing improved to 391MW with HRSG accommodating 403 MW. This leads the final DLGI to 0.967.

In pathway 2, Step 4 recommended the same as pathway 1 to improve the turbine set and generator of T1. Step 5 is similar to pathway 1 as well but with an additional upgrade of supplementary firing system for T3 to 340 MW. The DLGI for Step 5 is improved from 0.843 to 0.858. In Step 6, the upgrades are identical to pathway 1 to focus on upgrading the T3 system.

Moving on to pathway 3, T2 turbine set and generator sets are recommended to be upgraded to 856 MW and 321 MW respectively with a DLGI of 0.665. In Step 5, either T1 or T2 turbine set and generator set need to be further upgraded to 1030 MW and 397 MW respectively. By doing so, the DLGI will be improved to 0.872. Finally, Step 6 is similar to pathway 1 that yields a DLGI of 0.967.

Pathway 4 exercises a similar debottlenecking strategy as pathway 3 in Step 4. In the next step, the T1 turbine set and generator are suggested to be upgraded with 1030 MW and 397 MW respectively. On top of that, the supplementary firing system of T3 is also upgraded concurrently. This will improve the DLGI from 0.665 to 0.858. The debottlenecking strategy in Step 6 is identical to pathway 1.

As for pathway 5, Step 4 suggested upgrading T2 turbine set and generator as Step 4 in pathway 3 with additional enhancement on the supplementary firing system of T3. This improvement reflects a DLGI of 0.654. Moving on, Step 5 focuses on increasing the capacity of the

T3 system including upgrading the compressor set, generator, supplementary firing system and HRSG capacity to 676 MW, 249 MW, 391 MW and 403 MW respectively. The upgrading of T1 or T2 turbine and generator to 1030 MW and 397 MW is recommended in Step 6 that leads to DLGI of 0.967.

Based on the possible debottlenecking pathways, several factors need to be highlighted. As the T1 and T2 system are identical, the industrialist can select which unit to debottleneck first and define the first debottlenecking unit as T1. The possible pathway is generated to cater to the financial capability of the organisation. For instance, pathway 3 and 4 can have lower investment cost in Step 4 as the equipment required upgrade is smaller capacity compared to other possible pathways which also indirectly reflect on the DLGI. Similarly, for Step 4 in pathway 5, the additional upgrade in the supplementary firing system as compared to pathway 3 and 4 yields lower DLGI. This is mainly due to the consideration of operational and environmental factors. The system (i.e. turbine and generator as a set) upgrade is considered in the debottlenecking strategy with the understanding of the industry practice. Generally, the industrialist can select the possible pathway according to their financial capability and operation needs.

