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Novel Evaluation Approach for Biomass Supply Chain: An Extended Application of PCA

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The establishment of integrated biomass supply chain is a prospective solution to address the expanding global energy demand, at the same time bridging the world to a more sustainable future. The evaluation of sustainability performance of a supply chain is often compounded of a complex series of variables. The redundancies in variables often make the results become hard to be analysed and diagnosed. In order to address this issue, principal component analysis (PCA) is introduced. PCA allows to convert a huge series of correlated variables into a smaller set of uncorrelated variables known as principal components (PCs), without losing too much information. However, the optimisation of PCs is relatively difficult as PCs encompass of convex combinations of original variables. This paper proposes novel systematic optimisation approach that incorporates PCA and analytical hierarchy process (AHP) to determine the optimal transportation design and processing hub location in an integrated biomass supply chain.

1. Introduction

Several industries (e.g., power generation) started to shift their conventional business model which highly reliant on non-renewable energy to a more sustainable model after the first and second oil crisis held in 1973 and 1979. This is mainly driven by the intention of strengthening the nation's energy security and the snowballing global pressure on emission reduction. In order to keep pace with this expanding demand, the implementation of biomass supply chain, which converts biomass into valuable products (e.g., bio-fuels), is one of the prospective solutions (Lam et al., 2015).

Biomass supply chain concerns on the flow of biomass and biomass-derived products within an integrated value chain which encompassed of an integrated biorefinery that converts all biomass into products (Hong et al., 2016). To date, a vast number of research works have been conducted in order to discover the potential use of various biomass feedstock in the biomass industries. Chandel et al. (2007) had evaluated the economic potential of 26 types of biomass in bioethanol production. Ng et al. (2013) had discovered the economic potential of rubber seed oil as an alternative biofuel feedstock to crude palm oil. In the recent years, Cheah et al. (2016) had conducted a physio-chemical studies of Jatropha oil as a prospective feedstock for the biodiesel production in Malaysia. How et al. (2015) and more recently Atkins et al. (2016) had utilised P-graph method to determine the optimal design of the biorefineries.

Apart from economic performance, environmental impact and social benefit have been another main focus of the academicians, in order to attain sustainability of the supply chain. Lam et al. (2013) had developed a two-stage optimisation model to synthesise a palm biomass supply chain in Peninsular Malaysia with the aim of minimising the transportation cost, at the same time, keeping the carbon emission at minimal. How et al. (2016) had developed a graphical decision-making tool for the transportation design with the aim of minimising the carbon penalty and transportation expenses. Mota et al. (2015) had utilised a Ɛ-constraint method to determine the compromise solution based on economic, environmental and social performances. Čuček et al. (2012) presented a multi-criteria optimisation of a regional biomass-energy supply chain through simultaneous maximisation of profit and minimisation of environmental and social footprints.

In addition to the conventional approach mentioned above, Principal Component Analysis (PCA) can also be used to evaluate the sustainability performance of the supply chain. PCA is a multivariate statistical technique

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that able to convert a series of correlated variables into a set of uncorrelated variables known as principal components (PCs), without losing too much information (Aitchison, 1983). In other words, PCA can substantially reduce the complexity of the proposed problems by removing the redundancies in variables. It has been used abundantly in many forms of analysis, including image compression (Dash et al., 2014), chemical plant design (Pozo et al, 2012) and biomass properties analysis (Jenkins et al., 1998). However, to date, PCA approach has not been applied to optimise the sustainability performance of the biomass supply chain. Note that the sustainability performance of a supply chain is often compounded of a complex series of variables. In fact, the redundancies in variables often make the results become hard to be analysed and diagnosed (Shlens, 2003).
In this work, a novel systematic optimisation approach that incorporates PCA and analytical hierarchy process (AHP) is proposed to determine the optimal biomass flow design and processing hub location in an integrated biomass supply chain. A case study which is adapted from multiple biomass corridor design of How et al. (2016), was used to demonstrate the applicability of the proposed method. This paper is organised as follows. A problem statement of this work is given in section 2 while the research methodology used for this work is described in section 3. In section 4, the model formulation of this work is outlined. Section 5 presents result and discussion followed by the concluding remarks given toward the end of the paper.

