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Collaboration Quality Assessment for Sustainable Supply Chains: Benchmarking

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Abstract

Purpose – This paper proposes an instrument to evaluate the collaboration quality of sustainable supply chains by considering collaboration behaviour and sustainability factors.

Design/methodology/approach – The proposed model integrates Quality Function Deployment (QFD), Fuzzy Analytical Network Process (FANP), and Data Envelopment Analysis (DEA) to assess the efficiency score of each stakeholder involved. A case of a sugar company in Indonesia was analysed as the illustration of the application of the model.

Findings – The integration QFD-FANP-DEA is able to incorporate collaboration behaviour and sustainability factors in a single assessment model. The results of the case study showed the benchmarking results associated with the performance variance of stakeholders and the number of samples.

Research limitation/implications – Future research could consider other DEA approaches, extend the research by simulating a different number of scenarios and evaluating the improvement/deterioration, and expand the scope of collaboration.

Practical implications – Each stakeholder will be able to obtain the collaboration assessment results, and the improvements suggested by the model.

Social implications – Smallholders and farmers will be able to increase their benefits by using the existing resources.

Originality/value – This paper provides a methodological contribution by introducing new collaboration quality assessment methods that can accommodate any variance in multi-stakeholders, involve qualitative and quantitative measurements, and benefit all stakeholders.

Keywords Data Envelopment Analysis, Quality Function Deployment, Fuzzy Analytic Network Process, collaboration behaviour, sustainability

Paper type Research paper

Introduction

A sustainable supply chain is a system that considers the economic, environmental, and social dimensions in the supply chain process (Gimenez et al., 2012). Sustainability is an essential strategic concept to ensure the optimal benefit in the supply chain by maintaining the resources based on

economic, environmental, and social aspects (Ageron et al., 2012). Therefore, the system can balance the achievement of high profit and social benefits while reducing the environmental impacts such as waste and GHG emissions. Collaboration in the supply chain is crucial for achieving sustainability and supporting continuous improvement processes in order to build and improve business competitiveness (Hamprecht et al., 2005, Van Hoof and Thiell, 2014). Supply chain collaboration is considered as key to value creation in the business process of the entire supply chain and to enhance capabilities of all the stakeholders (Horvath, 2001).

A supply chain that incorporates many organisations is considered as a complex operation that requires relevant and concise information for the decision-making process. Maintaining a complex collaboration needs regular performance assessment that involves many aspects, including sustainability and collaboration behaviour (Hao et al., 2012). Collaboration quality is one of the aspects that need to be properly managed and continuously improved for ensuring fair and productive collaboration among the stakeholders involved (Yan and Dooley, 2014). This aspect needs to be assessed to ascertain that the collaboration process goes well and leads to productive outcomes. In the process of achieving a common goal, collaboration quality assessment may lead to positive impacts. When the stakeholders are involved in collaboration forms, they need to have the ability to maintain the relationship based on several dimensions of collaboration quality. The result of the assessment needs to help companies in planning and to control their management system. It represents the effectiveness and robustness of the collaboration among stakeholders. Also, it can be used to ensure that the collaboration generates satisfying results for the supply chain members (Jengchung et al., 2013). The measurement of collaborative performance is important both as a reflection and as an evaluation of collaboration quality to ensure that collaboration can function well.

Despite the benefits that collaboration can bring to shape and enhance the performance of a sustainable supply chain, sometimes it can generate ineffective and inefficient results (Elkady et al., 2014), or set out expected benefits that are unachievable (Nyaga et al., 2010). Also, in their business decision processes supply chain members are often confronted with challenges in assessing and managing the quality of their collaboration, particularly with the involvement of multiple stakeholders and competing interests in the assessment process. To avoid this, each stakeholder needs to be informed of their status in the collaboration system and the collaboration quality state of the whole system in relation to their expectations. Performance measurement for such purposes can be a tool for identifying supply chain problems which help to support optimal decisions and strategic actions to attain better business outcomes (Kumar and Banerjee, 2014).

As well postulated in the extant literature, a high quality collaboration system is featured with mutually fostering collaboration in the supply chain, underpinned by conducive collaboration behaviour. Key behavioural factors, such as joint efforts, sharing activities, collaboration values, adaptation, trust, commitment, power, continuous improvement, coordination, and stability, govern the activities (both patterns and outcomes) of stakeholders to interact with each other, to respond to their demand, and to

manage a healthy partnership (Dania et al., 2018). A major problem for business decision making is to clearly understand and properly manage how the way and the level in which supply chain stakeholders collaborate potentially affect the desired sustainability outcomes for individual organisations as well as for the entire supply chain. Therefore, an effective collaboration performance assessment is expected to help derive appropriate strategies and actions that ensure balanced planning and control for both collaboration behaviour factors and sustainability requirements to obtain high quality collaboration. Consequently, a key research question to be answered in this paper is "how to assess the quality of collaboration in a supply chain by linking collaboration behaviour factors and sustainability?". To this end, the rest of the paper is structured as follows: a literature review of extant studies on supply chain collaboration assessment and associated limitations are summarised in the next section, followed by the proposed methodology and framework for collaboration quality assessment, which integrates Quality Function Deployment, Fuzzy Analytical Network Process and Data Envelopment Analysis. Then, the detailed processes for quantitative evaluation of collaboration system requirements and collaboration efficiency are elaborated. A case study on a sugar supply chain is presented to demonstrate how the proposed methods can inform decisions for collaboration quality improvement by benchmarking results associated with the performance variance of supply chain stakeholders. The paper is concluded with discussions on key findings and directions for future research.

Literature Review

The measurement of collaborative performance is important both as a reflection and as an evaluation of collaboration quality to ensure that collaboration can function well. There have been many studies on collaboration performance. For instance, simulation is used to appraise Collaborative Planning, Forecasting and Replenishment (CPFR) performance (Kohli, 2005, Chen et al., 2007) as well as to assess the impact of the involvement of different stakeholders based on financial and operational objectives (Ramanathan, 2014). A business process framework is proposed to evaluate the impact of collaboration performance (Beckett, 2009). Data Envelopment Analysis is applied to examine the level of collaboration in the dyadic relationship as a contribution to improving the performance of supply chains (Janvier-James and Didier, 2011). The level of collaboration can also be assessed by using Graph Theory (Anbanandam et al., 2011, Chounta et al., 2014). Also, System Dynamic Modelling is applied to assess the impact of information sharing on collaboration in supply chain performance (Elkady et al., 2014). The most well-known tool that has been applied to measure the relationship between suppliers and retailers is the Supply Chain Collaboration Index (Simatupang and Sridharan, 2005, Kumar and Banerjee, 2014, Rota et al., 2018, Bezuidenhout et al., 2012). Table 1 present a summary of different approaches for collaboration quality evaluation that are reported in the extant literature.

