CHEMICAL ENGINEERING TRANSACTIONS
VOL. 76, 2019

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Petar S. Varbanov, Timothy G. Walmsley, Jiří J. Klemeš, Panos Seferlis

ISBN 978-88-95608-73-0; **ISSN** 2283-9216

DOI: 10.3303/CET1976094

Integration of Analytic Network Process in Adaptive Lean and Green Processing

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The manufacturing and processing industry have been an important part of the global economy. Many industry players are constantly looking for an alternative to improve their operation and environmental performance to remain competitive in the market. The lean and green approach aims to reduce operation and environmental waste within an organisation. In this study, a lean and green framework is proposed to evaluate the industrialist performance to achieve higher performance efficiency and reduce environmental impact. Three main clusters are incorporated in the framework such as environment, machine and resources. The analytic network process (ANP) method is used to establish the relationship between the three clusters with the input from industry expert from the respective field. A lean and green index is developed from the ANP model as a benchmarking for the industrialist. Backpropagation method is utilized as the continuous analysis tools to analyse the performance of the organization accordingly to the time step. The adaptive characteristic of backpropagation method is reflected from the ability for continuous improvement with time. In this study, the lean and green index will be further optimized with the adaptive approach. This paper proposes an adaptive model that can improve the industry's performance and practise continuous improvement through establishing the adaptive approach.

1. Introduction

Lean and green (L&G) approach has been a paradigm shift in the manufacturing sector. In the past decade, the lean approach has shown many positive outcomes in the manufacturing industry. For example, the lean effect reflected from Toyota practise is to produce the same vehicle with shorter time while maintaining the quality. Leong et al. (2019b) mentioned that lean is very prevalent in big organisations such as Toyota, Boeing, Ford, etc. The lean approach is defined as the reduction or elimination of non-value-added product from a production process (i.e. Toyota) (Womack and Jones, 1994). On the other hand, the green approach is known as a strategy that focuses on operation profitability by enforcing the proactive and environmentally-friendly process (Abdul-Rashid et al., 2017). Having said that, the green approach minimizes or removes environmental waste from the process.
The IEA (2018) reported that global energy demand has grown by 2.1 % in 2017, which was twice the rate of 2016. IEA (2018) also added that electricity and heat generation sector was the largest CO_2 generator in the industry sector. This requires effort from industrialists in improving their process to be L&G. As both L&G have

Paper Received: 02/04/2019; Revised: 19/06/2019; Accepted: 23/06/2019
Please cite this article as: Leong W.D., How B.S., Teng S.Y., Ngan S.L., Ng W.P.Q., Lim C.H., Lam H.L., Tan C.P., Ponnambalam S., 2019, Integration of Analytic Network Process in Adaptive Lean and Green Processing, Chemical Engineering Transactions, 76, 559-564 DOI:10.3303/CET1976094

the same objectives in reducing and eliminating waste or non-value-added product from the operation, the synergy between L&G can create greater impact simultaneously to the operation as well as the environment (Melnyk et al., 2002). Leong et al. (2019a) added that both L&G approaches complement each other to enhance the efficiency and effectiveness of the process compared with their individual applications.

In this paper, an adaptive method is proposed to improve the rate of L&G implementation. This study will focus on developing a self-monitoring model for the industrialist to accelerate the implementation of L&G approach. Analytic network process (ANP) is incorporated into the model to facilitate the industry expert input into the model. The outcome of this model is expected to reflect the actual operating condition based through continuous analysis of the operation and environmental waste reduction. The continuous analysis element reflects the adaptation functionality of the model.

2. Methodology

2.1 Lean and green framework

The L&G framework, illustrated in Figure 1, acts as the systematic step to guide the industrialist towards L&G processing. Leong et al. (2019a) mentioned that there are five main components to be considered for the L&G framework such as manpower (MP), machine (MC), money (MY), material (MT) and environment (EV) (4M1E).

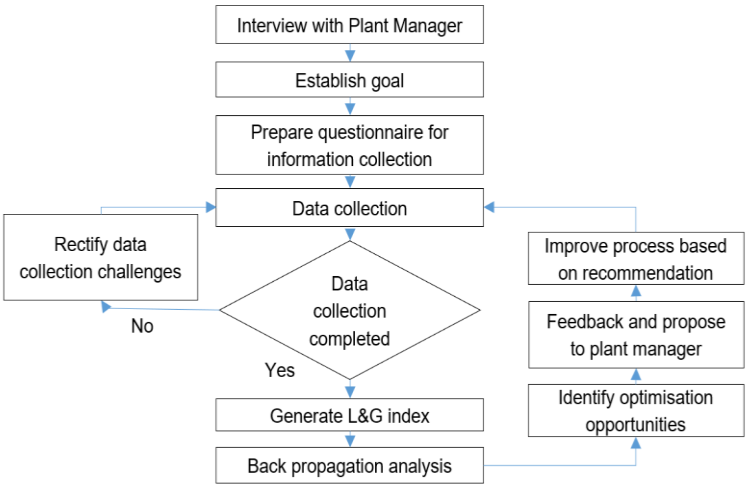

Figure 1: Lean and green framework for processing plants (Leong et al., 2019a)

