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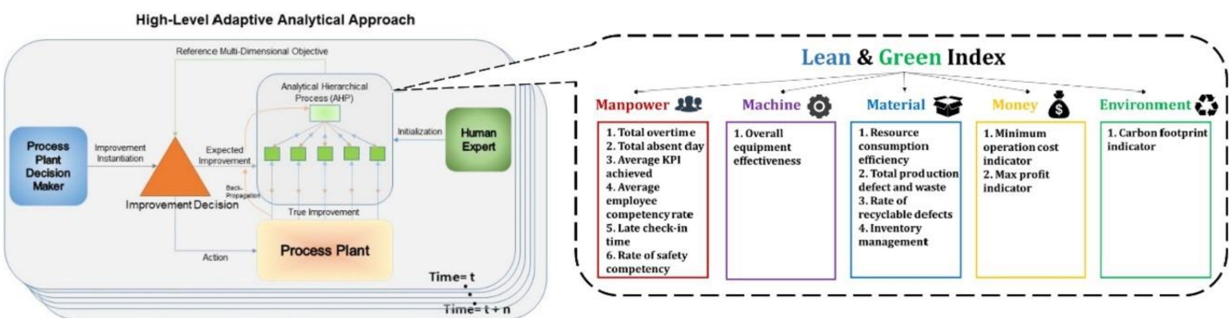
Keywords: Lean & Green manufacturing, Lean and green index, back-propagation, machine learning, process optimisation

Graphical Abstract



Highlights:

- Development of adaptive lean and green model in processing industries
- Adaptive analytical approach to 4M1E in lean and green approach.
- Continuous process improvement strategy with backpropagation algorithm.
- Adaptive model can direct industrialist to improve Lean and Green indicators.
- More data will enhance the stability and prediction of the adaptive model.

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Abstract
Many industry players are challenged by global warming and depletion of resources. Many industrialists are constantly looking for solutions to improve their operation and environmental performance. Based on the interview and literature study, manpower, machine, material, money and environment (4M1E) is known as the foundation to a facility to be able to operate. The common challenge faced by the industrialists is to perform continuous improvement effectively. The need to develop a systematic framework to assist and guide the industrialist to achieve lean and green (L&G) is required. In this paper, a novel development of an analytic model for lean and green (L&G) operation and processing is presented. The development of lean and green index (LGI) will act as a benchmarking tool for the industrialist. In this work, the analytic hierarchy process (AHP) is used to obtain experts opinion in determining the priority of the L&G components and indicators. The application of backpropagation (BP) optimisation method will further enhance the L&G model in guiding the industrialist for continuous improvement. An actual industry case study (combine heat and power plant) will be presented with the proposed L&G model.

1.0 Introduction

In early 1800, the first industrial revolution has introduced machining manufacturing to mankind. Since then, mankind has the privilege to enjoy better quality goods at a lower cost. As the global economy and manufacturing ecosystem evolved, the manufacturing industry is faced with greater challenges such as monetary fluctuation, geopolitical trade war effect, technological advancement, environmental pressure and another external factory that are constantly altering the competitive landscape (Issa and Chang, 2010). World Bank (2019) recorded that the manufacturing sector has been consistently adding value to the global economy. Mancini et al. (2017) stated that the overall global consumption depending on manufacturing is forecast to reach $62 trillion which is twice the 2013 level. Regardless of the developed or emerging market, the foundation of the economy still relies on the manufacturing industry for the source of trades. Chui et al. (2017) added that 64% of the global workforce working hours were spent on manufacturing-related activities.

The United Nations General Assembly has layout seventeen ambitious sustainable development goals (SDG) (SDG, 2019). Generally, the manufacturing industry covers two SDG (i.e. responsible consumption and production, and industry, innovation and infrastructure). Lean and green (L&G) manufacturing has paved along with the new paradigm shift in industrial revolution together with the aim of achieving sustainable manufacturing. Lean manufacturing (LM) was led and proven by example from Toyota. Toyota exhibit the ability to produce higher average vehicle output per plant (650,988 vehicles) compare with Ford (134,890 vehicles) and General Motor (193,887 vehicles) in 1980 (Vyas, 2011). LM approach is commonly defined as the elimination or reduction of non-value-added process or procedure to the final output (Leong et al., 2018a). There are seven wastes commonly encounter in LM (i.e. over-production, waiting, inventory, motion, transportation, over-processing and defects). Besides, lean principles are abode by five rules such as for define value, identify value-stream, create smooth value flow, implement pull-based production and strive for excellent (Leong et al., 2018a). Leanproduction.com (2017) stated that many lean tools have been

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developed to guide industrialists towards LM. On the other hand, green manufacturing (GM) has been focusing on the environmental aspect. GM is introduced to compensate for and enhance industry environmental performance (Leong et al., 2018a). GM was initiated in the early 1990s with the emerging of eco-innovation (Sezen and Cankaya, 2013). Maruthi and Rashmi (2015) highlighted that GM can achieve waste minimization through process design, consumption of products and materials.

1.1 Lean and Green Manufacturing

LM and GM have exhibited a similar objective in the reduction and elimination of non-value-added process/ components to the final product. The synergy of L&G will not only eliminate the non-value-added components in the process but also reduce execution time in achieving two significant outcomes. LM and GM show similarity, both approaches indicate a strong commitment to efficiency-driven practice and zero waste (Dües et al., 2013). A study on developing 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 (Hajmohammad et al., 2013). Dües et al. (2013) added that L&G has many common attributes that overlap with each other (i.e. waste and reduction method, lead time reduction, KPI, people and organisation). Adding to establish common attributes between the L&G approach, lean waste and green waste should be aligned to maximise the positive outcome (Hines, 2009). With that, a correlation is proposed between lean waste and green waste to improve operation performance (Verrier et al., 2016).

As the industry advances with technology, many reputable industry players are constantly improving their production process to stay competitive in the market. With the availability of financial resources and economies of scale, the return on investment (ROI) of large-scale optimisation and operational improvement can be attractive. Despite technology can improve operation performance, the demand for natural resources and energy in developing countries continue to rise at compounding rates (Chen and Grossmann, 2017). According to IEA (2018), the global energy demand grew by 2.1% in 2017, twice the rate of 2016. In fact, fossil fuel still contributes 70% of the growth of energy demand in the world despite strong growth in renewable energy. The carbon dioxide (CO_2) emission was found to continue on the rise despite the global financial crisis (Peter et al., 2012). IEA (2018) indicated that electricity and heat generation sector was the largest CO_2 emission source in 2016. However, the largest consumption of electricity and heat come from the industry sector. Generally, the manufacturing industry is one of the major contributors to CO_2. Besides that, data also confirmed that developing countries such as Asia region is the main source of global CO_2 emission due to the utility consumption.

In developing countries, there are many small stakeholders such as small-medium enterprise plays an important role in the country's economy. The lack of resources and expertise have become the main hurdle in optimising their facilities. According to Cheng (2018), a maintenance manager from the glove manufacturer, the lack of incentive and monetary instability has reduced the confidant of the manufacturer to invest in new equipment/technology. In fact, some of the manufacturers are still depending on low-efficiency technology. In many cases, the manufacturers are depending on a recommendation from their vendor to opt for upgrading process (Cheng, 2018). On top of that, the priority of potential upgrade to maximise the production output and performance is unclear.

To cope with the ever-changing global competition landscape, the industrialists are dealing with many different parameters to cope with production requirements daily. The elimination of major lean wastes (i.e. overproduction, transportation, defects, waiting for time, inventory, motion, extra processing and non-utilised talents) is the most effective way in improving the profit of an organisation (McBride, 2013). The elimination of lean waste must not compromise the environmental aspect. Thus, the major consideration in manufacturing can be simplified into five (5) main components such as manpower (MP), machine (MC), material (MT), money (MY) and environment (EV).

1.2 The Five Main Components (4M1E)

The five main components (4M1E) consist of manpower, machine, material, money and the environment. A literature review has indicated that the 5M (manpower, machine, money, material and method) is used to evaluate the performance of a facility. 5M is more associated with lean manufacturing rather than green manufacturing (5ME, 2019). Liliana (2016) demonstrated 4M, 5M, 6M and 7M (i.e. machines, methods, manpower, materials, maintenance, mother nature – environment and management) using Ishikawa diagram. The interview has been conducted with professionals from glove manufacturing, palm oil refinery and chemical processing plant. The 4M1E are selected based on discussion output with industry players. It is found that there is an overlap between the components such as maintenance can be included as a part of money or machine.

Manpower (MP) or talent is the backbone of an organisation. An organisation needs to consistently realign human resource strategy based on the fast-paced environment. In order to strengthen the organisation's performance, a dedicated talent pool should be nurtured. The continuous development of MP talent will not only improve their competitiveness but also prepare them to strive for innovation (Leong et al., 2018b). Kar (2018) highlighted that the manufacturing workforce is shrinking due to the misconception by younger generations (i.e. lack of competitive wages, innovation, unsafe etc.). Thus, the implementation of L&G approach is highly dependent on MP involvement and contribution.

In the manufacturing context, machine (MC) is the core equipment that processes raw material to products. The performance of the machine will directly impact the financial economy of the organization. Availability efficiency, performance efficiency and quality efficiency are the common and critical factor that the industrialists monitor on MC. The availability efficiency of the machine 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. These three main factors will contribute to overall equipment efficiency (OEE) that will reflect the performance of the MC (Singh et al., 2013).

Material (MT) reflects on the number of resources that are being consumed and produced in the manufacturing process. It also considers the recycling of defects products. The inventory of MT is also critical to ensure that the storage area is being utilized efficiently. In many conditions, the inventory has to be a continuous review of stocks level and replenishment are always performed when the stock level reaches the order limit (Silver et al., 1998). This is to ensure that production flow will not be interrupted due to lack of resources.

The fourth component is known as money (MY). Christodoulou and McLeay (2014) stated that the fundamental tools for evaluating a facility value and future value are MY. Many times, industrialists are often challenged financially in the global market due to the fluctuation of monetary policy. The sustainable of a manufacturing facility relies substantially on a healthy financial statement to maintain human resource, operation, material and treatment expenses. There are some internal factors that affect the operation such as the efficiency of human resource and equipment that will influence directly on operation cost.

Environment (EV) is one of the main components in the framework to measure the carbon footprint of a manufacturing facility. As the manufacturing sector is one of the main consumers of energy supply, effective energy management practice should be reviewed frequently. Besides that, another emission such as air, solid and water waste should be treated according to environmental regulation prior to discharging into the environment. As developing countries are the main hub for the manufacturing industry, industrialists should be assisted to reduce and control excessive greenhouse gasses (GHG) emission into the environment.

The need to develop analytic tools in assisting the industrialist to make a better decision is favourable. A novel L&G approach is developed in this research to assist the industrialist to make better optimisation decision. The L&G approach will evaluate the facility's condition based on manpower, money, material, machine and environment to identify areas that can maximise both operation and environmental performance. This paper will present an industry case study with the L&G approach. An L&G index will be developed as a benchmarking tool for the industrialist to track the effectiveness of their continuous improvement progress. Back-propagation optimisation will be introduced to enhance the L&G continuous improvement. This study will be focusing on the development of LGI and optimisation model.

2.0 Methodology

The development of a novel lean and green (L&G) approach towards industry will be able to guide and assist the industrialists to be more competitive and sustainable in the global market. The 4M1E model is being interpreted as Figure 1. In this paper, the methodology will be a macro approach towards the manufacturing facility. The interrelationship between the 4M1E varies differently industry sector. Thus, translate to different components priority can be observed for a different sector. The priority of the 4M1E components will be evaluated through the analytic hierarchy process (AHP). A group of industry and academic experts are being invited to contribute to this research. The battery limit of the model will be limited to the manufacturing process.