[Insert Table 1 about here]

As found in the review, most of the research focuses on a dyadic relationship that either between the manufacturer and the retailer or the supplier and the manufacturer. Meanwhile, most of the assessment approaches reported in the literature operate with using an aggregated index for collaboration quality, without presenting an individualised collaboration score for each stakeholder. In addition, only a small number of studies incorporate sustainability perspectives in collaboration quality measures as part of the approaches for improving performance. Moreover, the performance indicators used in those models are generally much qualitative and fall short of providing quantifiable measures and diagnostic analysis in examining the interdependency among different collaboration factors and the weighting of their impacts. Overall, none of the extant studies highlights the quality of the collaboration in the sustainable supply chains. Furthermore, the result of the assessment does not represent the efficiency of collaboration. Most of these models only reflect the collaboration level without considering how inputs contribute to the achievement of the output in the context of sustainability, such as economic benefits, GHG emissions and social welfare. In light of such limitations and the posed research question, this paper is set out to develop a structured model to assess the quality of collaboration. This collaboration quality assessment model will help to analyse the efficiency of collaboration that reflects the sustainability perspectives and collaboration behaviour in supply chains by focusing on 1) how to determine the importance of collaboration system requirements in relation to sustainability measures and 2) how to assess the efficiency score for each stakeholder in the supply chain in relation to collaboration behavioural factors. These will consider the collaboration behavioural factors that stakeholders have and their impact on sustainability factors. By using this assessment model, stakeholders will be able to analyse the demands of business partners and identify the problems that arise in the supply chain system and societies, and then find the solutions to keep them under control to minimise the negative impacts.

Research Methodology

The collaboration quality assessment model consists of two main tasks to answer each sub research question, which are identifying importance level of collaboration system requirements and measuring efficiency score of collaboration quality which is shown in Figure 1. Then, the result of the model will be implemented in a case study.

[Insert Figure 1 about here]

Identifying importance level of collaboration system requirements

This phase starts with an analysis of the degree of interdependency (inner and outer) among the factors of stakeholder requirements and collaboration system requirements. Then, the stakeholder requirements will be mapped against the collaboration system requirements that lead to the interdependency priorities of the system requirements. The correlations among the collaboration system requirements and the stakeholder requirements underpin the results of interdependency priority ranking. These results show

the importance level of the collaboration behavioural factors that support the achievement of sustainable sugar supply chains. They provide an overview to the stakeholders of what critical organisation behavioural factors need to be considered in fulfilling stakeholder needs and influencing collaboration quality. The evaluation step in this phase can be seen in Figure 2.

[Insert Figure 2 about here]

In this first phase, Quality Function Deployment and Fuzzy Analytic Network Processing (QFD-FANP) are employed to determine the importance level of collaboration behavioural factors. QFD is a systematic approach that deals with the voice of customers and translates that into a system design and subsequently into part of the characteristics, process plans, and system requirements (Kahraman et al., 2006). QFD can accommodate qualitative input in the form of linguistic data based on expert judgements and human perceptions in the importance evaluation and relationship analysis (Ertay et al., 2005). In this research, QFD will be used to translate the stakeholder requirements into collaboration system requirements

However, QFD has a limitation regarding absolute value usage in identifying the importance of the attributes. Therefore, to overcome this limitation, QFD needs to be integrated with Multiple Criteria Decision Making (MCDM) that will help in the process of finding the optimal solution. ANP as one of MCDM methods is incorporated with QFD to determine the weight and analyse the dependency among elements. ANP helps the decision maker to interpret the problem by creating a systematic network of inter-relationships among various decision criteria and customer criteria (Lin et al., 2010).

In a conventional ANP, the pairwise comparison relies on a discrete rating scale. However, human judgements are relatively subjective and vague. Due to the nature of the problem, Fuzzy Logic is effective in minimising the subjectivity, ambiguity, and vagueness of human judgement (Ignatius et al., 2016). Fuzzy Logic has several advantages such as the ability to handle linguistic terms and human experiments, making real-time decisions with insufficient and imprecise information, solving a complicated problem by transforming it into a low complexity computational system (Behnia et al., 2017, Kaur et al., 2017, Wu et al., 2017). In this process, the methodology of QFD-FANP will follow the process which was proposed by Buyukozkan et al. (2004). The result of QFD-FANP will be applied to calculate the efficiency score by using DEA to determine the level of collaboration.

Measuring efficiency score of collaboration quality

The next part of the assessment is the collaboration quality assessment based on the sustainability aspects by using Data Envelopment Analysis (DEA) to determine the efficiency score for each alternative. DEA is a technique that proficient in benchmarking process based on various assumptions and orientations (Hokey et al., 2017). In cooperating with QFD, DEA overcomes the limitation of QFD in terms of evaluating the relative performance of alternative product designs or system requirements. Cariaga et al. (2007) believed that QFD does not provide the end solution, it is only the systematic

process of finding a solution. DEA helps to analyse the efficiency of suppliers and to find the best partners that lie under the frontier. On the other hand, QFD-FANP also brings better weighting factors into the DEA process by considering the interrelationships among the variables. Islam and Manzoni (2009) stated that ignoring the interrelationships among variables could give immensely different results, so considering the multi-criteria decision model is suggested.

Each DMU has input and output parameters in carrying out the supply chain collaboration process. These inputs and outputs are used to analyse the efficiency of collaboration between stakeholders. Inputs are derived from collaboration system requirements, while outputs represent the sustainability result of collaboration. The variable of system requirements will be scaled to assess the degree of importance of the behavioural factors in supporting the collaboration. The output of collaboration activities will be based on the contextual information derived from the case study and consists of economic, environmental, and social indicators, such as revenue, GHG emissions, and social benefits. A comparison between input and output will result in an efficiency score for each stakeholder on each indicator. The combination of the indicators' efficiency score is considered as the overall performance efficiency score of each stakeholder in the supply chain collaboration. The process of the second stage is shown in Figure 3.