2. Problem statement

The supply chain problem described in this paper is adapted from How et al. (2016). The model aims to determine the optimal biomass flow and processing hub location based on both economic and environmental performances. It is formally stated as follow: given a set of biomass *r* supplied from a set of source points *i* is transported to a set of processing hubs *j* via a set of transportation mode *m*. It is then processed into a set of intermediates *l* and valuable products *p* via a set of technologies *t* and *t'*. Finally, products *p* will be transported to a set of customers *k* via transportation mode *m'*. On top of that, a set of pollutants *a* (e.g., CO_2) is emitted to the environment from the entire supply chain and would cause a set of environmental impacts *q* (e.g., GWP).

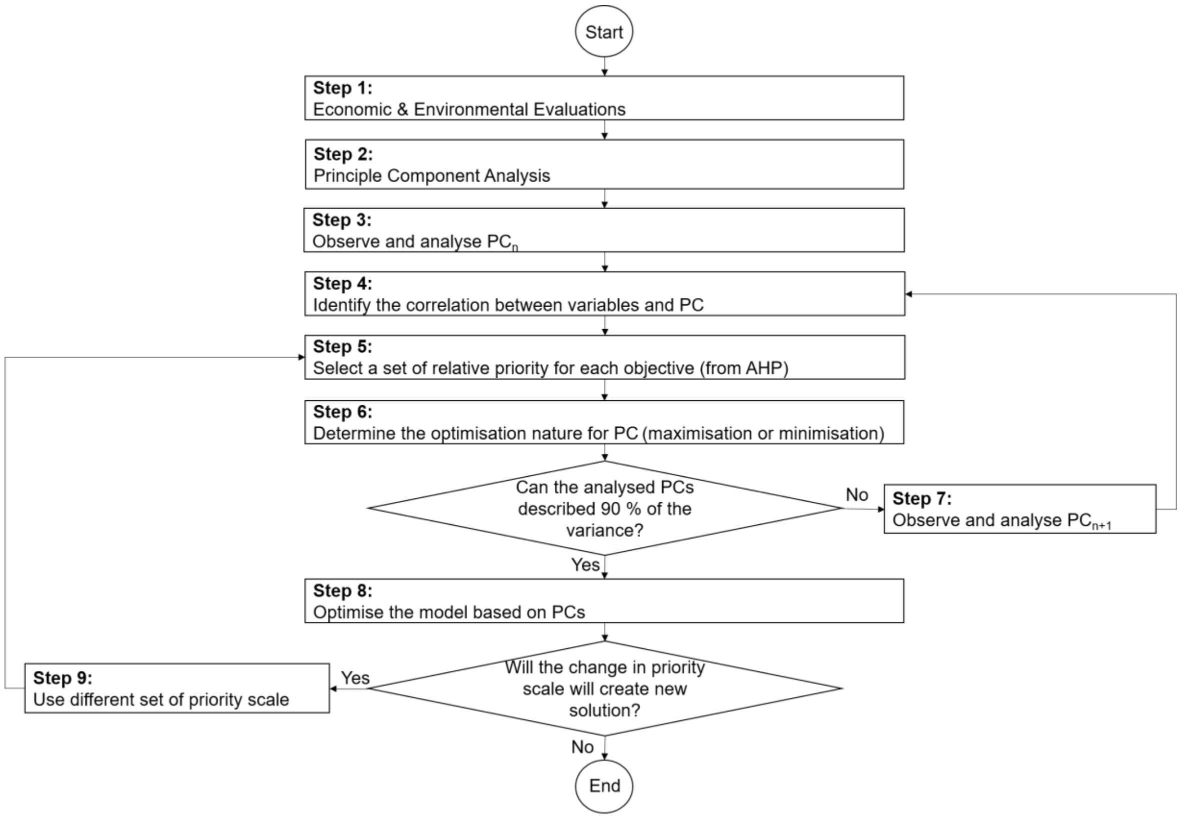

Figure 1: Research flow chart.