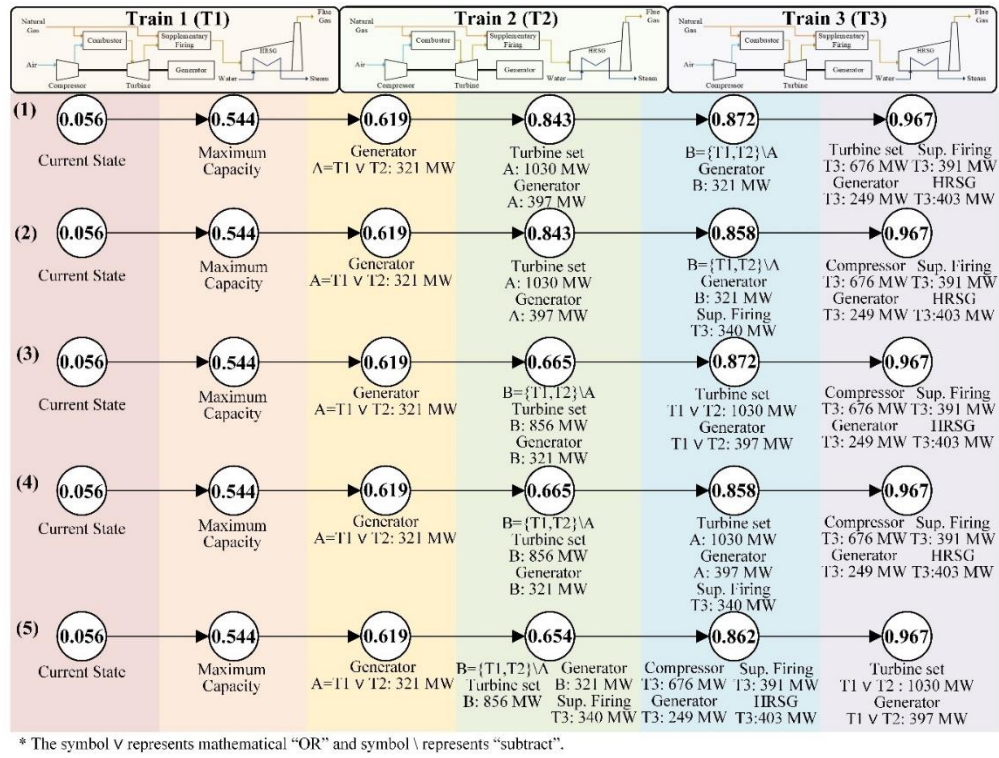


Figure 8-11: Process changes in specific areas with regards to states in pathways.

Figure 8-12 shows the cash flow diagram of all five strategies, where the red dotted lines refer to the cash flow for the base case (without debottlenecking), while the blue solid lines refer to the estimated cash flow attributed to each strategy. The intercept point of these lines indicates the breakeven point for the investment made. Therefore, the time required to achieve this breakeven point is notified as the PP. The NPV calculations are made by assuming that all five cases are "zero initial investment", where the elevated profit attributed from the first stage of debottlenecking will be fully reinvested into the second stage of debottlenecking. This causes the "zigzag" pattern on the NPV flow (see Figure 8-12(a) to (e)). Theoretically, the decision-maker can directly invest the full amount of capital to achieve BSP in a single step

instead of having multiple stages of the debottlenecking sequence. However, the “zero initial investment scheme” is a relatively realistic and lucrative strategy for most small and medium enterprises (SMEs) and even for large corporates, especially when budget constraints are significant.