[Insert Figure 3 about here]

A DMU can be declared as 100% efficient if and only if the improvement of input or output value of other DMUs does not have adverse impacts on some of its other inputs and outputs (Cooper and Seiford, 2011). The fittest DMU will have an efficiency score equal to 1, while a DMU that has an efficiency score below 1 is categorised as inefficient. DMUs are identified as inefficient if there are other DMUs or a linear combination of DMUs that can produce better outputs from the same or lesser inputs (Pal et al., 2007).

QFD-FANP for collaboration system requirements evaluation

The collaboration quality assessment process starts with the analysis of interdependency within and between factors related to stakeholder requirements (SR) and collaboration system requirements (DR). The development of the mathematical model for determining the interdependence and importance weight of system requirements comprises the following main tasks:

a. Determining SR and DR

The first important step in QFD process is generating SR (in QFD called WHATs) that refers to the extent to which the collaboration brings value to the economic, environmental, and social aspects. Once the SR is determined, the technical elements (in QFD called HOWs) to satisfy the SR need to be designed. SR and DR represent sustainability and collaboration behaviour factors respectively. The

factors are adapted from Dania et al. (2018). Both requirements will be mapped in the form of House of Quality (*HoQ*). The *HoQ* that provides SR and DR is illustrated in Figure 4.

[Insert Figure 4 about here]

HoQ consists of two main items of information which are correlation matrix and relationship matrix. The correlation matrix will show the inner dependency between criteria within SR as well as between criteria within DR, while the relationship matrix will show the interdependency between SR and DR. Value input of *HoQ* is based on the questionnaire of pairwise comparison which examines the importance level of each criterion in sugar supply chain collaborations compared to others.

In traditional QFD, a numerical scale is usually used and assumed to be being precise in representing human perceptions. However, although the numerical scale is easy to use and simple, it is difficult to deal with the uncertainty of human perception. Therefore, to minimise imprecision in human perceptions, linguistic terms as shown in Table 2 are used in pairwise comparisons instead of numerical numbers. Linguistic terms have several benefits such as being less specific than numerals, they are able to give a precise representation of an imprecise statement, and are highly dependent on the determination of a valid membership function (Kahraman et al., 2006).

[Insert Table 2 about here]

b. Constructing network diagram

In this study, all elements will be computed by FANP. The ANP method consists of two main stages, which are constructing a network diagram and determining the priorities of the criteria in the network diagram. Therefore, once the $SR = \{SR_1, SR_2, SR_3, \ldots., SR_n\}$ and $DR = \{DR_1, DR_2, DR_3, \ldots., DR_n\}$ are generated, the relationship network diagram is constructed.

In the construction of network diagram, all possible interactions among the criteria should be considered. The arrow from X to Y means that criterion Y depends on criterion X, or, in other words, criterion X influences criterion Y. The customer criteria are clustered into economic, environmental, and social dimensions, while design criteria are represented by collaboration system requirements. The example of network diagram is illustrated in Figure 5.

[Insert Figure 5 about here]

c. Generating the supermatrix

After the network diagram is constructed, all the relationships between two criteria are analysed to generate the supermatrix. Supermatrix is a partitioned matrix and consists of many sub-matrices (Geng et al., 2010). Its function is to limit the power to calculate the overall priorities, and hence the cumulative influence of each element on every other element is obtained (Buyukozkan et al., 2004). The supermatrix of the QFD framework is represented as follows:

$$W = \begin{array}{c} \\ Goal\ (G) \\ SR_s \\ DR_s \end{array} \begin{array}{c} \begin{array}{ccc} G & SR_s & DR_s \end{array} \\ \begin{bmatrix} 0 & 0 & 0 \\ w_1 & W_3 & 0 \\ 0 & W_2 & W_4 \end{bmatrix} \end{array} \quad 1$$

where w_1 is a vector that represents the impact of the goal, which is "high collaboration quality", W_2 is a matrix that denotes the impact of the SR_s on each of the DR, W_3 and W_4 are matrices that represent the inner dependency within SR and DR, respectively.

d. Calculating the weight of the criteria for each submatrix

Calculating the weight of each criterion for each submatrix is carried out to determine the priorities of DR_s. In this stage, a pairwise comparison is applied to evaluate the input in ANP process by calculating w_1, W_2, W_3, and W_4. The pairwise comparison that is used in ANP is similar to that used in the AHP approach. This procedure will evaluate the importance weight of the criteria based on the opinion of each group of stakeholders. Geometric mean is applied to obtain the average value of each criterion. Moreover, to assure the data collected by pairwise comparison is consistent, a consistency check has to be conducted. If there is *m* stakeholders as the respondents, w_i^h is the priority vector, and e_{ij}^h is the geometric mean, the consistency ratio is as follows:

$$\lambda_{max} = \frac{1}{m}\left(\sum_{i=1}^{m} \frac{\sum_{j=1}^{m} e_{ij}^h \times w_i^h}{w_i^h}\right),\ i,j = 1,2,\ldots\ldots,m \quad 2$$

$$CI = \frac{\lambda_{max} - m}{m-1} \quad 3$$

$$CR = \frac{CI}{RI} \quad 4$$

where λ_{max} is the largest eigenvalue of matrix *E*, *CI* is the consistency index of matric *E*, *RI* is the random index of matrix *E*, and *CR* is the consistency ratio of matrix *E*. RI for (n) matrix that was developed by Saaty (1980) can be seen in Table 3.