The methodology of L&G approach:

a. From the interview with the plant manager, the critical parameters of 4M1E will be identified.
b. An operation goal will be established based on the expectation of the operation team.
c. Questionnaires will be distributed to the operation team for data collection.
d. Based on the collected data, an initial L&G index (LGI) will be developed as the benchmark for the process.
e. The operation team will then set an LGI target to achieve for the next LGI analysis.
f. Based on the predetermined LGI target, the back-propagation optimisation model will analyse the potential improvement for the process.
g. Data will be collected and analysed after improvement steps have been performed.

2.2 Lean and green index

In the processing sector, the characteristic of operation varies between different sector. Therefore, the priority and importance of operation criteria are dependent on different processes. To get the priority and ranking of the indicators for specific processing plants, the analytic network process (ANP) is used. Analytic hierarchy process (AHP), introduced by Saaty (1980), is widely applied in research areas as well as business applications over the past decades (How and Lam, 2017). ANP is the generic form of AHP that is used to analyse data that has more complex, interdependent and feedback relationship among the relationship in the hierarchy (Ngan et al. 2018). The supermatrix approach is used in ANP to allow interaction between and within clusters in deriving the final composite weightage for all components in the model (Saaty and Takizawa 1986). Ngan et al. (2018) further

added that the ANP approach assists decision-makers in determining the priorities of the indicator alternatives by ranking the alternatives for specific goals.
Based on Figure 2, questionnaires will be distributed to a group of an industry expert in the field to provide their insight and opinion. The input for the ANP-based questionnaire is based on a 9-point fundamental scale illustrated in Table 1. The data will be obtained from the group of industrialists as the input to develop the pairwise comparison matrix. Table 2 explains the indicators that are reflected in Figure 2. These indicators are discussed and selected by the industry expert for this case study. The eigenvector generated from the calculation will form the local priority matrix. Finally, a consistency ratio (CR) is calculated to ensure the consistency of the input. According to Saaty (1980), CR of less than 0.10 is deemed to be acceptable.
The input of supermatrix is formed by combining the local priority matrix from ANP. The supermatrix reflects the relationship between clusters and the elements in the model. Eq (1) shows the matrix of local priority for individual cluster, while Eq (2) indicates the relationship between each cluster. If there is no relationship between the cluster, the block matrix will be represented by 0. The weighted supermatrix is formed by normalizing the unweighted supermatrix where is it transformed into a stochastic matrix where the sum of all columns is equal to 1.

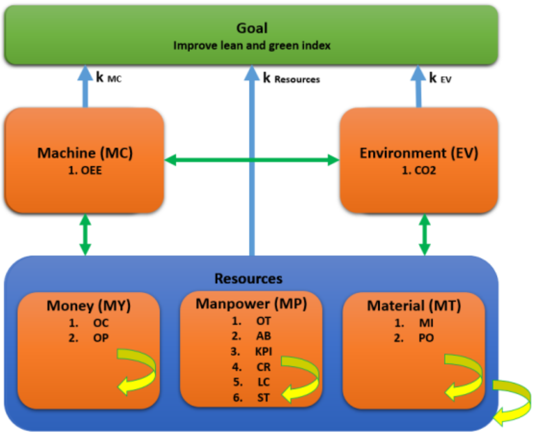

Figure 2: ANP model

Table 1: 9-point fundamental scale (Saaty, 2012)