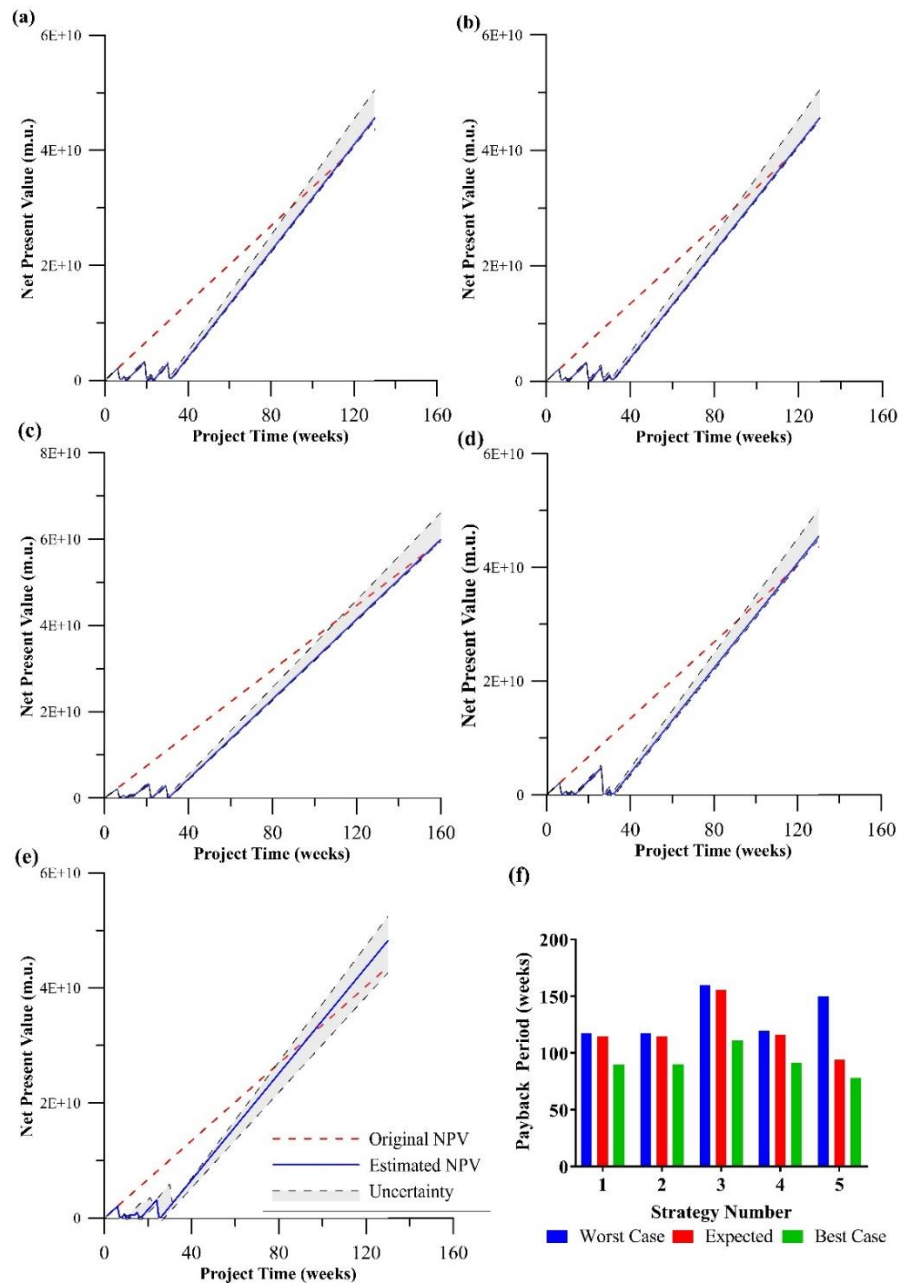


Figure 8-12: Graphical plot for (a) Net present value of pathway 1, (b) Net present value of pathway 2, (c) Net present value of pathway 3, (d) Net present

value of pathway 4, (e) Net present value of pathway 5, (f) Payback period (PP) of each pathway

Among the five pathways, pathway 1, 2 and 4 provide the most interesting PP with 114.5 weeks, 114.6 weeks and 115.9 weeks, respectively. On top of the low PP, these pathways are also associated with lower risk (less deviations between the best- and worst-case scenarios). These pathways focus on upgrading the turbine generator set for electricity generation followed by the supplementary firing system at the later stage. Besides, upgrading of the turbine generator set also has an advantage with shorter upgrading downtime which contributes to faster payback. On the other hand, pathway 5 provides the best expected PP with 93.9 weeks. This shows that the early instalment of larger supplemental firing units can lead to a better NPV growth (i.e. due to greater power generation) as compared to the late instalment (as opted in pathway 1, 2 and 4). However, Figure 8-12(f) indicated that this strategy associates with a higher uncertainty as the deviations between the best and the worst-case scenarios is large. This higher uncertainty level is attributed to the effects of the capacity output from upgrading the CHP T3 system in pathway 5. Moreover, the PP of pathway 5 can be affected by the fuel efficiency for steam generation in the supplementary firing. In contrast, pathway 3 should never be selected due to the high expected PP with 155.6 weeks. As mentioned above, the timing to upgrade the supplementary firing unit has a significant impact on the PP. In this pathway, the supplementary firing unit is upgraded to the largest capacity at the final debottlenecking stage. The high-value

investment cost (i.e. turbine set 1030 MW) at the later stage has prolonged the PP of the project. This further restricts the NPV growth of the process and therefore, requires a longer time to payback. The PP for all pathways are highly related to the investment cost and sequence of debottlenecking. With the potential debottlenecking pathway, the industrialist can develop the debottlenecking strategy according to the production demand and financial condition.