[Insert Table 3 about here]

Since pairwise comparison involves psychological aspects in assessing the importance of variables, a matrix larger than ten is not recommended because of the limitation of humans to compare many variables and process the information consistently. Moreover, the relative priorities would be not much different to each other, and as a consequence, the result would be misrepresented (Saaty, 1987). (Saaty, 1987). Therefore, if the variables are more than ten, clustering is suggested. Data is categorised as consistent and acceptable if $CR < 0.1$. Otherwise, the value of matrix *E* should be revised or reassessed. Then, after the data appears consistent, an evaluation is conducted based on steps as follows (Buyukozkan et al., 2004):

1. Determining the importance degrees of SR_s with linguistic data by assuming that there is no dependence among the SR_s: calculation of w_1. Since the number of variables is more than ten,

the calculation of w_1 has to be done in two steps. First, calculate the relative priority of the dimensions (economic (EC), environmental (EV), and social (SC)). Second, calculate the relative priority of the criteria within dimension SR_s. If the w_{D_n} is the weight of dimension D_n and $w_{D_nC_s}$ is the weight of criterion C_S within dimension D_n, the overall weight of each criterion C_S (w_{C_S}) will be derived from:

$$w_{C_S} = w_{D_n} \times w_{D_nC_s} \text{ for } n = 1, 2, \ldots, n \text{ and } s = 1, 2, \ldots, s \quad (5)$$

2. Determining the importance degrees of DR_s with respect to each SR with linguistic data by assuming that there is no dependence among the DR_s: calculation of W_2.

3. Determining the inner dependence matrix of the SR_s with respect to each SR with linguistic data by using the schematic representation of inner dependence among SR_s: calculation W_3.

4. Determining the inner dependence matrix of the DR_s with respect to each DR with linguistic data by using the schematic representation of inner dependence among DR_s: calculation W_4.

5. Determining the interdependent priorities of the SR_s: calculation of w_C by $w_C = W_3 \times w_1$

6. Determining the interdependent priorities of the DR_s: calculation of w_A by $w_A = W_4 \times w_1$

7. Determining the overall priorities of the DR_s : calculation of w^{ANP} reflecting the interrelationships within the *HOQ* by $w^{ANP} = W_A \times w_C$

As described above, the QFD-FANP process involves human perception to assess the pairwise comparison. However, human perception is subjective and high ambiguity. Ertay et al. (2005) argued that linguistic data could provide highly accurate results with the help of fuzzy theory. Therefore, a triangular fuzzy number (TFN) will be applied to deal with this vague linguistic data. TFN enables the application of intervals in human judgement for the preference of one element over another (Sarmah, 2014). TFN for M is denoted by (l, m, u), whereas those indicators represent the smallest possible value, the most promising value, and the largest possible value, respectively ($l \leq m \leq u$). Each TFN is denoted by linear representations of membership function μ that can be defined as follows (Zaim et al., 2014):

$$\mu_M(x) = \begin{cases} 0, & x < l \text{ or } x > u \\ \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \end{cases} \quad (6)$$

The basic operation of TFN M_1 (l_1, m_1, u_1) and M_2 (l_2, m_2, u_2) consist of addition, subtraction, multiplication, scalar multiplication, and inverse as follows (Natee et al., 2016):

$$M_1 \oplus M_2 = \left(l_1 + l_2,\ m_1 + m_2,\ u_1 + u_2,\right) \quad 7$$

$$M_1 \ominus M_2 = \left(l_1 - l_2,\ m_1 - m_2,\ u_1 - u_2,\right) \quad 8$$

$$M_1 \otimes M_2 = \left(l_1 \times l_2,\ m_1 \times m_2,\ u_1 \times u_2,\right) \quad 9$$

$$\lambda \otimes M_1 = (\lambda l_1, \lambda m_1, \lambda u_1) \quad 10$$

$$M_1^{-1} = \left(1/u_1, 1/m_1, 1/l_1\right) \quad 11$$

Considering TFN, fuzzy scale for the linguistic scale and the membership function for each fuzzy number is described in Table 4.

[Insert Table 4 about here]

There are various ways cited in the literature to calculate w_1, W_2, W_3, and W_4. by using Fuzzy AHP, such as the Lambda-Max Method, Logarithmic Least Square Method, Chang's Extent Analysis Method, and Eigenvalue Method (Kahraman et al., 2006, Liu and Wang, 2010, Geng et al., 2010, Chang, 1996). This study follows Chang's Extent Analysis method (Chang, 1996). In this analysis, the synthetic extent value S_i of the pairwise comparison is presented, by applying the principle of the comparison of fuzzy numbers.

If $X = \{x_1, x_2, \ldots, x_n\}$ is an object set, and $U = \{u_1, u_2, \ldots, u_m\}$ is a goal set, the extent analysis is performed for each goal of the object. Therefore, there is m extent analysis value for each object, with the signs as follows:

$$M_{gi}^1, M_{gi}^2, \ldots, M_{gi}^m, \qquad i = 1,2, \ldots, n \quad 12$$

where all the M_{gi}^j $(j = 1,2, \ldots, m)$ are triangular fuzzy numbers (TFNs).

The steps of the analysis are as follows:

1. First, the value of fuzzy synthetic extent with respect to the i_{th} object is defined as

$$S_i = \sum_{j=i}^{m} M_{gi}^j \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1} \quad 13$$

whereas, to obtain $\sum_{j=1}^{m} M_{g_i}^{\ j}$, the fuzzy addition operation of m extent analysis values is performed for a particular matrix:

$$\sum_{j=1}^{m} M_{gi}^j = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right) \quad 14$$

Moreover, to obtain $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1}$, the fuzzy addition operation of M_{gi}^j $(j = 1,2, \ldots, m)$ values is applied:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i\right) \quad 15$$

Then, the inverse of the vector of the previous equation is computed:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i},\right) \quad 16$$

Second, the degree of possibility of $M_1 = (l_1, m_1, u_1) \geq M_2 = (l_2, m_2, u_2)$ is defined as $V(M_1 \geq M_2) = \sup_{x \geq y}\left[min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right]$. When $x \geq y$ and $\mu_{M_1}(x) = \mu_{M_2}(y) = 1$, and d is the ordinate of the highest intersection point D between M_1 (μ_{M_1}) and M_2 (μ_{M_1}), can be equivalently expressed as follows:

2. $V(M_2 \geq M_1) = hgt(M_2 \cap M_1) = \mu_{M_1}(d)$

$$= \begin{cases} 1, & if\ m_2 \geq m_1 \\ 0, & if\ l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases} \quad 17$$

To compare M_1 and M_2, both the values of $V(M \geq M_1)$ and $V(M \geq M_2)$ is needed.