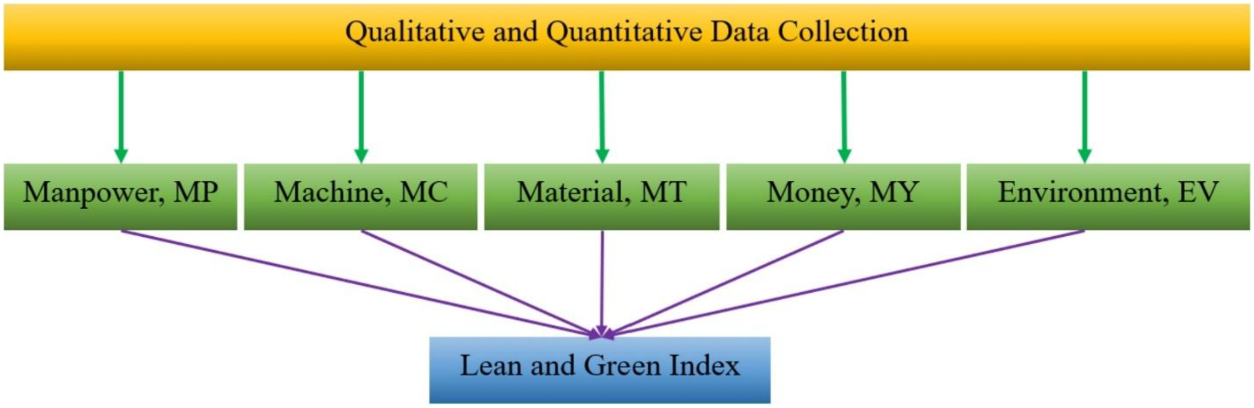

Figure 1: Relationship of 4M1E (i.e. Manpower, Machine, Material, Money and Environment)

Figure 2 does not only illustrate the boundary of this study but also the framework of L&G approach for the industry. The methodology of this paper will follow as below:

1. Interview with plant manager / operation manager / maintenance manager / human resource manager to understand the standard operating procedure and operation behaviour of the factory. The interview session is utmost critical as to encourage and initiate the industrialist participation in L&G approach for continuous improvement.

2. Have a clear understanding of the operation process, critical equipment and process requirements. L&G questionnaires will be distributed to operation management teams to gain their opinion on their decision-making hierarchy. This is critical during analysis as an indicator used to evaluate the facility will be different with sectors.

3. Establish the main person-in-charge and coordination team with the factory to ease data collection planning. Data collection shall be over a period of 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. Data collection requirements are based on the L&G checklist shown in Figure 3. In case of interruption occurs during data collection, inform the coordination team and re-arrange with the person-in-charge on the data collection schedule.

4. Review collected data prior to performing the analysis. If data dispute is found, inform coordination team to discuss for action plant 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.

5. Lean and green index (LGI) will be generated to indicate the level of lean and green (L&G) of the factory. The first LGI generated for each factory will be the benchmarking index for the factory performance. Subsequent generated LGI will reflect validate the performance improvement based on the implemented action plan.

6. As the LGI is generated from the model, the industrialist can set an achievable target. The back-propagation optimiser will be used to assist and guide the industrialist to achieve the expected target. Monthly progression can be traced with back-propagation modelling.

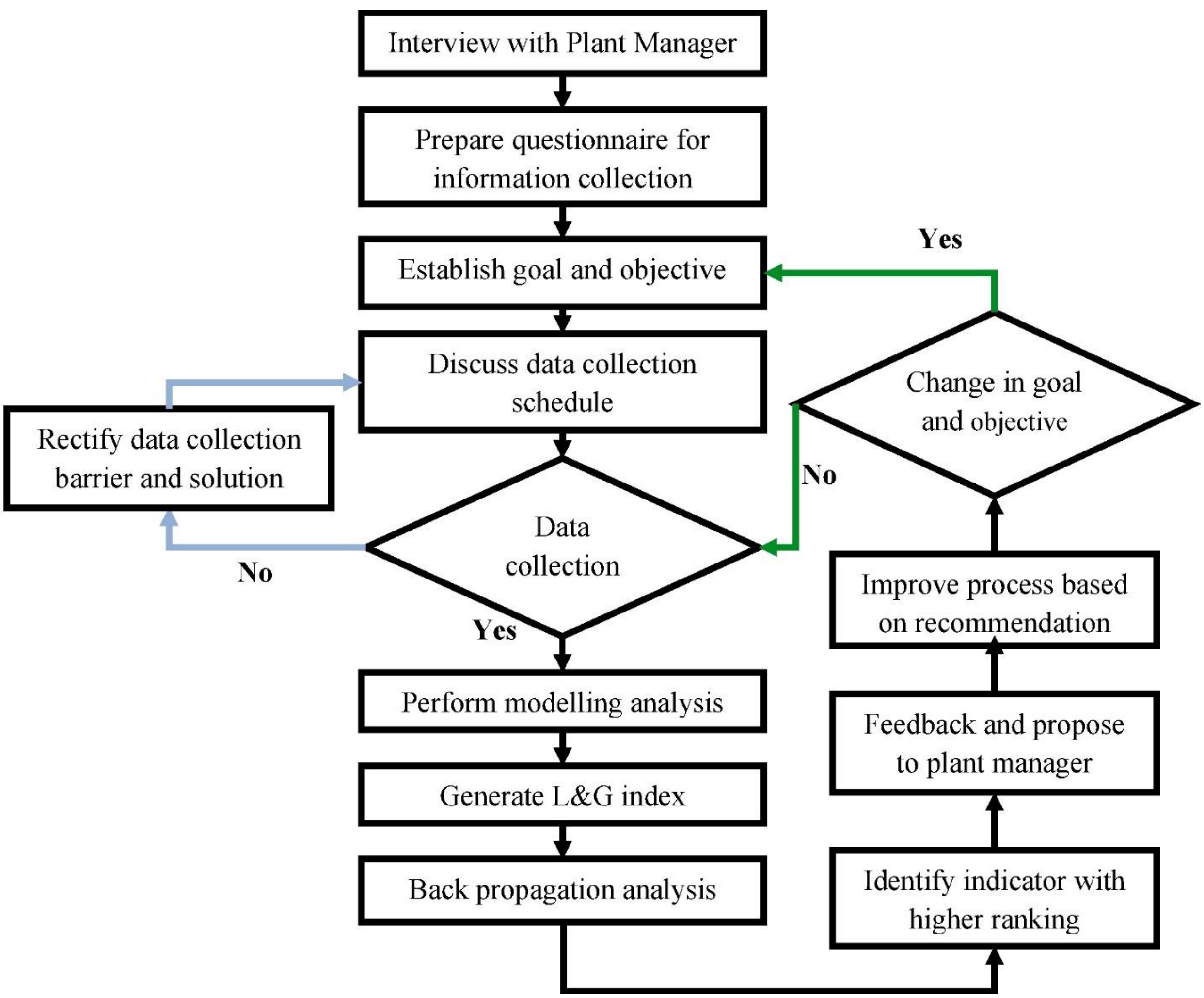

Figure 2: Structured flow chart of L&G approach

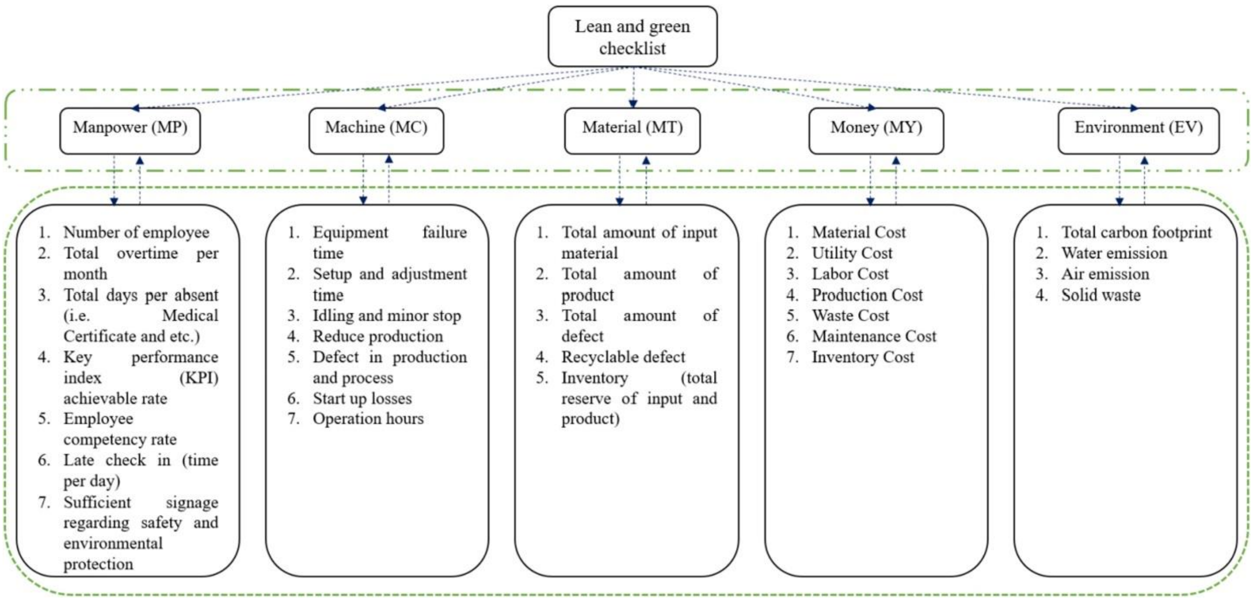

Figure 3: lean and green (L&G) checklist for data collection

Referring to Figure 3, the L&G checklist is developed through feedback and interview from professionals from different industry sectors (i.e. glove manufacturing, palm oil refinery, cogeneration plant and chemical processing facility). The L&G checklist provides a general guideline of required data to perform L&G modelling.

2.1 Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) introduced by Thomas Saaty (1980), is an effective multi-criteria decision making (MDCM) tools that are widely applied in 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 Cao, 1992). The mathematical simplicity of AHP has allowed the method to be applied in various field such as business, engineering, health care, environmental science etc. 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 a 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 research front end, it is also used to develop systems for refurbishment building assessment scheme to prioritize factors such as energy, waste, economics, social and cultural and others for the reduction of energy consumption and CO_2 emission building in Malaysia (Kamaruzzaman et. al, 2018). Thus, in this study, the AHP model is integrated with the backpropagation algorithm to dynamically improve the lean and green performance of the cogeneration plant.

In this work, the AHP network model is established after the interview and discussion with industry experts. Figure 4 illustrates the indicators contributing to improving lean and green index (LGI) of a generic processing facility. The AHP methodology is as below:

1. Interview the plant manager for an in-depth understanding of the processing facilities requirement and operating condition. The interview involves personnel from the maintenance, operation and process department. The total number of participants is between 5-10 individuals.

2. Develop a model for decision making based on goals and criteria (i.e. main components and 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 main five components (i.e. 4M1E) that contribute to the final goal. The third level reflects the 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. In this AHP analysis, Saaty's pairwise comparison scale is adopted to represent the intensity of the relationship between the pairing (Saaty, 2012). The 9-point fundamental scale is described in Table 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. Eq. 1 demonstrated the input from the experts are used to fill the upper right part of the matrix (i.e. w12) while the lower left is the inverse of upper-right value (i.e. 1/w12). Ngan et al. (2018) stated that the geometric mean method is used for multiple inputs. The consistency ratio (CR) is calculated to ensure the input is consistent. Saaty (1980) indicated that the CR of 0.10 or less than 0.10 is deemed as acceptable. On the other hand, the judgement of the analysis needs to be reviewed if CR is more than 0.10 which reflects inconsistency.