3. Method

The economic and environmental performances of each possible solution is determined by using the formulated model and analysed through PCA in order to remove the redundancy. In this work, the number of processing hub is optimised based on the PCs score. However, the optimisation based on PCs scores is not that straight forward, as PCs encompass of convex combinations of original variables (Pozo et al., 2012). Therefore, this work proposes a systematic optimisation approach which utilises analytical hierarchy process (AHP) to assign relative priority scale to the contradicting objectives, helping decision-makers to decide whether the correspond PCs should be maximised or minimised. In general, AHP is a theory of measurement through pairwise comparison and relies on the expert's judgements to derive priority scales (Saaty, 2008). Last but not least, Pareto analysis is conducted in order to check the effect of priority scales on the final result. Figure 1 presents the research flow chart of this work. Note that the detailed formulations for the evaluations and PCs optimisation are given in next section.

4. Model formulation

The description of the formulations, including the evaluations for each objective, PCA, AHP and optimisation approach are presented in the subsections below.

4.1 Economic evaluation

The evaluation of economic performance considers three components, i.e., annual gross profit, C^{GP} [RM/y], annualised hub investment cost, C^{Inv_Hub} [RM/y], and annual transportation cost, C^{Tr} [RM/y]. The overall net profit, C^{NP} is defined as follow:

$$C^{NP} = C^{GP} - C^{Inv\_Hub} - C^{Tr} \tag{1}$$

The calculation is similar to the model developed by How et al. (2016). It is worth mentioning that C^{Tr} is determined by summation of operating expenditures and capital expenditure with the consideration of vehicle capacity constraints. Readers may refer to the work of How et al. (2016) for a detailed description of the transportation cost calculation.

4.2 Environmental evaluation

In contrast to the model developed by How et al. (2016), this work does not merely focusing on carbon emission, but also considers various forms of environmental impacts (e.g., acidification, water usage, land usage, etc.). To achieve this, the impact categories *q* which introduced by Heijungs et al. (1992) is used to evaluate the environmental impacts. The environmental impact from impact category *q*, EI_q [t-eq/y] is defined as:

$$EI_q = EI_q^{Process} + EI_q^{Prod} + EI_q^{Elec} + EI_q^{Tr} \qquad \forall q \in Q \tag{2}$$

where $EI_q^{Process}$ [t-eq/y] refers to environmental impact due to the pollutant *a* emitted from the conversion process, EI_q^{Prod} [t-eq/y] refers to direct effect (environmental-burdening) and indirect effect (environmental-unburdening such as substitution of fossil-based energy) caused by products, EI_q^{Elec} [t-eq/y] refers to environmental impact attributed by the energy consumption, while EI_q^{Tr} refers to environmental impact caused by fuel consumption during the transportation.

4.3 PCA

PCA allows to transform a larger series of original variables into a smaller series of PCs. The PCs of a data set are determined by solving an eigenvalue-eigenvector problem for the covariance matrix of the data set. Note that, correlation matrix, R is opted instead of covariance matrix when the original variables are not expressed in a same unit. In our case, eigenvector, X^{PC_n} can be computed by using Eq(3).

$$R\, X^{PC_n} = \lambda^{PC_n} X^{PC_n} \tag{3}$$

Note that the first PC (PC1) is corresponded to the largest λ^{PC_n}, indicates that PC1 explains the largest portion of the problem's variance, followed by second PC (PC2), and so on. The new coordinates of the data set (or so-called factor score) can be determined using Eq(4):

$$\text{Factor score}^{PC_n} = S\, X^{PC_n} \tag{4}$$

where S refers to the standardized original data set. In this work, a threshold cut (TC) of 90 % is set to ensure the considered PCs are sufficient to describe the problem, keeping the loss of information at minimal.

Table 1: Optimisation of PCs.

Variable	Correlation	Direction	Contribution (%)	Priority scale (%)	Score
V1	+	+	10	40	+0.1*0.4
V2	-	-	50	40	+0.5*0.4
V3	+	-	40	20	-0.4*0.2
		Net Direction=			+0.16

4.4 AHP

Similar to the PCs, the priority scale of each objective is obtained based on the eigenvector determined from the comparison matrix, C:

$$C\,w = \lambda_{max} w \qquad (5)$$

where w refers to the priority scale of each objective, while λ_{max} refers to the eigenvalue of matrix C.