Third, the degree possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $M_i = (1, 2, \ldots., k)$ can be defined by

3. $V(M \geq M_1, M_2, \ldots., M_k) = V[(M \geq M_1)\ and\ (M \geq M_2)\ and\ \ldots.and\ (M \geq M_k)\ ]$

$$= min\, V(M \geq M_i), \quad i = 1, 2, 3, \ldots., k \quad 18$$

Assume that

$$d'(A_i) = min\, V(S_i \geq S_k)\ \ for\ k = 1, 2, \ldots.n; k \neq 1 \quad 19$$

Then the weight vector is given by

$$W' = \left(d'(A_1), d'(A_2), \ldots., d'(A_n)\right)^T \ where\ A_i (i = 1, 2, \ldots., n)\ \ are\ n\ elements \quad 20$$

W' is still in the form of fuzzy values. Therefore, it has to be transformed into a real value for the purpose of decision making analysis, which is called defuzzification. One of the method that can be applied for defuzzification is normalisation. By using normalisation, the normalised weight vectors are

$$W = \left(d(A_1), d(A_2), \ldots., d(A_n)\right)^T \quad 21$$

where W is a non-fuzzy number.

DEA for measuring efficiency score of collaboration quality

Once the collaboration system requirements have been analysed by integration of QFD-FANP, the next stage is the calculation of the efficiency score of collaboration quality. As described before, the DEA process requires input and output since the concept of DEA is to find the ratio between input and output. In this study, the outputs are represented by sustainability factors, which are revenue, GHG emissions, and social impacts. While, the input of the collaboration comprises the collaboration behaviours which adhere to the organisation, such as joint efforts, sharing activities, collaboration values, adaptation, trust, commitment, power, continuous improvement, coordination, and stability (Dania et al., 2018)

This proposed model will use the important priorities of DR_s from QFD-FANP process as the weight factor to calculate the input value of DEA model. If x_{ij} is the input amount of input i consumed by the j_{th} DMU, DR_{ij} is the collaboration behaviour i consumed by j_{th} DMU, and w_i^{ANP} is importance priority for each output, then the input value that will be used in DEA process is given by:

$$x_{ij} = DR_{ij} \times w_i^{ANP} \quad 22$$

Once the input and output values are determined, the relative efficiency of each DMU is calculated based on the ratio of its total weighted output to its total weighted input. The assessment of relative efficiency relies on benchmarking and peer-evaluations from all the performances of the DMUs involved. Then, DEA identifies both the efficient and inefficient DMUs. DEA will create the efficiency frontier zone which is generated by converting input and output in an optimum way and formed by best practice DMU. The efficient DMU will perform as a best practice frontier (Zhu, 2015). Any DMU that has a value below the frontier is considered as inefficient and appropriate modifications should be made in their inputs and outputs to reach the frontier zone and be considered as efficient.

Various DEA models can be applied in the case study, depending on the characteristics of the data available to solve the problem. This study argues that the increase of all inputs twice will lead to the more or less value of outputs and does not exactly increase all output twice. Therefore, BCC (variable return to scale) is adopted. This model is appropriate to be applied in cases in which changing of input cannot give a proportional changing in output (He-Boong et al., 2016). Moreover, the case with the various sizes of DMU is more appropriate being solved with VRS DEA model (Zhu, 2015). Therefore, the small-sized organisation is not benchmarked against the large sized organisation. In DEA, minimising input or maximising output is also considered to choose the appropriate model. Given the fact that organisations cannot directly control the collaboration behaviour in the supply chain as the input, the basic concept of DEA that is adopted here is efficiency based on maximising output or is output oriented. This concept explains how the existing elements of collaboration (collaboration behavioural factors) influence the achievement of sustainability.

Besides input and output, the total population of stakeholders that will be assessed, called decision-making units (DMUs), also needs to be determined. DEA considers n DMUs to be assessed, where each DMU requires m different inputs to produce s different outputs. The desirable number of DMUs (n) is:

$$n \geq max\ \{m \times s, 3 \times (m + s)\} \quad 23$$

The efficiency score of each DMU is calculated after inputs, outputs, and DMUs are determined, The function of DEA is an efficiency assessment based on a ratio of output and input given by the following equation:

$$Efficiency = Outputs/Inputs \quad 24$$

Let

j index on observed DMUs

n number of DMU, $j = 1, \ldots, n$

i index on input

m number of input, $i = 1, \ldots, m$

r index on output

s number of output, $r = 1, \ldots, s$

x_{ij} amount of input i consumed by the j_{th} DMU

y_{rj} amount of output r produced by the j_{th} DMU

λ_{ij} priority scale of input i of the j_{th} DMU

u_i weight of input i

v_r weight of output r

It is assumed that DMU_j needs amount x_{ij} of input i to produce y_{rj} of output r. Therefore, $X = \{x_1, x_2, x_3, \ldots, x_n\}$ to produce $Y = \{y_1, y_2, y_3, \ldots, y_n\}$. Each input and output is a non-negative real number and it is assumed that each DMU requires all the inputs and all the outputs. The input data matrix X and the output data matrix Y can be arranged as follows.

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ x_{m1} & \cdots & \cdots & x_{mn} \end{pmatrix} \quad 25$$

$$Y = \begin{pmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ y_{s1} & \cdots & \cdots & y_{sn} \end{pmatrix} \quad 26$$

where X is an $(m \times n)$ matrix and, Y is an $(s \times n)$ matrix. The multiple inputs and outputs are linearly aggregated using weights and the efficiency needs to be maximised. This ratio forms the objective function for the particular DMU that being evaluated. Therefore, the mathematical model for the efficiency in VRS output-oriented is given by:

$$min \quad E_{oj} = \frac{\sum_i^m u_i^* x_{ij} - \xi^*}{\sum_r^s v_r^* y_{rj}} \quad 27$$

Subject to

$$\frac{\sum_i^m u_i^* x_{ij} - \xi^*}{\sum_r^s v_r^* y_{rj}} \leq 1 \;\; j = 1, \ldots, n$$

$$u_i \geq \varepsilon \;\; i = 1, \ldots, m$$

$v_r \geq \varepsilon \;\; r = 1, \ldots\ldots, s$

u_i is the weight assigned to input i and v_r is the weight assigned to output r. The objective is to obtain a vector of weights (u_i, v_r) that maximise the efficiency score of the assessed DMU. Therefore, u_i^*, v_r^*, and ξ^* are an optimal bundle of weights. ξ is the free variable that indicates the type of return of scale. Increasing return-to-scale prevails at (x_0, y_0) if and only if $\xi^* < 0$, while decreasing return-to-scale applies if and only if $\xi^* > 0$, and constant return-to-scale if and only if $\xi^* = 0$ for all optimal solutions (Banker et al., 2004). The output-oriented scale tends to result in a decreasing return of scale. This prevents the negative cross-efficiency that usually arises in the input-oriented VRS since its constraint of being output-oriented prevents it (Zhu, 2015).