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

Table 2: Description of indicators

No	Indicator	Description
1	MC-OEE	Overall equipment effectiveness
2	EV-CO2	Carbon dioxide footprint
3	MY-OC	Operation cost
4	MY-OP	Operation profit
5	MP-OT	Employee total overtime
6	MP-MC	Medical leave
7	MP-KPI	The achievable key performance index
8	MP-CR	Employee competency rate
9	MP-LC	Employee late check-in time
10	MP-ST	Employee safety competency rate
11	MT-MI	Total material/resource into the production
12	MT-PO	Total product output

$$m = \begin{array}{c|cccc} & e_1 & e_2 & \cdots & e_n \\ e_1 & 1 & w_{12} & w_{1\ldots} & w_{1n} \\ e_2 & 1/w_{12} & 1 & w_{2\ldots} & w_{2n} \\ \vdots & 1/w_{1\ldots} & 1/w_{2\ldots} & 1 & w_{\ldots n} \\ e_n & 1/w_{1n} & 1/w_{2n} & 1/w_{n\ldots} & 1 \end{array} \qquad (1)$$

$$S = \begin{array}{c|ccc} & L_1 & L_2 & L_3 \\ L_1 & 1 & S_{12} & S_{13} \\ L_2 & S_{21} & S_{22} & S_{23} \\ L_3 & S_{31} & S_{32} & S_{33} \end{array} \qquad (2)$$

Based on the ANP outcome, the LGI is calculated as below:

$$LGI = w_{MC} \times MC + w_{EV} \times EV + w_{Resource} \times Resource \qquad (3)$$

where the $w_{Resource}$, w_{MC}, and w_{EV} represent the weight of Resource, machine and environment respectively. The weights are developed based on the cluster categorized in Figure 2.

MC is known as the heart of the processing or manufacturing as it contributes mainly by adding value to the raw material to produce products. In the Machine (MC) cluster, MC focuses on the equipment that is used for processing. One of the common specific components for MC is the overall equipment effectiveness (OEE). It measures the availability, performance and product quality of the MC. The availability measures the actual operation time of the process by monitoring setup and adjustment time, and equipment failure time. Next, the performance of OEE mainly focuses on monitoring the idling and minor stoppage time and reduce speed time of the equipment as this will slow down the production. The final factor of OEE is quality, which identifies the total amount of defects being produced from the operation.

The second cluster indicates the environment (EV) factor as an important role in the manufacturing processing industry. EV has a direct relationship contribution to global warming and climate change. Teng et al. (2019) mentioned that global warming potential (GWP) could be a good indicator for EV and obtained state-of-art results using novel statistical L&G optimization in a real refinery plant. Besides, Ng et al. (2014) have also shown that environmental impact can be reduced with proper waste management. The common specific components used in EV are carbon, water and solid emission. Many industrialists struggle to reduce waste emission and schedule waste as the additional cost is required to handle the waste.

The last cluster is represented by resources which consist of manpower (MP), money (MY) and material (MT).

MP, MY and MT are categorized as resources as these are manipulating factors that can affect the performance of the production. The MP indicator reflects the performance of human resources in the facilities. Indicators such as key performance achievable (KPI), safety competency rate, medical leave, etc. are essential to evaluate the condition and performance of the employee. It is adding on, MT targets on resources that are consumed within the process such as raw material, by product and waste. In many cases, inventory management is critical to processing facilities. The continuity of the operation highly depends on the availability of resources. This indicator contributes to the sustainable development goal (SDG) 12, which focuses on responsible consumption and production (SDG, 2019). Lastly, MY is one of the most critical components in across all component as it reflects the feasibility and profitability of a processing facility. MY does not only reflect the profitability of the facilities. It also indicates the Return On Investment (ROI) of the organization. Besides that, MY is also a powerful factor that motivates the employee in improving their performance (Aguinis et al., 2013).

The priority of the indicators will be evaluated with the ANP model. The output from ANP will be further optimized with the proposed adaptive model for continuous improvement.

3. Adaptive model

The initial LGI developed from the calculation will be the benchmarking point for the process. This will act as the reference point for continuous process improvement. In many scenarios, static analytic methods are mainly used in model prediction. The static model becomes ineffective and inaccurate when it copes with dynamic conditions in the continuous processes.

The adaptive model constantly updates the data according to time and provide responsive action to the industrialist. The adaptive model relies on the backpropagation (BP) algorithm to perform optimisation. According to Griewank (2012), the BP algorithm is based on the reverse mode of differentiation. Rumelhart et al. (1986) highlighted that the reverse mode of differentiation was popularized with an application such as a neural network. Lerun (1998) has also shown the application of the backpropagation method in a neural network. Gori and Maggini (1996) work have shown that BP method is able to achieve the local optimum solution.