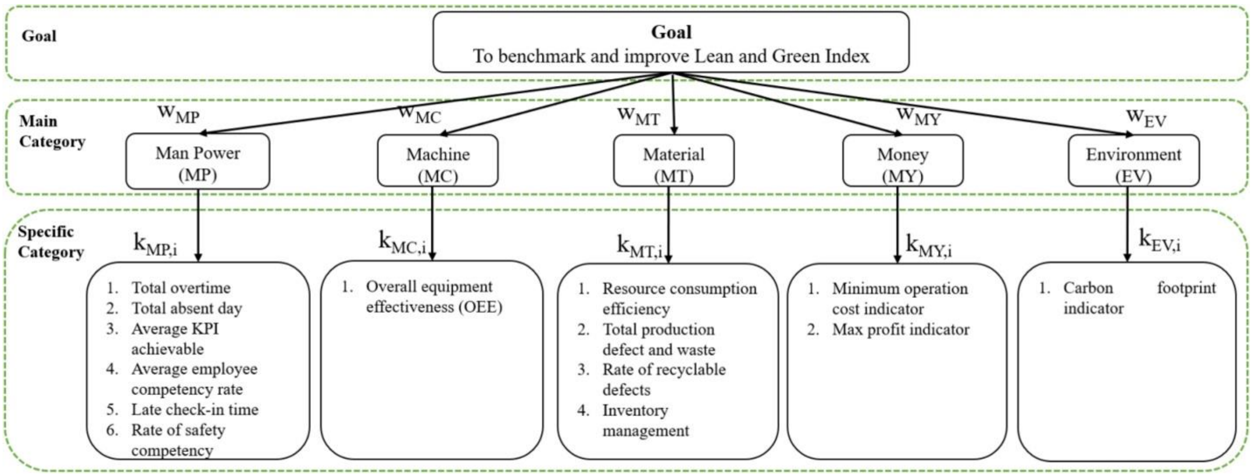

Figure 4: Analytic Hierarchy Process (AHP) model structure

Table 1: Saaty pairwise comparison scale (Saaty, 2012)

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

$$m = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & C_{\dots} & C_n \end{array} \\ \begin{array}{c} C_1 \\ C_2 \\ C_{\dots} \\ C_n \end{array} & \begin{bmatrix} 1 & w_{12} & w_{1\dots} & w_{1n} \\ 1/w_{12} & 1 & w_{2\dots} & w_{2n} \\ 1/w_{1\dots} & 1/w_{2\dots} & 1 & w_{\dots n} \\ 1/w_{1n} & 1/w_{2n} & 1/w_{\dots n} & 1 \end{bmatrix} \end{array} \tag{1}$$

2.2 Lean and green index (LGI)

Lean and green index (LGI) will be generated to evaluate based on the 4M1E input. There are several related to lean and green or lean, agile, resilient and green (LARG) being developed. However, the application of the index does not focus on the manufacturing sector. In a study, Almeida (2014) developed lean index and green index to evaluate the company's performance. This paper proposes LGI as the composite index for lean index and green index. Besides that, the evaluation indicators differ from Almeida's (2014) index. In this work, LGI includes 4M1E (manpower, machine, material, money and environment) components. Data required on L&G checklist (Figure 3) will be collected for analysis.

The LGI can be a benchmarking and evaluation tool for the manufacturing sector. LGI is contributed by 4M1E index in Eq. 1. The w_{MP}, w_{MT}, w_{MC}, w_{MY} and w_{EV}represents the weight of the components in obtained from industrialist feedback.

$$LGI = w_{MP} \times MP + w_{MT} \times MT + w_{MC} \times MC + w_{MY} \times MY + w_{EV} \times EV \tag{2}$$

2.2.1 Manpower index, MP

In the manufacturing sector, talents are known as the most valuable asset to manage production. Based on Figure 3, the industrialists from the manufacturing have indicated that employee attitude and performance will contribute to L&G performance. The key indicators in the manpower component will be the attendance rate, key performance indicator (KPI) and competency. According to Cheng (2018), an outstanding employee is a competent employee who is committed (maximum attendance rate) to fulfil his responsibility (i.e. KPI). More importantly, the employee must be kept updated with the latest safety regulation within the manufacturing premises. This can be done through a short quiz to ensure employee understand the safety response. In the development of manpower, MP index, the indicators required are as below:

a. Total overtime per employee per year, MP_{OT} (hr/year.pax)

$$MP_{OTi} = \frac{Total\ employee\ over\ time\ per\ year}{Average\ number\ of employee\ working\ in\ a\ year} \tag{3}$$

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

$$MP_{OT} = \frac{hr_{opt,year} - MP_{OTi}}{hr_{opt.year}} \tag{4}$$

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

$$MP_{ABi} = \frac{Total\ employee\ absent\ day\ per\ year}{Average\ number\ of employee\ working\ in\ a\ year} \tag{5}$$

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

$$MP_{AB} = \frac{hr_{opt.year} - MP_{ABi}}{hr_{opt.year}} \tag{6}$$

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

$$MP_{KPIi} = \frac{Total\ employee\ KPI\ achievable\ per\ year}{Average\ number\ of employee\ working\ in\ a\ year} \tag{7}$$

Normalise the indicator by 100% achievable

$$MP_{KPI} = \frac{MP_{\text{KPIi}}}{100} \tag{8}$$

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

$$MP_{CRi} = \frac{Total\ employee\ competency\ rate\ per\ year}{Average\ number\ of employee\ working\ in\ a\ year} \tag{9}$$

Normalise the indicator relative to the full rate.

$$MP_{CR} = \frac{MP_{CRi}}{100} \tag{10}$$

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

$$MP_{LTi} = \frac{Total\ employee\ late\ check\ in\ time\ per\ year}{Average\ number\ of employee\ working\ in\ a\ year} \tag{11}$$

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

$$MP_{LT} = \frac{hr_{opt.year} - MP_{LTi}}{hr_{opt.year}} \tag{12}$$

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

$$MP_{SCi} = \frac{Total\ rate\ of\ safety\ competency\ per\ year}{Average\ number\ of employee\ working\ in\ a\ year} \tag{13}$$

Normalise the indicator in relative to full rate.

$$MP_{SC} = \frac{MP_{SCi}}{100} \tag{14}$$

MP index is represented as below:

$$MP = k_{MP,OT} \times MP_{OT} + k_{MP,AB} \times MP_{AB} + k_{MP,KPI} \times MP_{KPI} + k_{MP,CR} \times MP_{CR} + k_{MP,LT} \times MP_{LT} + k_{MP,SC} \times MP_{SC} \tag{15}$$

2.2.2 Machine index, MC

For machine (MC) index, overall equipment effectiveness (OEE) is used to represent MC index. OEE is developed by Nakajima which consists of three main indicators namely availability, performance and quality (Nakajima, 1988). Dadashneijad and Valmohammadi (2017) stated that OEE is a measurement of manufacturing performance that will be able to apply to manufacture in many different industries allowing simple comparison despite dissimilarity processes. The objective of OEE is to numerically indicate the production efficiency through simple and clear metric. It is also able to pinpoint bottleneck of the process through operation data analysis. The 6 main losses are used to calculate the matric for OEE and are defined in Table 2. The relationship of 6 main losses will be illustrated in Figure 5.

Table 2: Overall equipment effectiveness (OEE) six major losses (Ahaju and Khamba, 2008)

No	6 main losses	Description
1	Equipment failure	Losses due to equipment failure. Types of failure include critical equipment failure that caused the production stop. Any activities that cause the unplanned production shutdown due to equipment faulty is deemed under this category.
2	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.
3	Idling and minor stoppage	Idling and minor stoppage refer to temporary stop or idle of production due to sensor faulty. Many industrialists do not take this loss into consideration as the total time contributes to idling and minor stoppage is very minimal during normal operation. However, it is important to evaluate this loss to maximise L&G outcome.
4	Reduced speed	Reduced speed refers to production at designed or desired production rate.
5	Defects in process	The amount of time or volume of defects that required to handle or re-processing on the product. This also includes in financial expenses on re-processing and handling of defects.
6	Start-up losses	Time loss during start-up, running in and stabilise before production can initiate.

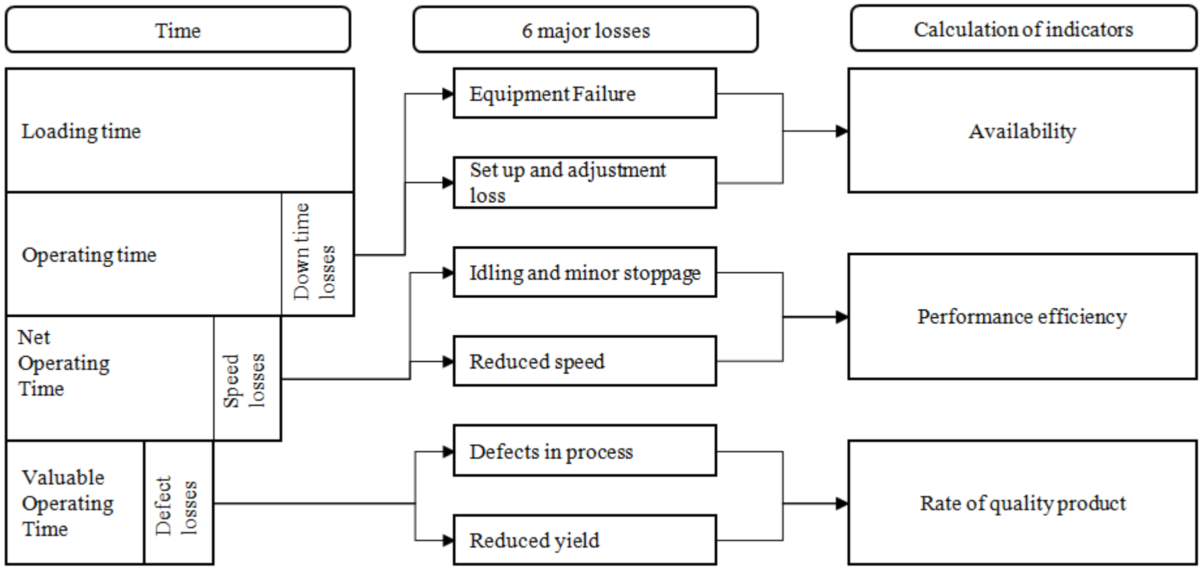

Figure 5: How six major losses relate to Overall Equipment Efficiency (OEE)

Referring to Figure 5, the Availability (A) 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:

$$A = \frac{Planned\ operation\ time - (equipment\ failure\ time - set\ up\ and\ adjustment\ loss)}{Planned\ operation\ time} \quad (16)$$

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

$$P = \frac{Total\ processed\ amount \times Ideal\ production\ rate}{Actual\ operation\ time} \quad (17)$$

The rate of quality product (Q) measured the amount of total 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:

$$Q = \frac{Processed\ amount - Defect\ amount}{Processed\ amount} \quad (18)$$

The OEE is calculated by obtaining the product of A, P and Q reflected in Eq. 19. Samual 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.

$$OEE = A \times P \times Q \tag{19}$$

2.2.3 Material index, MT

In material (MT) component, the main data required is focused on resources, product and inventory management. In lean practices, pull-based production is desired (Leong et al, 2018a). The MT indicator will assist the industrialist in identifying the optimum inventory capacity through its inventory storage data. Besides that, the rate of resources conversion to quality products is critical in contributing to the sustainable development goal (SDG) 12 which emphasize responsible consumption and production (SDG, 2019). Table 3 summarises the indicator used in MT.