4.5 Multi-objective optimisation approach

As already mentioned, PCs consist of a convex combinations of original variables, while each variable has different optimisation direction (maximise or minimise). Hence, it is vital to identify the correlation between these variables and PCs (whether directly proportional or inversely proportional). Table 1 demonstrates on how the PCs can be optimised, where "+" and "-" sign in 2nd column indicates the variable is increased or decreased with PCs, "+" and "-" sign in 3rd column shows the variable has to be maximised or minimised, 4th column refers to the contribution of each variable on PCs based on the described variance, 5th column refers to the priority scale set for each variable. The score is used to determine optimisation direction for PCs, where "+" sign is used when 2nd and 3rd columns have the same sign (e.g., V1 and V2), while "-" sign is used when 2nd and 3rd columns have different sign (e.g., V3). Note that "+" sign for the net direction indicates that the corresponding PC has to be maximized while "-" sign indicates minimisation case.

The objective function of this work is the overall degree of satisfaction based on the sustainability performance of the biomass supply chain, λ^{SCM}. It is described as follow:

$$\max\ \lambda^{SCM} = \sum_n (\lambda^{PC_n} \times VAR_n) \qquad (6)$$

where (λ^{PC_n} refers to the degree of satisfaction of nth PC (defined based on fuzzy concept), VAR_n [%] denotes the total variance explained by nth PC, while n refers to the amount of PCs used to describe at least 90 % of the variations.

5. Results and discussions

The case study used in this work is adapted from the multiple biomass corridor design of How et al. (2016). This biomass corridor utilised four types of biomass (i.e., palm oil biomass, paddy residues, sugarcane bagasse and pineapple peel) to produce various form of products. The case study is aimed to determine the optimal number of processing hubs and the optimal biomass flow design.

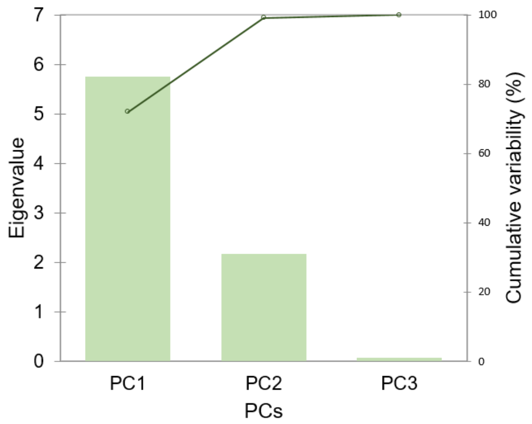

Figure 2: PCA for transportation design.

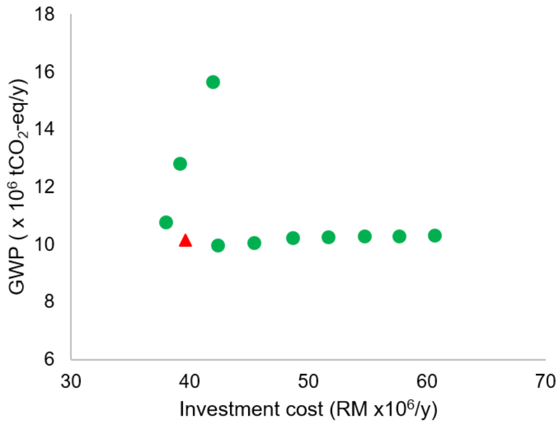

Figure 3: Pareto analysis.

Table 2: PCA results.

Variable	Correlation (PC1)	Correlation (PC2)	Direction (PC1)	PC1 Contribution (%)	PC2 Contribution (%)
Cost	-	+	-	4.519	33.291
GWP	+	+	-	16.924	1.131
AP	+	+	-	16.966	1.024
POCP	+	+	-	16.966	1.024
NP	+	+	-	16.966	1.024
ATP	+	+	-	0.531	42.805
ADP	+	+	-	16.917	1.138
LF	-	+	-	10.211	18.564

GWP=Global warming potential; AP= acidification potential; POCP= ozone creation potential; NP=nitrification potential; ATP= aquatic toxicity potential; ADP= abiotic depletion potential; LF= land footprint