When the pathway reached the BSP, it is expected to yield a 54.2 % improvement in carbon emission per unit power production, 46.3 % improvement in OpEx, 59.0 % improvement in heat energy production, 58.9 % improvement of power production with an additional investment of 48.7 % of the original capital costs. The industrialists can determine their improvement strategy based on the possible pathway solutions to maximise operation, environment and economic performances. As debottlenecking of the system takes time, the possible pathway offers the industrialist an insight on potential system upgrade with financial consideration.

8.4. Conclusion

This paper formally extends the methodology for bottleneck tree analysis (BOTA) towards problems of multi-dimension. It has been demonstrated that process variations can be effectively modelled using a data-driven neural network ensemble method. This highlights that enhanced BOTA has a model-agnostic property and can be flexibly used with any type of process models. The enhanced BOTA can result in 54.2 % improvement in carbon emission per unit

power production, 46.3 % improvement in operating expenditure, 59.0 % improvement in heat energy production, 58.9 % improvement of power production with an additional investment of 48.7 % of the original capital costs. By taking a zero initial investment case, the average PP can be between 114 to 116 weeks with low uncertainty (pathway 1, 2, 4) when de-bottleneck activities are primarily focused on the turbine generator set. Nevertheless, industrialists can also choose to focus de-bottlenecking activities on the supplementary firing unit to give an average PP of 93.9 weeks. Increasing the capacities with a zero initial investment scheme is very lucrative for most small and medium enterprises (SME) and even for larger corporates with difficulties with funding allocation. The enhanced BOTA has successfully demonstrated a systematic debottlenecking pathway for CHP facility. With that, the objective of this work as illustrated in Section 1.3.5 has successfully achieved.

Chapter 9: Conclusion

9.1. Conclusion

The research outcome presented in this thesis has successfully developed the adaptive analytical lean and green (L&G) model for the industry sector. The initiative for L&G approach is to create a sustainable manufacturing environment by improving the operational and environmental performance concurrently. All the objectives milestones are achieved by demonstrated with a case study. Chapter 4 and 5 developed the lean and green index (LGI) and the structured L&G framework respectively. Chapter 6 and 7 reflected the benefits and advantages of a machine learning method in complementing the adaptive analytical approach with the ensemble solver. In Chapter 8, the L&G debottlenecking strategy analyses the optimum pathway for the industrialists to increase production capacity. The capability of the adaptive L&G model in dealing with dynamic industry case study has shown a positive outcome as illustrated from the case study. The enhanced adaptive model allows the industrialist to perform continuous self-improvement based on the operation condition. In short, the development of the adaptive L&G model has successfully attracted industrialist's confidence in appreciating the importance of data for process improvement. This enables the industrialist to be more versatile in coping with tough economic situations.

9.2. Research Limitation

Despite the research outcome has been successful, there is some limitation when developing the adaptive L&G model. The research limitations are listed as below:

- a) Data collection boundaries are limited as the industrialists are very sensitive in sharing their operation data.
- b) The duration of this research project is restricted to be completed within 3 years. With the extension of the project schedule, more data can be collected to observe the performance of the adaptive L&G model.
- c) It can be challenging in getting the commitment and participation from the industrialist in implementing the proper action plan according to the adaptive L&G model.
- d) Limited participants from different industry sector to contribute to the development of L&G checklist.
- e) There is a lack of efficient and effective data collection and storage infrastructure in most manufacturing facilities. This will affect the analysis of the adaptive L&G model.

9.3. Future work

The research on the adaptive analytical L&G model can be extended to further improve the performance and application of the adaptive model. Some potential improvement areas are listed below:

- a) Expansion on the L&G checklist to include different industry sector and processes (i.e. chemical processing, waste recovery plant, landfill, etc).

- b) Improve the adaptive model to cope with unforeseen circumstance occurring in the processing plant.
- c) To educate the industrialists on the importance of data acquisition and infrastructure for data collection and analysis for process improvement.
- d) Incorporate supply chain demand into the adaptive analytic L&G model for advance production planning and control.

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Appendix

Appendix I – Questionnaire for AHP data collection

The following is the list of the key indicators in impacting lean and green performance in cogeneration plant.