Table 3: L&G material (MT) indicator

Indicators	Description
The total amount of input material	The total amount of consumable resources (i.e. raw material, combustion fuel, steam and etc) 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 based on the analysis.

The indicators defined in Table 1-2 provides a guideline for the users during data collection. The relationship between each MT indicators are illustrated in the equation as below:

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

$$MT_{RE} = \frac{Total\ amount\ of\ product}{Total\ amount\ of material\ input} \tag{20}$$

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

$$MT_{DI} = \frac{Total\ amount\ of\ product - Total\ product\ defects}{Total\ amount\ of product} \tag{21}$$

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.

$$MT_{RD} = \frac{Total\ amount\ of defects - Recycable\ defects}{Total\ amount\ of defects} \tag{22}$$

A part of the material, 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.

$$MT_{IN} = \frac{(Minimum\ monthly\ material\ input + average\ monthly\ production\ )}{(Averagemonthly\ input\ material + maximum\ monthly\ production\ )} \tag{23}$$

Finally, the MT index is generated to represent the performance of resource consumption.

$$MT = k_{MT,RE} \times MT_{RE} + k_{MT,DI} \times MT_{DI} + k_{MT,RD} \times MT_{RD} + k_{MT,IN} \times MT_{IN} \tag{24}$$

2.2.4 Money index, MY

Economic feasibility is one of the critical components in all organisation regardless of manufacturing or services sector. A profitability process with a healthy and sustainable return of investment (ROI) and operation capital (OpEx) is desirable. Sonneborn (2016) highlighted optimising internal standard and leveraging on industry-standard will help the organisation gain efficiencies and gain more profitability in this competitive global market. The money (MY) reflects the financial performance of a process through two 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 labour cost, maintenance cost, energy cost, raw material cost and etc. To obtain optimise the performance of MY_{OC}, the cost of operation needs to be reduced to maximise profits.

$$MY_{OC} = \frac{Minimum\ operation\ cost\ /\ unit\ of\ product}{Average\ \ operation\ cost/unit\ of\ product} \tag{25}$$

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.

$$MY_{TP} = \frac{Maximum\ profit\ cost\ /\ unit\ of\ product}{Average\ \ profit\ cost/unit\ of\ product} \tag{26}$$

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

$$MY = k_{MY,OC} \times MY_{OC} + k_{MY,TP} \times MY_{TP} \tag{27}$$

2.2.5 Environment index, EV

Global warming and climate change have been an inevitable issue in the manufacturing sector. Total carbon footprint is the main indicator contributing to the environment (EV) component. Čuček et al. (2012) studied the importance of including global warming potential (GWP) as one of the environmental indicators. GWP is developed to compare the impact of different greenhouse gases (GHG). It measures the total energy one ton of specific gas absorbs relatively to one ton of carbon dioxide (CO_2). Therefore, larger GWP reflects higher heat-absorbing capacity compare to CO_2 at that period (EPA, 2017). The emission of GHG from the production process should be recorded. The calculation in total carbon footprint is based on GWP value for common GHG illustrated by Myhre et al. (2013). The need for the industrialist to be efficient in water consumption is required to reduce the environmental impact and to converse the sustainability of water supply (Ong et al., 2015). Moreover, Ng et al. (2014) showed that environmental impact can be reduced with proper management and reduction in the production of solid waste. Based on Figure 3, EV targets several 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 flowrate and composition of the exhaust air will be used to evaluate the carbon footprint (tCO_2/unit of product) of exhaust gas component (*i*). The global warming potential (GWP) can be obtained from EIA (2017).

$$\begin{aligned} &Carbon\ emission\ of\ i = Total\ operation\ hours \times \\ &exhaust\ gas\ mass\ flowrateof\ i\ gas\ \times GWP\ of\ component\ i \end{aligned} \tag{28}$$

$$CO2\ footprint\ indicator, EV_{CO2} = \frac{minimum\ monthly\ CO2\ emission/total\ i\ monthly\ production}{average\ monthly\ CO2\ emission\ /total\ i\ \ monthly\ production} \tag{29}$$

For water emission, the flow rate and composition of wastewater are required. The targeted wastewater components,*j* should be defined. Specific wastewater component, *j* can be defined and evaluated independently depending on the industrialist criteria.

$$Water\ emission\ of\ j = Total\ operation\ hours \times j\ mass\ flowrate \tag{30}$$

$$Wastewater\ indicator, EV_{WW} = \frac{minimum\ monthly\ wastewater\ emission/total\ monthly\ production}{average\ monthly\ wastewater\ emission\ /total\ monthly\ production} \tag{31}$$

The types of solid waste produced vary from industry to industry. Industrialist can opt to analyse specific solid waste, s based on the operation criteria.

$$Solid\ waste, s = Total\ operation\ hours \times rate\ of\ waste, s\ generation\ per\ unit\ of\ product \times rate\ of\ production \quad (32)$$

$$Solid\ waste\ indicator, EV_{SW} = \frac{minimum\ monthly\ generated\ solidwaste/total\ monthly\ production}{average\ monthly\ generated\ solidwaste\ /total\ monthly\ production} \quad (33)$$

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.

$$EV = k_{EV,CO2} \times EV_{CO2} + k_{EV,WW} \times EV_{WW} + k_{EV,SW} \times EV_{SW} \quad (34)$$

All five (5) main components (4M1E) generate the component index individually. Referring to Figure2-2, prior to data collection, a common understanding and process indicator should be established with the plant manager. The modification can be performed on the 4M1E indicator to suit operation criteria.

2.3 Analytical Continuous Improvement by Back-propagation (BP)

A static analytical model for lean and green processing is exceptionally good at value prediction but is unable to cope with changes with the dynamic changes in the real world. Continuous improvement of the analytical model must be carried out with an updating algorithm through the depths of time. 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). Le Cun et al. (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). In this work, BPis proposed to be incorporated into the lean and green analytical framework for continuous improvement. A significant difference between our analytical approach of the BP method when compared with the computational approach is (i) error prediction by analytical methodologies (ii) slower update frequency.

Continuous improvement of the adaptive analytical model must be carried out with an updating algorithm through the depths of time. Figure 6 explains the concept of a high-level adaptive analytical approach for this application. The adaptive model reflects the output from the process plant by comparing it with the expected improvement value. The adaptive model will then adjust the improvement priority of the indicators in the AHP model. On top of that, the "human expert" input will vary among different industry sector due to the nature of industry practise.

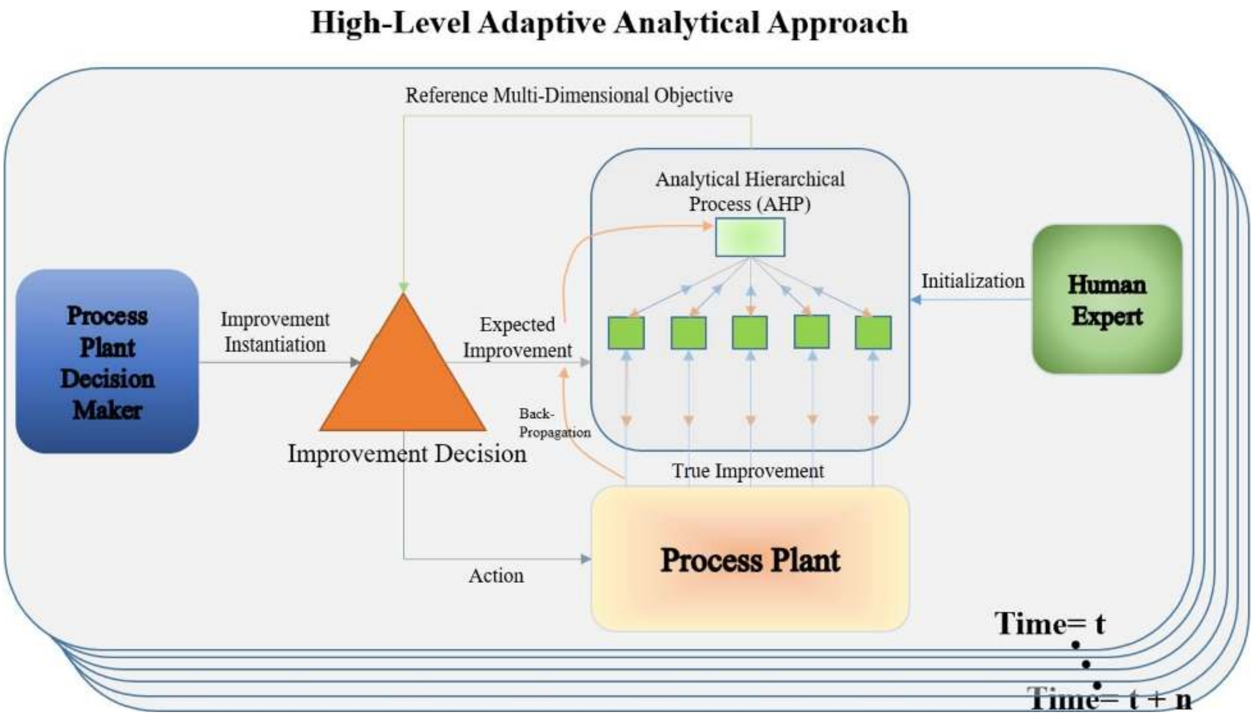

Figure 6: High-Level adaptive analytical approach

In analytical green and lean management, the expectations for the green and lean index can vary over time. There is a constant requirement of correcting the accessed green and lean index with respect to the expected index. The BP algorithm can be 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:

$$E = \frac{1}{2}\left(LGI_{accessed} - LGI_{expect}\right)^2 \tag{35}$$

Where E is the error, LGI is the lean and green index which can be an expectation or assessed. The expectation index can be quantified when an improvement is planned, but not implemented. On the other hand, the accessed GLI is measured after the improvement has been implemented and directly computed using historical processing values. In our case, simple gradient descent with chain rule is implemented for the use of BP. The updating of AHP weights for the intermediate layers (4M1E) is computed using the following equation:

$$w_{i+1} = w_i - \eta\frac{E_i - E_{i-1}}{w_i - w_{i-1}} \tag{36}$$

w_i is the weights for the 5 main components (4M1E) on the current month. w_{i+1} is the new weight for the next time step (next month in this case study). Vice-versa, w_{i-1} is the weight 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. A heuristic learning rate of 0.05 is used since the predicted maximal change of the lean and green index 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, 2001).

$$k_{i+1} = k_i - \eta \frac{E_i - E_{i-1}}{w_i - w_{i-1}} \times \frac{w_i - w_{i-1}}{k_i - k_{i-1}} \tag{37}$$

k_i is the weights for each of the indicators under the 5 main components, where i is the time step. The error is passed down the analytical model using the chain rule and updated for each time step.

3.0 Case study

An actual industry case study was used to demonstrate the proposed L&G model. Figure 7 illustrates a cogeneration process which consists of a gas turbine with a heat recovery steam generator (HRSG). Cogeneration or combined heat and power (CHP) plant is considered a thermodynamically efficient way of converting energy (Ferreira et al., 2014). The gas turbine acts as the prime mover in CHP plant by rotating the alternator for electricity generation and release high-temperature exhaust air. The waste of high-temperature exhaust air by heat recovery through HRSG as steam.