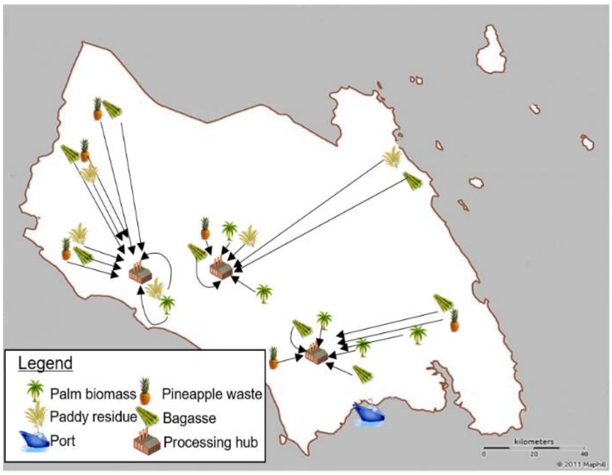

Figure 4: Optimal biomass flow (Maphill, 2013).

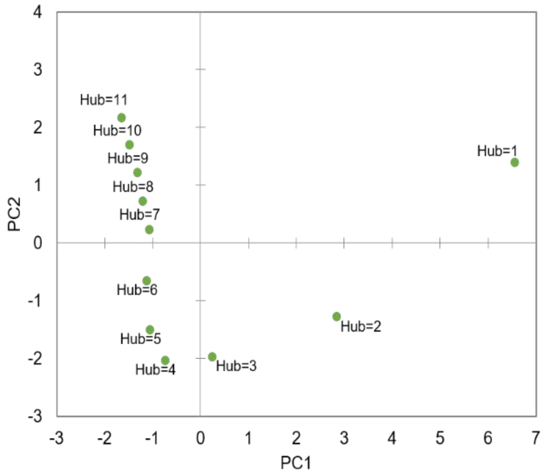

Figure 5: Factor score of the solutions.

Figure 2 shows that PC1 and PC2 are sufficient to describe the technology selection since the cumulative variability of PC1 and PC2 is above 90 % (> TC). The contribution of each variables on PC1 and PC2 are tabulated in Table 2. The results shows that both PC1 and PC2 have to be minimised (the net direction is negative). The priority scale obtained from AHP is favouring economic performance (i.e., 67 %), it is expected that the model will synthesise a cost effective biomass supply chain. The optimised result (after optimisng PCs) shows that four processing hubs are optimal for the proposed case study. Pareto analysis is conducted to investigate the effect of the priority scale on the optimized result. Figure 3 presents a Pareto curve of total investment cost (transportation cost and hub investment cost) against GWP under different number of hubs. The economic and environmental performance obtained from different number of hubs are presented in green dots, while the optimal number of hub obtained (when priority scale for economic performance = 67 %) is shown as red triangular-mark. Note that the proposed method shows similar optimal biomass flow design compared to the optimization model previously developed by How et al. (2016) (see Figure 4). Aside from this, the use of PCA method to reduce the complexity and redundancy of data without losing substantial amount of information is a practical advantage of this approach. Instead of comparing the solutions based a huge set of variable, the solutions can now be compared based on these simplified PCs scores. To illustrate, from Figure 5, it shows that higher PC1 score is assigned to three processing hubs. This indicates the environmental impacts for three hubs are higher compared to four hubs. In fact, when the number of processing hubs is reduced from four to three, the annual GWP, AP, POCP, NP and ADP are increased by 6.5 %. This further reveals the potential of the proposed method in debottlenecking process for the biomass supply chain synthesis problems.

6. Conclusion

This paper had developed a transportation design for a multi-biomass supply chain with the consideration of both economic and environmental sustainability. The main contributions are sated below:

(1) A novel evaluation approach which incorporates PCA and analytical hierarchy process (AHP) is developed to determine the optimal design of an integrated biomass supply chain.

(2) The case study presented shows that the proposed method is applicable to provide reliable solutions that maximising the economic potential, while ensuring the environmental impact is kept at minimal.
(3) Pareto study is conducted to analyse the effect of priority scale of each objective on the optimised result.
Future work will focus on extending this method to cover the social sustainability of the supply networks (e.g., safety concern, job creation). In addition, the proposed method can be extended into broader framework to plan for debottlenecking of the biomass supply chain. The PC score can be used as an indicator to benchmark each solution, while the variable that contributes the most to that PC will serve as the potential bottleneck.

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