Main Indicators	Sub Indicators	
Manpower	MP _{OT}	Total overtime per employee per year
	MP _{AB}	Total absent day per employee per year,
	MP _{KPI}	Average KPI achievable per employee per year,
	MP _{CR}	Average employee competency rate per employee per year,
	MP _{LT}	Late check-in time per employee per year,
	MP _{SC}	Rate of safety competency per employee per year,
Machine	MC _{OEE}	Overall equipment effectiveness
Material	MT _{RE}	Resource consumption efficiency
	MT _{DI}	Total production defect and waste
	MT _{RD}	Rate of recyclable defects
	MT _{IN}	Inventory management
Money	MY _{OC}	Minimum operation cost indicator
	MY _{TP}	Max profit indicator
Environmental	EV _{CO2}	Carbon footprint indicator

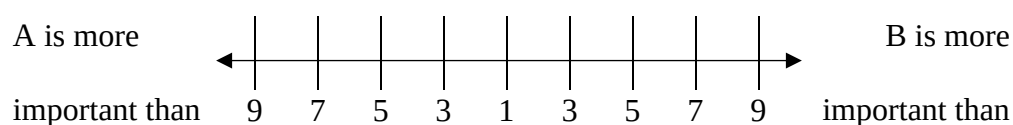
Instruction

Please compare the pair of variable in the same row, and indicate the level of importance based on the scale of 1,3,5,7,9 with a tick sign “√”. The

description of the scale level is as below:

1 – equally 3 – moderately 5 – strongly 7 – very strongly 9 – extremely

For example, if A is **very strongly** more important than B, please insert the tick sign on the “7” column closer to A, vice versa.



B A

A		$\sqrt{\quad}$								B
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Based on your expertise and experience, please make the pairwise comparison judgment by comparing the two variables in the same row.

Part I: Main Indicator vs Main Indicator

Indicators	9	7	5	3	1	3	5	7	9	Indicators
MP : Man power (i.e. workforce in the processing facility)										MC : Machine (i.e. equipments in the processing facility)
MP : Man power (i.e. workforce in										MT : Material (i.e. material resources and

the processing facility)									inventory management)
MP : Man power (i.e. workforce in the processing facility)									MY : Money (i.e. operation cost and product profitability)
MP : Man power (i.e. workforce in the processing facility)									EV : Environment (i.e. environment emission)
MC : Machine (i.e. equipments in the processing facility)									MT : Material (i.e. material resources and inventory management)
MC : Machine (i.e. equipments in the processing facility)									MY : Money (i.e. operation cost and product profitability)
MC : Machine (i.e. equipments in									EV : Environment (i.e.

the processing facility)									environment emission)
MT : Material (i.e. material resources and inventory management)									MY : Money (i.e. operation cost and product profitability)
MT : Material (i.e. material resources and inventory management)									EV : Environment (i.e. environment emission)
MY : Money (i.e. operation cost and product profitability)									EV : Environment (i.e. environment emission)

Part II: Sub-Indicator vs Sub-Indicator

Main components (i.e. Machine and Environment) have only one indicator.

Thus, no comparison is required.

Part II - Manpower, MP

Sub-indicators	9	7	5	3	1	3	5	7	9	Sub-indicators
MP _{OT} : Total overtime										MP _{AB} : Total absent day
MP _{OT} : Total overtime										MP _{KPI} : KPI achievable
MP _{OT} : Total overtime										MP _{CR} : Employee competency rate
MP _{OT} : Total overtime										MP _{LT} : Late check-in
MP _{OT} : Total overtime										MP _{SC} : Safety competency rate
MP _{AB} : Total absent day										MP _{KPI} : KPI achievable

MP _{AB} : Total absent day									MP _{CR} : Employee competency rate
MP _{AB} : Total absent day									MP _{LT} : Late check-in
MP _{AB} : Total absent day									MP _{SC} : Safety competency rate
MP _{KPI} : KPI achievable									MP _{CR} : Employee competency rate
MP _{KPI} : KPI achievable									MP _{LT} : Late check-in
MP _{KPI} : KPI achievable									MP _{SC} : Safety competency rate
MP _{CR} : Employee competency rate									MP _{LT} : Late check-in