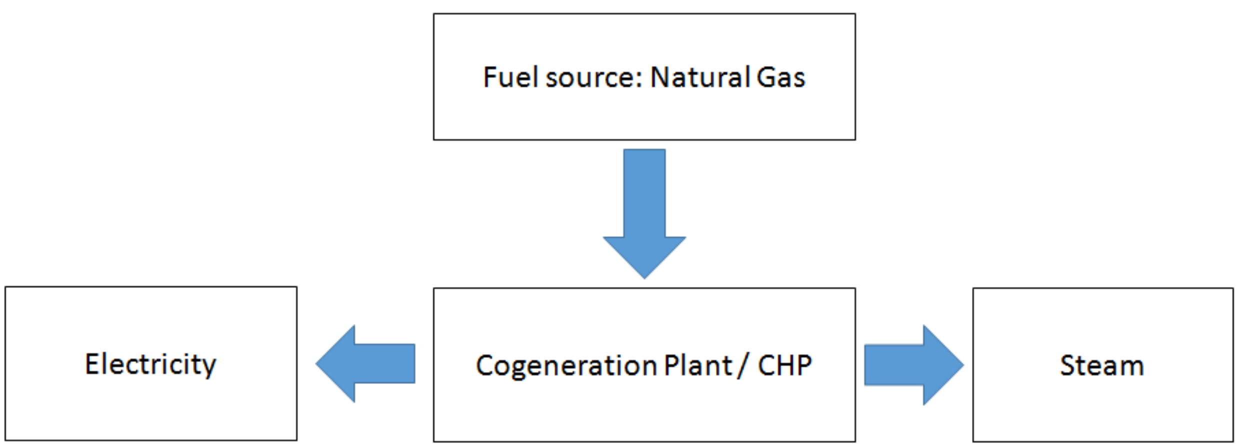

Figure 7: Flow Diagram of case study

A 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
b. Maximum electricity generation : 6.5MW @ 32degC
c. Maximum steam recovery : 16 tonnes / hour @ 10barG saturated steam

An interview is conducted with the plant manager prior to visiting the CHP plant. The CHP is operated and evaluated as an independent plant that produces electricity and steam for supply. The boundary of this case study is limited to the CHP operation as shown in Figure 8. The supply of electricity and steam from the CHP plant is dependent on the adjacent processing plant. Lean and green (L&G) analysis will then applied to the case study for analysis.

3.1 Data collection

Prior to data collection, L&G flow chart (Figure 2) and L&G checklist (Figure 3) are explained to the operation team. In this case study, four years of CHP operation data are being collected from the year 2015 to the year 2018. Table 5, 6, 7, 8 and 9 show the data for manpower, machine, material, money and environment for the year 2015 respectively.

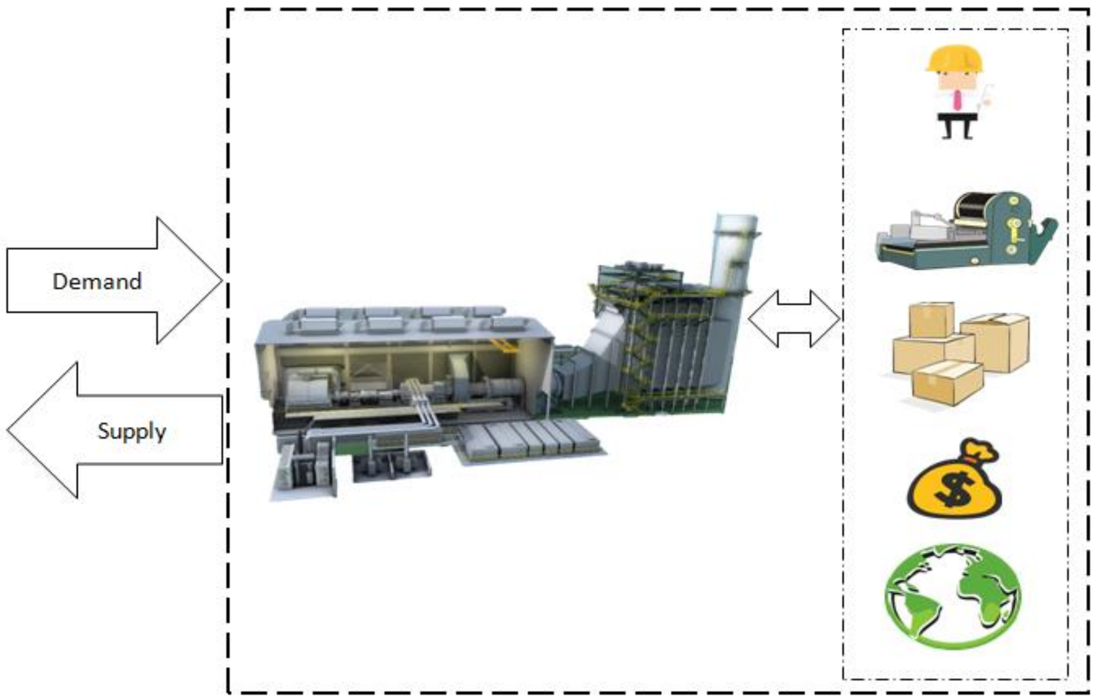

Figure 8: Boundary limit of CHP case study

Table 4 shows the fluctuation of natural as per million British thermal unit (Btu) and generation cost per tonne of steam. There are some additional data furnish 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 4: Cost of natural gas and steam generation

	RM/MMBtu	RM/Ton of steam		RM/MMBtu	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

Table 5: Data collection for manpower (MP) index in the year 2015

Indicators	Unit	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Number of Employee	pax	6	6	6	6	6	6	7	7	7	7	7	7
Total overtime	hr / month	540	500	400	600	450	400	550	450	400	400	600	430
Total absent days (exclude planned leave)	days / month	12	7	8	15	2	6	5	6	2	10	5	3
Employee competency rate	%	33	33	33	33	50	50	43	43	43	43	57	57
Late check in	hr/ month	10	10	14	10	4	4	4	10	10	12	10	8
Rate of safety competency	%	100	100	100	100	100	100	86	86	100	100	100	100

Table 6: Data collection for machine (MC) index in the year 2015

No.	Indicators	Unit	Jan	Feb	Mar	Apr	May	Jun
1	Equipment failure time	hr/month	6	5	4	3	3	8
2	Setup and adjustment time (planned stop)	hr/month	3	3	3	3	3	2
3	Idling and minor stop	hr/month	1	2	1.5	2	3	1
4	Reduce production	kWh/month	3,841,575	3,590,111	3,446,194	4,289,535	3,841,575	3,717,653
5	Defect in production and process	unit/month	0	0	0	0	0	0
6	Start-up losses (natural gas)	kWh/month	65,430	58,160	50,890	43,620	43,620	72,700
7	Ideal Production Output	kWh/month	14,146,977	13,690,623	14,146,977	13,690,623	14,146,977	13,690,623
8	Total production	kWh/month	10,305,402	10,100,512	10,700,783	9,401,088	10,305,402	9,972,970

No.	Indicators	Unit	Jul	Aug	Sep	Oct	Nov	Dec
1	Equipment failure time	hr/month	8	8	3	4	3	2
2	Setup and adjustment time (planned stop)	hr/month	3	3	3	4	3	3
3	Idling and minor stop	hr/month	1.5	2	3	2	1	2
4	Reduce production	kWh/month	3,709,781	4,942,688	3,717,653	3,841,575	1,982,748	3,709,781
5	Defect in production and process	unit/month	0	0	0	0	0	0
6	Start-up losses (natural gas)	kWh/month	79970	79970	43620	58160	43620	36350
7	Ideal Production Output	kWh/month	14,146,977	14,146,977	13,690,623	14,146,977	7,301,666	14,146,977
8	Total production	kWh/month	10,437,195	9,204,288	99,729,691	10,305,402	5,318,917	10,437,196

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Table 7: Data collection for material (MC) index in the year 2015

No.	Indicators	Unit	Jan	Feb	Mar	Apr	May	Jun
1	Total amount of input material (natural gas)	kWh/month	12,052,800	11,880,000	12,648,000	11,520,000	12,052,800	11,664,000
2	Total amount of product (electricity + steam)	kWh/month	10,305,402	10,100,512	10,700,783	9,401,088	10,305,402	9,972,970
	Total Electric Generated	kWh/month	2,901,600	2,880,000	3,124,800	2,736,000	2,901,600	2,808,000
	Total Steam Generated	kWh/month	7,403,802	7,220,512	7,575,983	6,665,088	7,403,802	7,164,970

No.	Indicators	Unit	Jul	Aug	Sep	Oct	Nov	Dec
1	Total amount of input material (natural gas)	kWh/month	12,276,000	11,755,200	11,664,000	12,052,800	6,220,800	12,201,600
2	Total amount of product (electricity + steam)	kWh/month	10,437,196	9,204,289	9,972,970	10,305,402	5,318,917	10,437,196
	Total Electric Generated	kWh/month	2,976,000	2,604,000	2,808,000	2,901,600	1,497,600	2,976,000
	Total Steam Generated	kWh/month	7,461,196	6,600,289	7,164,970	7,403,802	3,821,317	7,461,196

Table 8: Data collection for money (MY) index in the year 2015

No	Indicators	Unit	Jan	Feb	Mar	Apr	May	Jun
1	Natural Gas Price	RM/MMBtu	19.77	19.77	19.77	19.77	19.77	19.77
2	Natural Gas Consumption	RM/month	812431.34	800783.58	852551.41	776517.41	812431.34	786223.88
3	Maintenance Cost	RM/month	145833.33	145833.33	145833.33	145833.33	145833.33	145833.33
4	Labor Cost	RM/month	18000.00	18000.00	18000.00	18000.00	18000.00	18000.00
5	**TOTAL OPT COST**	**RM/month**	**976264.68**	**964616.91**	**1016384.74**	**940350.75**	**976264.68**	**950057.21**
6	Electric Generation	kWh/month	2901600.00	2880000.00	3124800.00	2736000.00	2901600.00	2808000.00
7	Steam Generation	ton/month	9597.60	9360.00	9820.80	8640.00	9597.60	9288.00
8	Electric Selling Price	RM/month	1131624.00	1123200.00	1218672.00	1067040.00	1131624.00	1095120.00
9	Steam Generation	RM/month	563002.45	549064.65	576095.53	506828.91	563002.45	544841.08
10	**TOTAL SALES**	**RM/month**	**1694626.45**	**1672264.65**	**1794767.53**	**1573868.91**	**1694626.45**	**1639961.08**
	PROFIT	**RM/month**	**718361.77**	**707647.74**	**778382.79**	**633518.16**	**718361.77**	**689903.87**

No	Indicators	Unit	Jul	Aug	Sep	Oct	Nov	Dec
1	Natural Gas Price	RM/MMBtu	21.80	21.80	21.80	21.80	21.80	21.80
2	Natural Gas Consumption	RM/month	912442.33	873732.65	866954.00	895852.47	462375.47	906912.37
3	Maintenance Cost	RM/month	145833.33	145833.33	145833.33	145833.33	145833.33	145833.33
4	Labor Cost	RM/month	23000.00	23000.00	23000.00	23000.00	23000.00	23000.00
5	**TOTAL OPT COST**	**RM/month**	**1081275.66**	**1042565.99**	**1035787.33**	**1064685.80**	**631208.80**	**1075745.71**
6	Electric Generation	kWh/month	2976000.00	2604000.00	2808000.00	2901600.00	1497600.00	2976000.00
7	Steam Generation	ton/month	9672.00	8556.00	9288.00	9597.60	4953.60	9672.00
8	Electric Selling Price	RM/month	1160640.00	1015560.00	1095120.00	1131624.00	584064.00	1160640.00
9	Steam Generation	RM/month	210849.60	186520.80	202478.40	209227.68	107988.48	210849.60
10	**TOTAL SALES**	**RM/month**	**1371489.60**	**1202080.80**	**1297598.40**	**1340851.68**	**692052.48**	**1371489.60**
	PROFIT	**RM/month**	**290213.94**	**159514.81**	**261811.07**	**276165.88**	**60843.68**	**295743.89**