With the L&G approach, during the improvement of the process, the expectation from L&G approach will increase over time. There is a need to constantly monitoring and improve the process parameter in order to meet the expected LGI outcome. The gradient descent optimisation model is used as the update rule. The error between the expected LGI outcome and actual LGI outcome is calculated as below:

$$E = \frac{1}{2}\left(LGI_{accessed} - LGI_{expect}\right)^2 \tag{4}$$

where E is the error, $GLI_{accessed}$ is actually obtained LGI while LGI_{expect} is the expected LGI. This will allow BP to monitor and the LGI based on historical data. Based on the BP method, the weights of each cluster will be back-calculated in Eq(5) while the indicators will be calculated in Eq(6).

$$w_{i+1} = w_i - \eta\frac{E_i - E_{i-1}}{w_i - w_{i-1}} \tag{5}$$

$$k_{i+1} = k_i - \eta\frac{E_i - E_{i-1}}{w_i - w_{i-1}} \times \frac{w_i - w_{i-1}}{k_i - k_{i-1}} \tag{6}$$

where w_i and k_i are the weight of the current month, w_{i+1} and k_{i+1} are the weightage for next month, w_{i-1} and k_{i-1} are the weight of the previous month. η is known as the learning rate where it is normally defined as 0.05 which also define as the changes of LGI will not be more than 5 %. The learning rate is critical in gradient descent optimizer as larger learning rate will tend to cause the output to fluctuate. Larger fluctuation might indicate that the learning rate is too large where the local optimum cannot be identified. Therefore, a smaller learning rate should be used to obtain the optimum point.
Figure 3 demonstrates the BP method. Example, *i*1, *i*2 and *i*3 represents the 4M1E while o1 represents the LGI. The expert inputs are generated from ANP and to be fixed in this method. The initial actual outcome is generated as a baseline; the industry player can set an LGI target as the future achievable outcome. In the BP method, if the targeted outcome is not equal to the actual outcome, the error percentage will be backpropagated to evaluate the priority of the components to be improved in the next cycle. With the improvement, the weight of *i*1, *i*2 and *i*3 can be improved to achieve better LGI. This process will repeat until the actual and target outcome is equal.

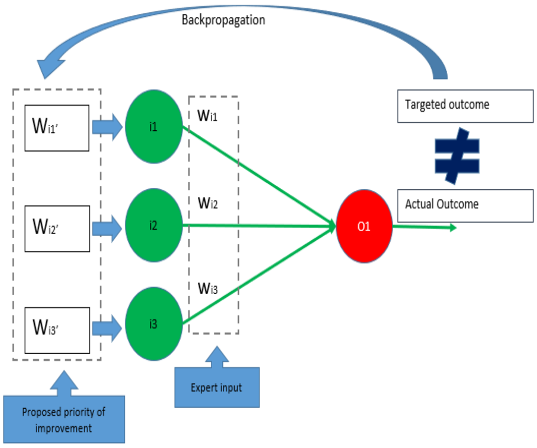

Figure 3: Illustration of backpropagation (BP) method

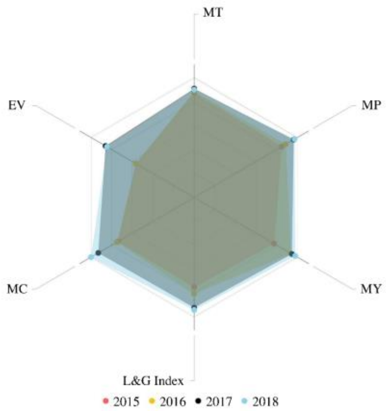

Figure 4: L&G Index (Leong et al., 2019c)

Figure 4 illustrates the performance of L&G framework using AHP approach. The improvement in operating performance can be observed through the LGI. The application of ANP method in L&G framework will demonstrate the complexity and inter-relationship between all components. Thus, producing a more comprehensive LGI representation of the organisation. Based on AHP approach, the deviation of LGI from BP method is 1.3% between actual and targeted outcome.

4. Conclusions

The L&G approach in manufacturing processing has shown positive results from the industry feedback. The need to strengthen the implementation effort of L&G from the industry is highly important. The development of L&G framework can be a systematic guideline to the industrialist to assist them in implementing L&G practices. The framework can also assist the industrialist in changing the operation behaviour from existing practices towards L&G. The development of LGI does not only act as a benchmarking tool but also continuous improvement tools for every industry sector. The backpropagation model will assist the industrialist by recommending improvement steps by reflecting the important indicators by comparing to the expected and targeted outcome. The gradient descent optimization model is used in backpropagation method where the performance of LGI can be further improved. The future work on this research will be extended to review better performing gradient descent method that can enhance the optimisation performance of the model. A case study will be used to demonstrate the effectiveness of the model.

Acknowledgements

The authors would like to acknowledge financial support from the Ministry of Higher Education (FRGS/1/2016/TK03/MUSM/01/1). Research funding and support from Newton Fund and the EPSRC/RCUK (Grant Number: EP/PO18165/1) is also gratefully acknowledged. The authors also highly appreciate the valuable input from the industry experts in providing industry experience and knowledge to this research paper.

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