Besides desirable outputs (economic and social impact), this proposed model also considers undesirable output (GHG emissions). DEA can solve the problem of a lack of consideration of the measurement of waste and emissions (Korhonen and Luptacik, 2004). By considering emissions as an undesirable output, eco-efficiency can be achieved. There are many ways to include the undesirable outputs in the model. Assume the output corresponding to indices $1, 2, \ldots\ldots, s$ are desirable and the outputs corresponding to indices $s+1, s+2, \ldots\ldots, t$ are undesirable outputs. Therefore, the output data matrix Y can be arranged as $Y = \begin{pmatrix} Y^d \\ Y^u \end{pmatrix}$. Generally, people wish to optimise Y^d and to minimise Y^u to achieve the highest performance. However, in the standard DEA model, all outputs are supposed to be increased or decreased as indicators of high efficiency. Therefore, modification of the model is needed to accommodate both the desirable and undesirable outputs in the one model.

There are many ways to handle the undesirable output in DEA model such as additive inverse, multiplicative inverse, considering undesirable outputs as input, and translating the negative output with the adding positive large scalar β (TR β). This study will adopt TR β since this approach is already used in many other studies (Hua et al., 2007), is suitable for BCC model, and keeps the positive value of undesirable outputs.

It is assumed that there is no duplicated unit in dataset and consider a $s \times n$ matrix Y^d as desirable outputs and a $(t-s) \times n$ matrix Y^u as undesirable output. Therefore, vector y_j is decomposed into two parts: $y_j = \begin{pmatrix} y_j^d \\ y_j^u \end{pmatrix}$, where the vectors y_j^d and y_j^u refers to the desirable and undesirable output value unit j. Incorporating undesirable outputs in DEA can be done by adding a sufficient large scalar β to the y_j^u and give the result of output values $f(\bar{y}_j^u) = -y_j^u + \beta$ are positive for each DMU_j. Therefore, by considering the desirable and undesirable outputs, the mathematical model is modified as follows:

$$min \;\; E_{oj} = \frac{\sum_i^m u_i^* x_{ij} - \xi^*}{\sum_r^s v_r^* y_{rj}^d - \left[\sum_{s+1}^t v_r^* y_{rj}^u + \beta\right]} \qquad 28$$

To obtain the optimal solution of efficiency, the envelopment form linear programming is given by:

$$max\ E_{oj} \quad 29$$

Subject to:

$$-E_{oj}\left(\sum_{r}^{s} v_r^* y_{rj}^d - \left[\sum_{s+1}^{t} v_r^* y_{rj}^u + \beta\right]\right) + Y\lambda \geq 0$$

$$\sum_{i=1}^{m} u_i x_{ij} - X\lambda \geq 0$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda \geq 0$$

While the dual multiplier form of output-oriented VRS is given by:

$$min \sum_{i=1}^{m} u_i x_{i0} - \xi \quad 30$$

Subject to:

$$\sum_{i=1}^{m} u_i x_{ij} - \sum_{r}^{s} v_r^* y_{rj}^d - \left[\sum_{s+1}^{t} v_r^* y_{rj}^u + \beta\right] - \xi \geq 0, j = 1, \ldots\ldots, n$$

$$\sum_{r}^{s} v_r^* y_{r0}^d - \left[\sum_{s+1}^{t} v_r^* y_{r0}^u + \beta\right] = 1$$

$u_i, v_r \geq \varepsilon \ \ \forall i, r, \ \xi$ free in sign

The term of ε is an infinitesimal positive number. Assume that a solution is available from equation (30), then the point of efficient frontier is $(\hat{x}_{ij}\hat{y}_{rj})$ which is derived from:

$$\hat{x}_{ij} = x_{ij} - s_i^{-*}, \ \ 1 = 1, \ldots\ldots, m \quad 31$$

$$\hat{y}_{rj} = E_{oj}^*\left(y_{rj}^d - y_{rj}^u + \beta\right) + s_i^{+*}, \ \ 1 = 1, \ldots\ldots, s \quad 32$$

where $E_{oj}^*, s_i^{-*}, s_i^{+*}$ are the optimal solution for VRS output oriented. Slacks s_i^{-*}, s_i^{+*} denote the amount of excess inefficiency presented by non-efficient DMUs. It occurs when after a proportional alteration outputs or inputs, DMUs still cannot reach the efficiency frontier. Slack will help to push the DMUs to the efficient frontier. DMU will considers as fully efficient if and only if $E_{oj} = E_{oj}^* = 1$ and all slacks are zero. Input slacks will be equal to zero if and only if $\sum_{i=1}^{m} u_i x_{ij} - X\lambda = 0$, while output slacks will be equal to zero if and only if $E_{oj}\left(\sum_{r}^{s} v_r^* y_{rj}^d - \left[\sum_{s+1}^{t} v_r^* y_{rj}^u + \beta\right]\right) - Y\lambda = 0$ (for the given optimal value of E_{oj} and λ).