Table 9: Data collection for environment (EV) index in the year 2015

Indicator	Unit	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CO_2	m3/ hr	160,460	160,460	160,460	160,460	160,460	160,460	160,460	160,460	160,460	160,460	160,460	160,460
NO_X	ton/ month	1,051	1,017	1,051	1,017	1,051	1,017	1,051	1,051	1,017	1,051	542	1,051
GWP													
CO_2 (x1)	tCO_2/ month	160,927	155,736	160,927	155,736	160,927	155,736	160,927	160,927	155,736	160,927	83,059	160,927
NO_X (265x)	tCO_2/ month	278,489	269,505	278,489	269,505	278,489	269,505	278,489	278,489	269,505	278,489	143,736	278,489
TOTAL	**tCO_2/ month**	**439,416**	**425,241**	**439,416**	**425,241**	**439,416**	**425,241**	**439,416**	**439,416**	**425,241**	**439,416**	**226,795**	**439,416**

3.2 Discussion

This case study is supported by industry data obtained from year 2015 to 2018. Referring to Figure 3, the plant manager responded that some of the indicators in level three do not apply for the cogeneration 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 manufacturer is responsible for the maintenance of the gas turbine. Therefore, no inventory is required.

3.2.1 Analytic Hierarchy Process (AHP) analysis

Based on the analytic hierarchy process (AHP) analysis, the distribution of weight based on main components (i.e. 4M1E) is presented in Table 10. Based on the feedback from the respondents, money (MY) is ranked first in improving lean and green index of a cogeneration plant with 26.10%, followed by environment (21.54%), manpower (18.7%), machine (18.28%) and material (15.38%).

The cogeneration plant is a highly complicated system where it required sophisticated prime mover (i.e. gas turbine, gas engine and steam turbine). Due to technology limitation, industrialists who want to implement cogeneration plant in Malaysia are still heavily dependent on imported technology. The dependence on foreign technology exposes the local industrialist to several risks (i.e. monetary risk, geopolitical risk and local maintenance support) (Leong et al., 2018a). Moving on, environment components are rated as the second most significant component by the experts. The Malaysia government has the intention to reduce its greenhouse gas (GHG) emission intensity of gross domestic product (GDP) by 45% by 2030 comparing 2005 GDP (MITI, 2017). Based on the ranking, the industrialists are committed to contributing to the national goal. In addition, the facility has a stringent environmental policy to ensure environmental emission is minimised.

Despite the cogeneration has been a matured technology, the complexity of the machine still requires manual operation from operators. In operation of the cogeneration plant, human resource is important to set up the equipment for operation planning. The lack of experienced talent in the cogeneration plant has also increased the challenge of the employee in retaining the talent. On the machine aspect, the reliability of prime mover (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, the industry player is able to enjoy a consistent supply of high-quality NG supply.

Table 10: 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

CR: 0.0283

Table 11 demonstrates the priorities of manpower (MP) indicators. It is observed that employee safety is the utmost priority in MP (24.17%), followed by an absent day (23.40%), employee competency rate (18.37%), KPI achievable rate (13.59%), late check-in time (10.84%) and lastly overtime (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 cogeneration plant involves electricity and steam generation, the health and working condition of the employee are ranked as the utmost priority. The number of absent days 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.

Table 11: Pairwise comparison matrix of Manpower (MP) indicators

	MP-OT	MP-AB	MP-KPI	MP-CR	MP-LC	MP-SC	Eigenvector	Ranking
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	5
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

Apart from MP, Table 12 shows the dominance of profit indicators over operation cost for money (MY) components. This can be explained as the manufacturer has established a maintenance contract with the owner of the plant. Therefore, the profit of cogeneration output is being prioritised as the maintenance cost is deemed to be fixed by contract.

Table 12: 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

3.2.2 Lean and green index (LGI)

The indicators of manpower (MP) is presented in Figure 8. Figure 8 presented the historical performance record of MP indicator. The MP indicators are calculated with Eq. 15. The average key performance indicator (KPI) rate and employee competency rate indicators need to be improved to increase the MP index. In the year 2015, the KPI and competency rate of the employee have shown lower performance rate. Extensive training and guidance are required to develop a competent team to manage the new facility (Cheng, 2018). However, based on Figure 9, it shows that the average safety competency rate of an employee is above 90% which reflects the priority of employee safety in the facility.

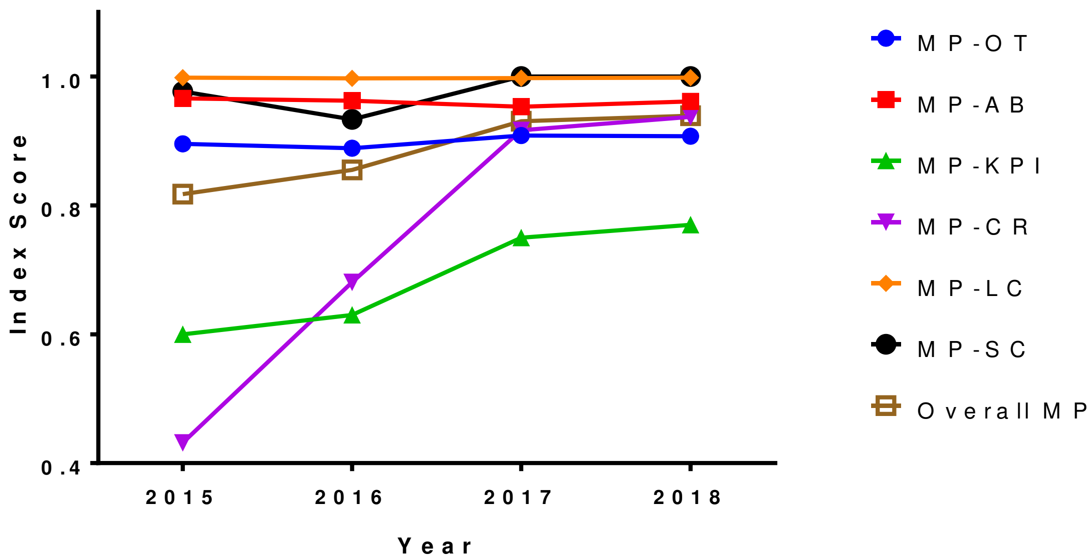

Figure 9: Manpower (MP) indicators

Figure 10 indicates the machine (MC) performance 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. As the competency of the employee increases, the MC index can be further improved.

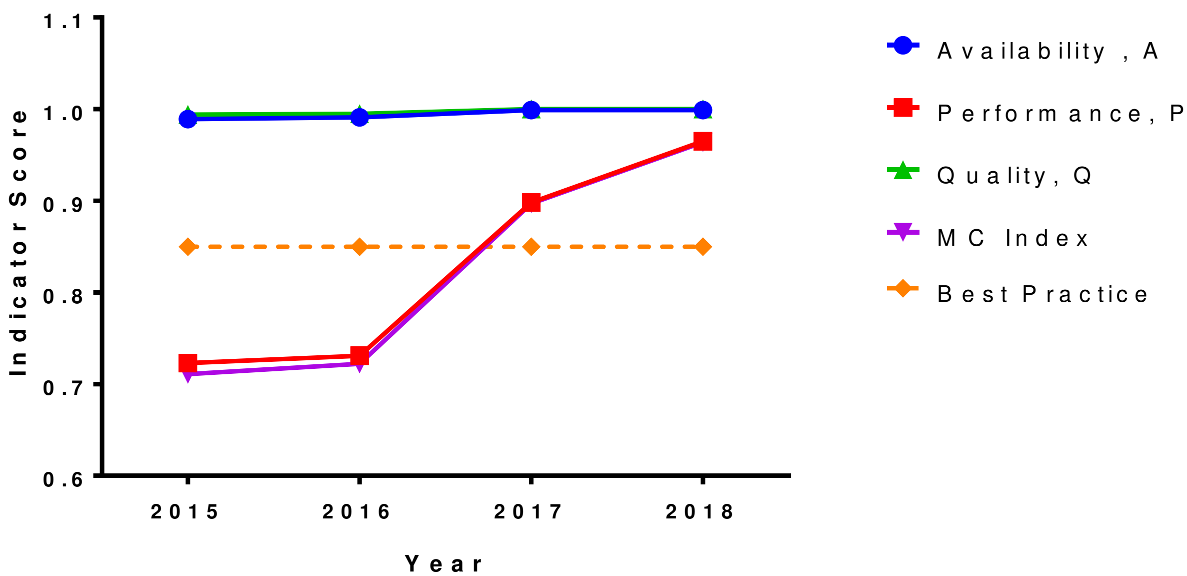

Figure 10: Machine (MC) performance indicators

Figure 11 illustrated the input resource and output product performance of the CHP plant. The material (MT) index reflects directly on the supply demand. However, 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 CHP plant, there is no storage or inventory requires as the natural gas is supplied directly from the main gas supply pipeline.

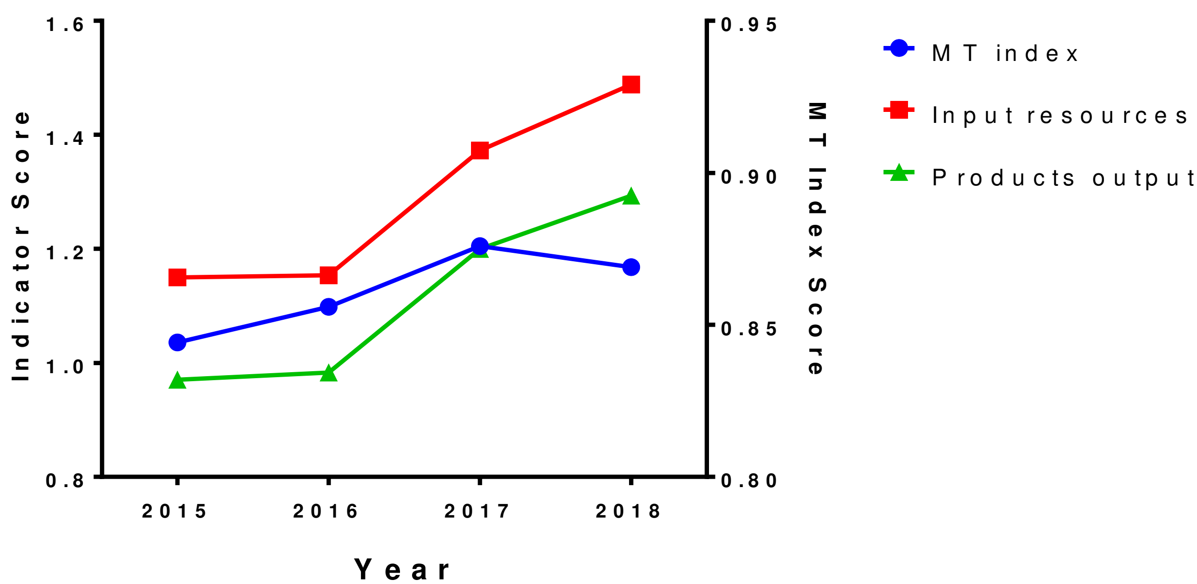

Figure 11: Material (MT) performance indicator

Money (MY) index is one of the significant indexes in all industry sector. MY index is evaluated based by comparing the minimum operation (production) cost with the average operation (production) cost and maximum profit with average profit. In the year 2015, Figure 12 indicated that 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 year 2016 have also contributed to lower MY index.