MP _{CR} : Employee competency rate										MP _{SC} : Safety competency rate
MP _{LT} : Late check-in										MP _{SC} : Safety competency rate

Part II - Material, MT

Sub- indicators	9	7	5	3	1	3	5	7	9	Sub- indicators
MT _{RE} : Resource consumption efficiency										MT _{DI} : Total production defect and waste
MT _{RE} : Resource consumption efficiency										MT _{RE} : Rate of recyclable defects
MT _{RE} : Resource										MT _{DI} : Inventory management

consumption efficiency										
MT _{DI} : Total production defect and waste										MT _{RE} : Rate of recyclable defects
MT _{DI} : Total production defect and waste										MT _{DI} : Inventory management
MT _{RE} : Rate of recyclable defects										MT _{DI} : Inventory management

Part II - Money, MY

Sub- indicators	9	7	5	3	1	3	5	7	9	Sub- indicators
MY _{OC} : Minimum operation cost indicator										MY _{TP} : Max profit indicator

Appendix II – Mathematical Proof for Ensemble Solver Model

Preliminary. We denote the complex function of the plant as P . The manipulated variables of P is represented as $X = \{x_1, x_2, x_3, \dots\}$. An ensemble set of solvers can be denoted as $S = \{s_1, s_2, s_3, \dots\}$ with criteria of $C = \{c_1, c_2, c_3, \dots\}$. The implementation time constraint can be represented as T and average solver time for one step is t with $T \gg t$.

Proposition 1. Supposed expert initialization provides a high-dimensional function $F(C(X))$. Considering the case for (1) a single solver L and (2) an ensemble solver S , for the subsequent time-step:

(1) $F(C(X_L))$ is the maximization objective value.

(2) $F(C(G))$ is the maximization objective value where $G = \operatorname{argmax} F(C(X_s)), \forall s$.

Proof. Since $T \gg t$, if $L \in S$, $(F(C(G)) \geq F(C(X_L)))$. We hence show that without limiting constraint on computation time, the objective value of ensemble solver can be larger than that of a solver it contains.

Appendix III – Pseudocode for Ensemble Neural Network Debottlenecking

model

Algorithm 1: Selection and Training Neural Networks for Ensemble

Act_func ← ['activation 1', 'activation 2', ...] ► Define all activation function available

Total_net ← 2000 ► Set total number of neural networks to be evaluated

Network_select ← 5 ► Set number of neural networks to be selected for ensemble network

Best_network_error ← [+inf]*Network_select ► Initialise selected error vector with correct size

while ($i \leq \text{Total_net}$):

 HL_num ← random_uniform (1, Max_HL) ► Sample number of hidden neurons randomly

 Input_act ← Act_func[random_int(1, len(Act_func))] ► Sample activation function of input randomly

 HL_act ← Act_func[random_int(1, len(Act_func))] ► Sample activation function of input randomly

 Output_act ← Act_func[random_int(1, len(Act_func))] ► Sample activation function of output layer

 Network ← Train_Network(act=[Input_act, HL_act, Output_act],
 num_neuron=HL_num) ► Train neural network

 Val_error ← Network.get_validation_loss() ► Obtain the loss/error from validation set

if (Val_error < max (Best_network_error)): ► Check if the loss is better than previously recorded

 Best_network_error.append_sort(Val_error) ► Update the record

```

Network.save_remove_worse()    ► Save neural network model and remove
the worse if required

if (len(Best_network_error) > Network_select):    ► Check if record is
too big

    Best_network_error←Best_network_error[0:Network_select]

    ► Remove excess record

i = i+1    ► Update number of networks evaluated

```

Algorithm 2: Ensemble Learning Inference

```

Predict = []    ► Define a vector for prediction

for Network in Saved_Networks:    ► Loop over all the selected top performing
neural networks

    Network.load_network()    ► Load the network

    Predict.append(Network.predict(x))    ► Give the network an input, x and
append the prediction

y = predict.average()    ► Average all the predictions from all the networks

```