Since the DMUs consist of stakeholders who possibly have a different range of values, standardisation variables are important to make them equal for comparison. Wang et al. (2014) argue that normalisation of a data set is necessary since a large variable will dominate another smaller variable. One of the normalisation methods that can be applied is rescaling. Rescaling will bring all values into the range

$[0,1]$ by considering the minimum and maximum values. The equation used for the scaling normalisation is:

$$y_{rj}{}' = \frac{y_{rj} - min(y_{rj})}{max(y_{rj}) - min(y_{rj})} \quad 33$$

Therefore, the proposed multiplier form of output-oriented VRS by considering the standardisation variable is given by:

$$min \sum_{i=1}^{m} u_i x_{i0} - \xi \quad 34$$

Subject to:

$$\sum_{i=1}^{m} u_i \hat{x}_{ij} - \sum_{r}^{s} v_r^* \hat{y}_{rj}^d - \left[\sum_{s+1}^{t} v_r^* \hat{y}_{rj}^u + \beta\right] - \xi \geq 0, j = 1, \ldots\ldots, n$$

$$\sum_{i=1}^{m} u_i \hat{x}_{ij} - \sum_{r=1}^{s} v_r \left(\frac{\hat{y}_{rj}^d - \min(\hat{y}_{rj}^d)}{\max(\hat{y}_{rj}^d) - \min(\hat{y}_{rj}^d)}\right)$$

$$-\left[\sum_{s+1}^{t} v_r \left(\frac{\hat{y}_{rj}^u - \min(\hat{y}_{rj}^u)}{\max(\hat{y}_{rj}^u) - \min(\hat{y}_{rj}^u)}\right) + \beta\right] - \xi \geq 0, \qquad j = 1, \ldots\ldots, n$$

$$\sum_{r=1}^{s} v_r \left(\frac{\hat{y}_{r0}^d - \min(\hat{y}_{r0}^d)}{\max(\hat{y}_{r0}^d) - \min(\hat{y}_{r0}^d)}\right) - \left[\sum_{s+1}^{t} v_r \left(\frac{\hat{y}_{r0}^u - \min(\hat{y}_{r0}^u)}{\max(\hat{y}_{r0}^u) - \min(\hat{y}_{r0}^u)}\right) + \beta\right] = 1$$

$u_i, v_r \geq \varepsilon \ \ \forall i, r, \ \xi$ free in sign

By using the equation (34), the relative efficiency of each DMU and the overall efficiency that reflects the collaboration among stakeholders can be captured.

Case Study: Collaboration Quality Assessment in Sugar Industry

In this section, the application of the collaboration quality assessment approach using QFD-FANP and DEA is demonstrated through a case study on a sugar supply chain in Indonesia. As a typical sugar supply chain, several players are engaged in the supply chain collaboration, including sugarcane farmers, sugar mills, and distributors. The presence of dominant players can affect the overall performance of collaboration, leading to some stakeholders gaining more benefits than others. While collaboration exists in this supply chain, there is lack of clear information about the level of collaboration quality and what aspects of collaboration need to be improved or maintained without quantitative analysis to measure the efficiency of collaboration. The application of the proposed model is to examine the characteristics of collaboration behaviour and their impact on the sustainability performance in the case context, to assess the efficiency score of collaboration for each stakeholder, and as a result to identify current gaps and provide recommendations for improvement.

Sampling and Data Collection

In the context of this case study, Company X (the name is coded for confidentiality reason) is a sugar mill and one of the biggest sugar company in Indonesia. It has a good reputation in terms of the production system and partnership activities with farmers and distributors. The collaboration system of the selected sugar supply chain covers 19 zones within one district, including around 4,300 farmers to produce and supply sugarcanes. The distributors in the region buy sugar from Company X through the auction process. Two sets of questionnaires are applied in this case study to collect data from these key stakeholders, which are a pairwise comparison, and collaboration behavioural assessment and company's general information.

One representative from each category of stakeholders (farmer, miller and main distributor) who is considered as an expert is involved in completing the pairwise comparison questionnaire to examine the importance level of each criterion in sugar supply chains collaboration compared to others. Furthermore, the collaboration behaviour assessment process involves more respondents to obtain valid data. The total sample size of main distributors is nine, which are selected from those who won the auction process in 2016. However, since the number of farmers who supplied Company X in 2016 was too big and due to limited time, resources, as well as the availability of the farmers to be interviewed, a sampling process is applied. The sampling size is determined by following Slovin's formula as follows (Sevilla et al., 1992):

$$n = \frac{N}{1+Ne^2} = \frac{1011}{1+(1011)(0.1)^2} = 90.99 \approx 91$$

where n is the sample size, N is the total population and e is the margin of error. Therefore, this collaboration assessment process involves 91 farmers, 1 miller (Company X), and 9 distributors.

Results

By using QFD-FANP approach, the results of w_1, W_2, W_3, and W_4 are shown in the form of HoQ in Figure 6.

[Insert Figure 6 about here]

From the 10 collaboration behavioural factors, **t**he most important collaboration behaviour to answer the stakeholder requirements is a commitment (0.116). It is followed by trust (0.114), coordination (0.105), stability (0.104), continuous improvement (0.104), collaboration value (0.098), joint effort (0.092), sharing activities (0.091), power (0.088), and adaptation (0.088). This result will be used to adjust the value of the input in DEA process.

By using the proposed DEA approach, benchmarking among farmers, Company X, and distributors is performed. Three approaches are performed to get the result from different perspectives. In the first approach, the DEA model is applied to evaluate the collaboration efficiency score of the entire sample including Company X, farmers, and distributors (F-C-D benchmarking). In the second approach, the DEA model evaluates the efficiency score of farmers and distributors regarding their collaboration with

Company X (F-D benchmarking). In the third approach, the DEA model assesses the performance of each type of stakeholder (farmers and distributors) independently (F/D benchmarking). The comparison between the actual output and projected output, and the efficiency score for each stakeholder can be seen in **Appendix A**. In the tabulation of the result, F_1-F_{99} represents the farmers, D_1-D_{10} represents the distributors, and C_1 represents the sugar Company X. Three approaches of the DEA calculation lead to different efficiency score of each stakeholder.

In the **first approach**, the benchmarking process is applied to the entire stakeholders in the sugar supply chain, including Company X, farmers, and distributors (F-C-D benchmarking). The overall efficiency score by using this approach is 98.5%. Among 101 stakeholders, 56 stakeholders are indicated as fully efficient (the efficiency score is 100%). These are comprised of Company X, seven main distributors, and 48 farmers. For those DMU_S who are fully efficient, the current and projected values are identical. Slack values occur in all inefficient DMU_S although not in all factors. However, there is one efficient DMU considered as weakly efficient, which is F_{61}. This DMU has 100% efficiency score but has slack value in some factors.