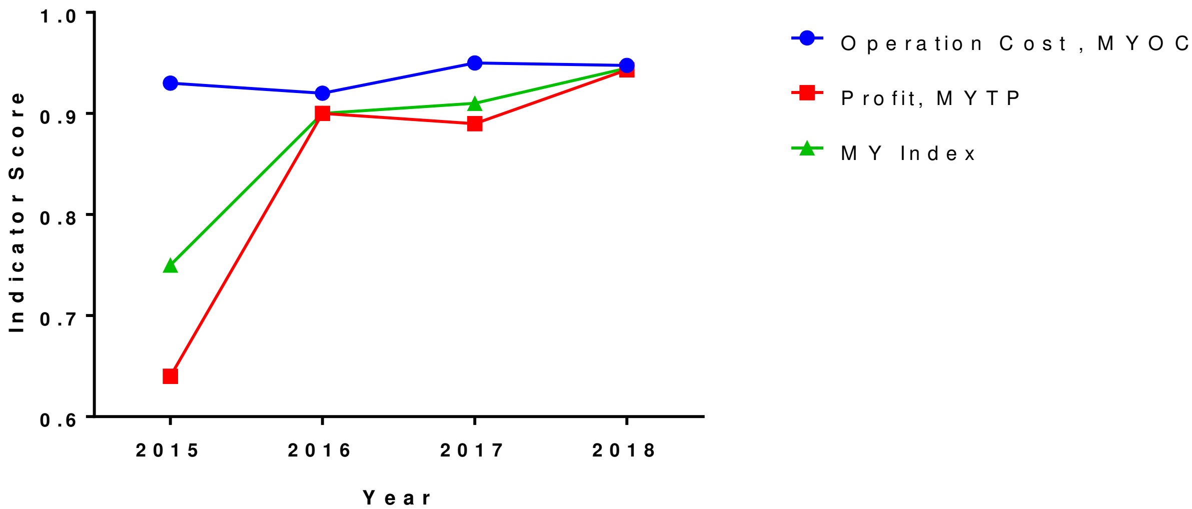

Figure 12: Money (MY) performance indicator

Environment (EV) performance indicator is relatively significant especially dealing with the environmental regulatory body. Referring to Figure 13, despite the carbon footprint emission has increased but the gap between minimum and average carbon footprint produced from the process has reduced. Based on gas turbine operation, it is very critical to maintain operation mode in dry low emission (DLE) mode to sustain low NOx emission. The operation of CHP in this study has always operated in stable DLE mode.

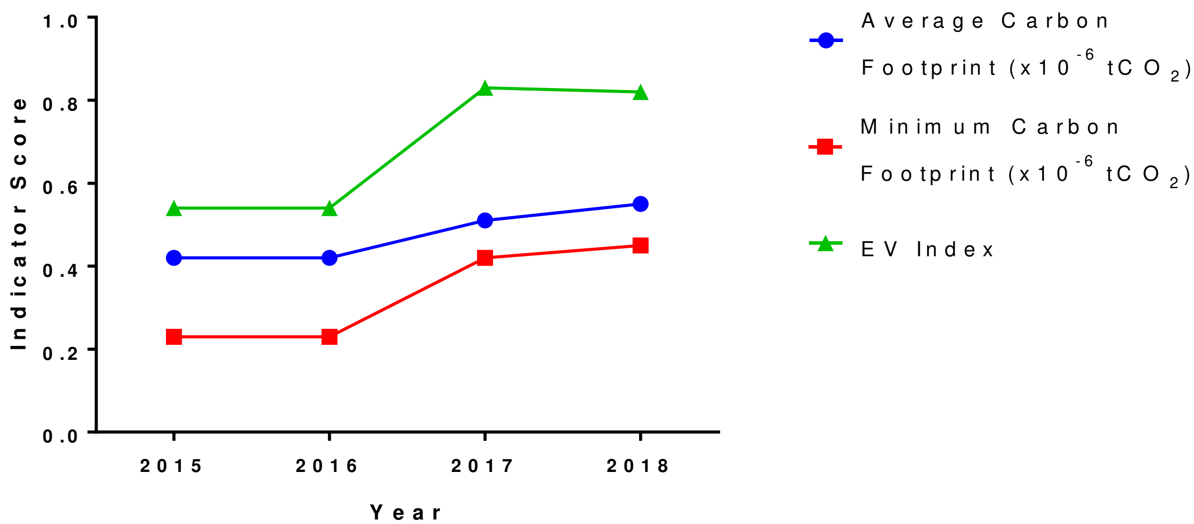

Figure 13: Environment (EV) performance indicator

Figure 14 and Table 13 illustrate the summary of the L&G outcome of the case study. The LGI has reflected a consistent improvement since the year 2015.

Table 13: Summary of L&G Index

	MP	MC	MT	MY	EV	L&G Index
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

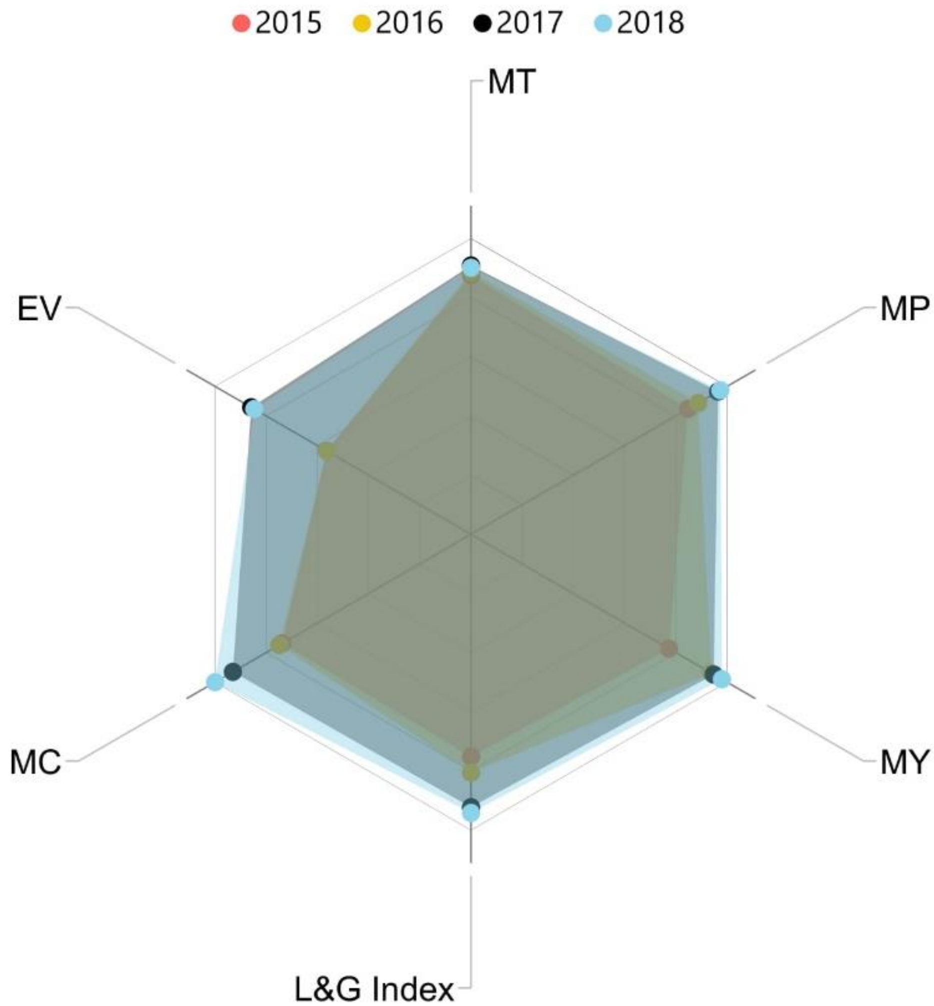

Figure 14: Progress of L&G performance index

3.2.3 Analytical continuous improvement in the lean and green index

According to the industrialist, the facility has been practising the same operation strategy based on the priority ranked by AHP outcome since the year 2015. Backpropagation (BP) optimisation is introduced in the July 2018where the facility is requested to establish a monthly target. As the facility is operating at a stable condition in the year 2018, Figure 15 illustrates the changes after implementation of BP optimiser. It reflects fluctuation of monthly LGI in July as the BP optimiser provides feedback on changes in components and indicators weightage for improvement. Starting from August, the monthly LGI shows an oscillation pattern as the BP optimiser feedback to the industrialist for improvement.

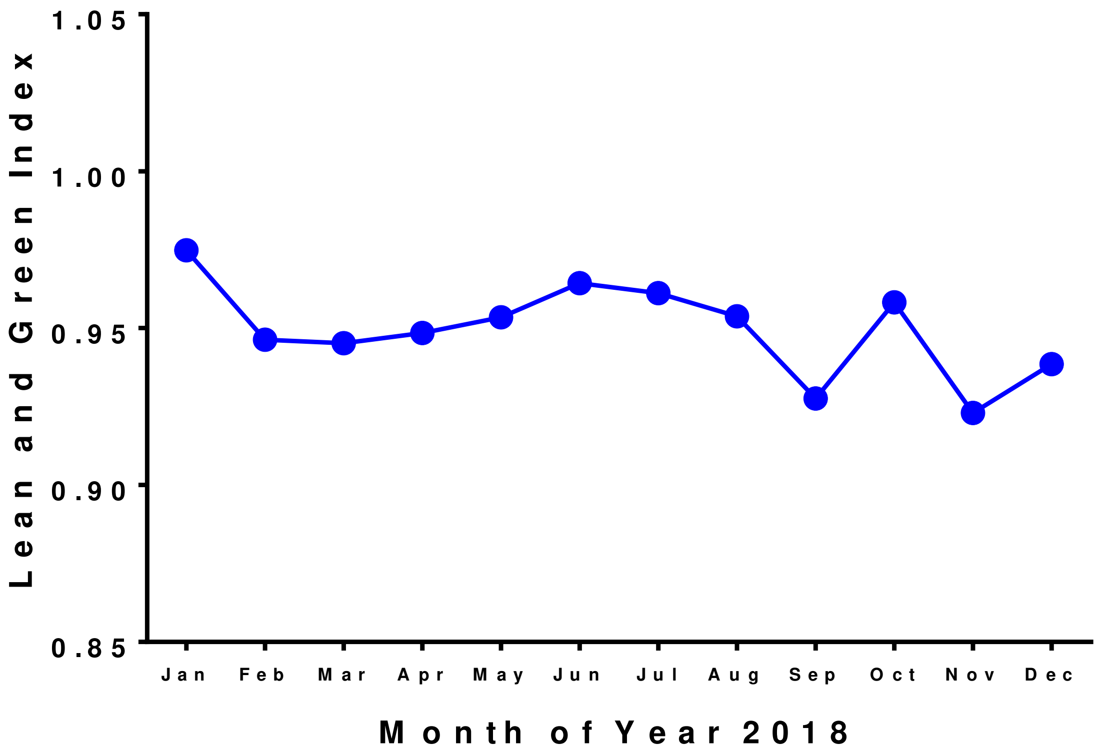

Figure 15: Monthly LGI update (BP optimisation initiated in July)

Figure 16, 17 and 18 demonstrate the weightage update of 4M1E components, MP indicators and MY indicators based on BP optimisation respectively. All three figures show a similar pattern as the BP optimise the L&G model. In the month of September and October, the BP explores some potential improvement area by using the previous data points. Based on the continuous feedback from BP and the industrialist, data from November and December shows sign of data converged. The convergence of these values of indicators demonstrates that the BP algorithm, which is based on gradient descent has found a maximum point. The converged values are very close to their initial weightage, and this validates that the expert has provided useful insights. These results from the BP algorithm is totally dependent on the input from the historical process parameter. Therefore, BP optimisation can support the industrialist in continuous process improvement.

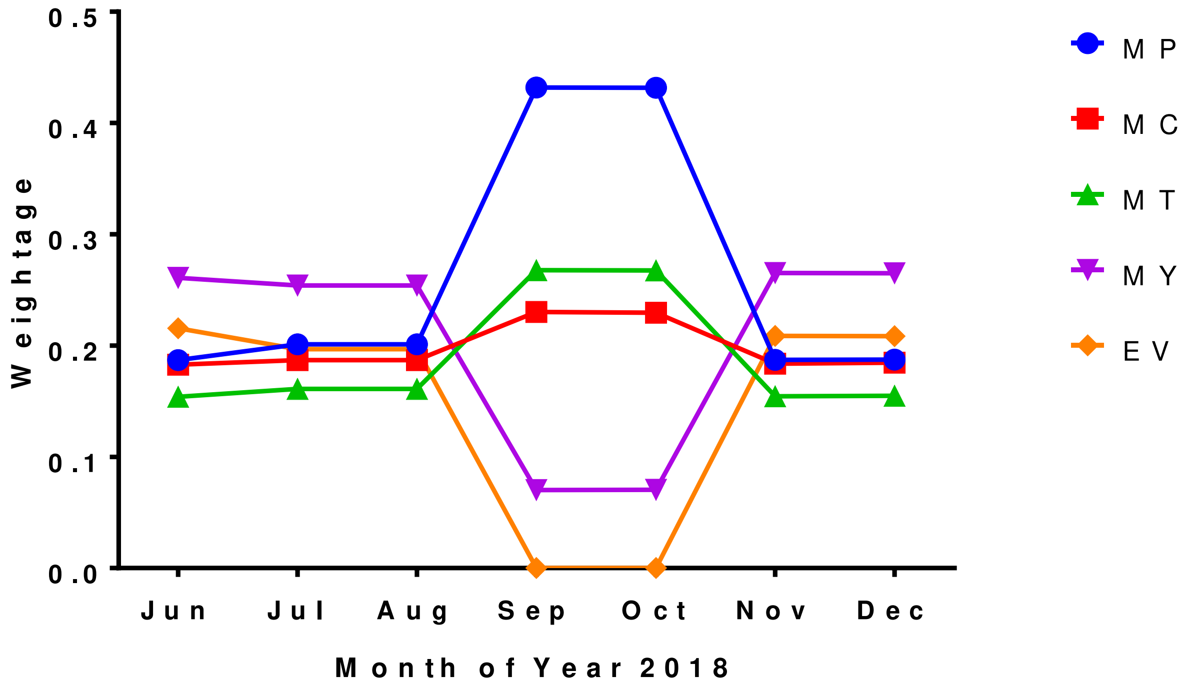

Figure 16: Backpropagation optimisation on 4M1E main components

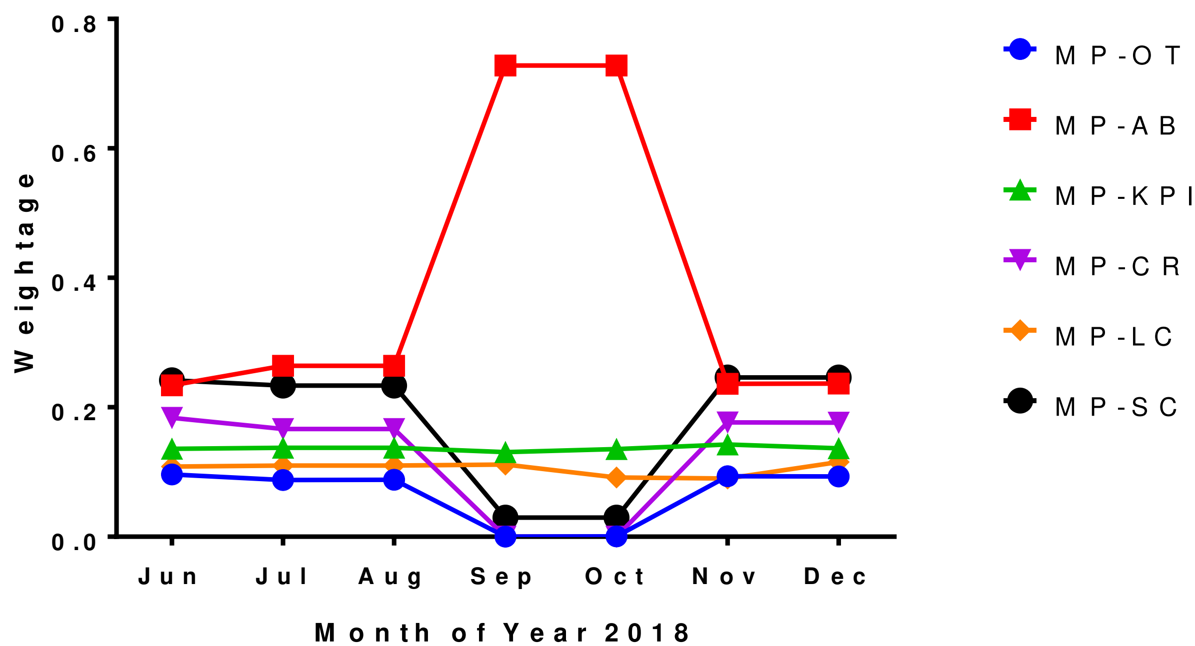

Figure 17: Backpropagation optimisation on MP indicator

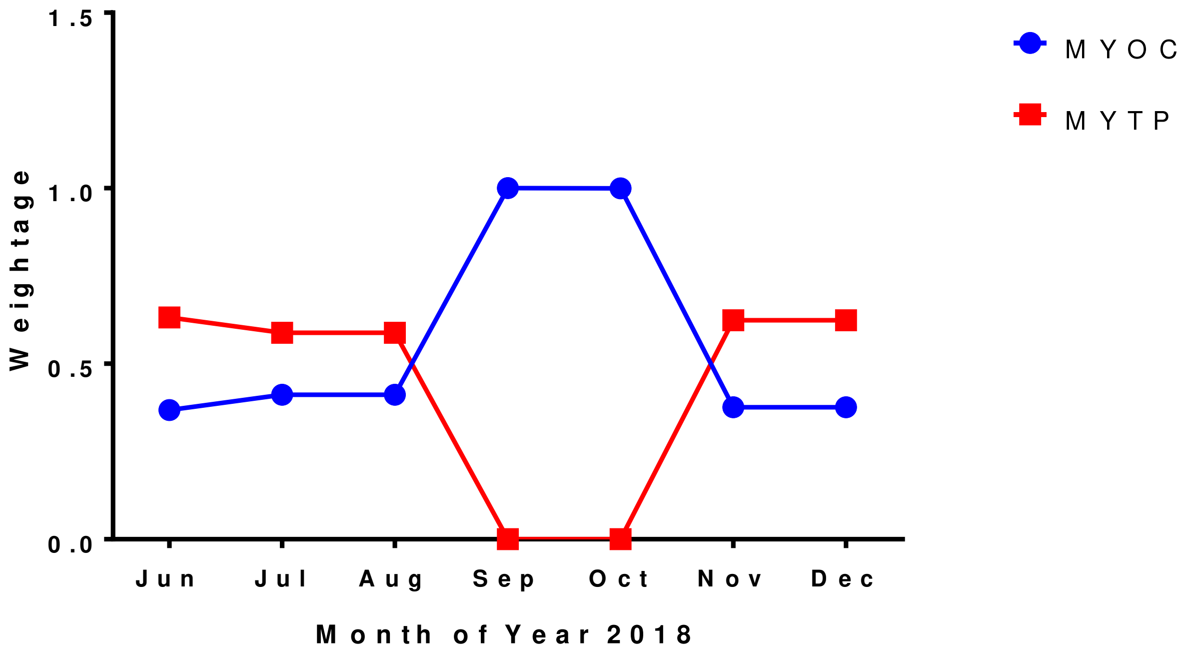

Figure 18: Backpropagation optimisation on MY indicator

4.0 Conclusion

The global manufacturing has received many challenges due to global warming and resource depletion. The development of a novel approach to lean and green (L&G) model with backpropagation (BP) optimisation will assist the industrialist in their continuous improvement program. The initiative of this paper is to provide a framework in guiding and assisting the industrialist to shift their operation from its existing practice towards lean and green (L&G) practice. This framework includes a concise consideration using the 4M1E approach (Money, Material, Manpower, Machine and Environment). Novel 4M1E indicators were also established considering multiple aspects in the processing industry. Traditionally, analytical models utilizing the indicator approach are static models which do not change with incidents or time. However, for this application, LGI has shown signs of variation over time. There is a necessity of adaptability of LGI towards the dynamic and harsh environment of the real world. The novelty of the paper is in the application of BP algorithms as an adaptive feature for analytical models applied in the processing and manufacturing industry. Using BP as an update rule, the analytical model can be continuously improved with time and experience. As the research of this topic is still in the front end, the applied method is considered the most suitable by the authors. With sufficient data or with the availability of big data collected through more time, the capability of performance and adaptability in the proposed framework can be fully showcased. Future research can also be extended to improve the flexibility of the L&G framework and debottlenecking aspects of process improvement. Finally, the application of more advanced machine learning can be applied coherently with this framework to enhance its effectiveness in the industry

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Abbreviation

4M1E	Manpower, Material, Machine, Money and Environment
AHP	Analytic hierarchy process
BP	Backpropagation method
CHP	Combine heat and power
DCS	Distributed control system
EIA	Energy Information Administration
EPA	Environmental protection agency
EV	Environment
GDP	Gross domestic product
GHG	Greenhouse gases
GM	Green manufacturing
HRSG	Heat recovery steam generator
L&G	Lean and green
LGI	Lean and green index
LM	Lean manufacturing
MC	Machine
MP	Manpower
MT	Material
MY	Money
ROI	Return of investment
SCADA	Supervisory control and data acquisition
TPM	Total productive maintenance

Appendix

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}	Rrate 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

<u>Instruction</u>

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.

A is more important than B	9	7	5	3	1	3	5	7	9	B is more important than A
A		√								B

Based on your expertise and experience, please make the pairwise comparison judgment by comparing the two variables in the same row.

Part I : Main Components vs Main Components

Risk factor	9	7	5	3	1	3	5	7	9	Risk factor
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 the processing facility)										MT : Material (i.e. material resources and 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 the processing facility)										EV : Environment (i.e. 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: Component Indicator vs Component Indicator

Main components (i.e. Machine and Environment) have only one indicator. Thus, no comparison is required.

Part II - Man power, MP

Risk factor	9	7	5	3	1	3	5	7	9	Risk factor
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

Risk factor	9	7	5	3	1	3	5	7	9	Risk factor
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 consumption efficiency										MT_{DI} : Inventory management
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

Risk factor	9	7	5	3	1	3	5	7	9	Risk factor
MY_{OC} : Minimum operation cost indicator										MY_{TP} : Max profit indicator

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