Among the distributors, D_3 is the most inefficient distributor (77.6%) compared to D_7 D_3 needs to improve the revenue up to 99.2%, reduce its carbon emissions up to 91.41%, and increase the social benefits by up to 12.58% to achieve the efficiency scale. Moreover, out of 91 farmers, 47.25% (43 farmers) are inefficient. The inefficient stakeholders need to increase their current output and reach the projected output to achieve 100% efficiency. Among the farmers, although the efficiency score is slightly different, F_{14} needs to expend the most effort compared to others in improving their scale efficiency since it has the lowest efficiency score (92.9%). However, from a total revenue perspective, F_9 needs to put in the most effort to increase its revenue up to 98.36%, while F_{76} only needs to make the least effort to increase the revenue up to 4.25%. Regarding the reduction of GHG emissions, F_{14} requires the most effort to reduce the GHG emissions up to 0.01 kg CO_2. For social impact, F_1 needs to put in the most effort to increase the social benefits to achieve efficiency.

In the **second approach**, the benchmarking process was carried out only among farmers and distributors who collaborate with the sugar Company X (F-D benchmarking). The overall efficiency score by using the second approach is 93.7%. This approach considers that 56 stakeholders out of 100 are on the frontier (100% efficient). Although the total number of efficient stakeholders are similar to the first approach, the efficiency score is different. This result implies that DEA analyses the relationship of the stakeholders to others and does not compute an absolute efficiency score. Overall, D_3 has the lowest efficiency score (29.2%) compared to the others. Among all the farmers, 42 farmers are inefficient: the farmer with the lowest efficiency score is F_1 (69.4%). In the partial assessment, from the total revenue perspective, F_{26} needs to apply the most effort to increase revenue up to 97.6%, while F_{76} needs to increase the revenue only up to 12.14%. Furthermore, regarding the reduction of GHG emissions, D_3 is the most inefficient among all the stakeholders. Then, from the social impact perspective, F_1 needs to improve the total benefits up to 66.64%.

In the **third approach**, the benchmarking of farmers and distributors was carried out independently based on the stakeholder category (F/D benchmarking). The overall efficiency score by using the third approach is 91.5%. Out of 91 farmers, 31 farmers were found to be inefficient, and one farmer was weakly efficient. Although F_{61} has 100% efficiency score, it is considered as weakly efficient since it has slack values. Despite the number of inefficient farmers decreasing by this measure, F_1 is still considered as the most inefficient farmer who needs to reduce GHG emissions up to 4.62% and increase the social benefits up to 68.05%. However, from the total revenue perspective, F_{35} requires the most effort to increase the revenue up to 86.69% to be efficient. Nevertheless, among nine main distributors, D_3 and D_7 are still considered as inefficient, and the position of D_3 is the farthest from the frontier (40%). D_3 should increase the total revenue up to 49.77%, reduce GHG emissions by up to 76.96%, and increase the social benefits up to 42.86% to achieve a maximum efficiency score (100%).

From the results, it can be concluded that the result of the efficiency score depends on the performance of other DMU_S in the system and the efficiency score is relative to all others. The comparison of efficiency score for the inefficient stakeholders is shown in Figure 7.

[Insert Figure 7 about here]

Discussion

Overall, the ranking of collaboration behavioural factors represents the factors that are most influential in the supply chain collaboration performance based on the input of the stakeholders involved. In this study, it is found that all ten collaboration behavioural factors play their roles and have positive effects on shaping the supply chain collaboration. Meanwhile, the priority scale for the factors differ in relation to the formation of a supply chain, the nature of the collaboration system, and the characteristics of the stakeholders. This priority scale will influence the result of the efficiency score. Reasonably, the factors that attract higher scores of importance will have stronger influences in the assessment, leading to deliver high-efficiency results. In this case, the three most important factors, i.e. commitment, trust and coordination, become the main determinants for a high-efficiency score in the collaboration quality assessment process. However, a factor that has the lowest score (adaptation and power) is still relevant to the collaboration but considered as have the least relative importance.

With regard to the efficiency score of each stakeholder in the supply chain, among those three approaches tested D_3 has the lowest efficiency score compared to others. Specifically, among the farmers, F_{14} has the lowest efficiency score in the F-C-D benchmarking, while F_1 is the lowest in the F-D benchmarking and F/D benchmarking. From the graph, it can be seen that when the benchmarking is done only among the farmers (F benchmarking), the result reveals that efficiency score is relatively higher than in other approaches. The reason is because the benchmarking process has been done among the stakeholders who have similar characteristics, process, and output level. Therefore, the gap between them is not too high. However, if the comparison process is only among the main distributors (D benchmarking), the efficiency score is lower than in the first approach (F-C-D benchmarking). This

discrepancy is due to the number of DMU_S analysed being less than the minimum standard (minimum 39 DMU_S, while the current number of main distributors is nine). Consequently, the result of benchmarking only among main distributors it is possibly less accurate. Unless the total distributors number more than 38, it is better to use the results from the first (F-C-D benchmarking) or second (F-D benchmarking) approaches to analyse the efficiency score for the main distributors.

For all stakeholders in this study, higher efficiency could be reached by increasing the output level until the projected value is achieved without changing the input level. This improvement is called radial movement or the proportional distance to the efficiency frontier. They have to increase the revenue from the range 4.25% - 98.36% by using the first approach, within range 12.14% - 97.60% by using the second approach, and within the range 4.99% - 90.47% by using the third approach to be DEA efficient. Besides radial movement, a **slack movement** also exists in DMU_S which need additional improvement to reach the efficient frontier due to their inability to be fully efficient with modifications of their input and output. When compared to the entire system, only F_{61} is 100% efficient but has slack in the inputs. The efficient score only occurs in a joint effort, trust, commitment, power, coordination, total revenue, and social impact factors. However, when the benchmarking is only carried out on the farmers, the total revenue was changed into inefficient factors, while the rest remains same. Slack movement is required if the radial movement is not enough to guarantee the achievement of the efficient frontier (Hua et al., 2007). Slacks are also considered as an indicator of inefficiency. The lower efficiency value and the greater amount of slack values, the farther distance i^{th} DMU from the efficiency frontier and the worse their performance relative to the efficient DMU in the model (Weber, 1996). Also, a DMU with slacks values of zero in certain factors indicates that they efficient only in these factors.

The findings have important implications for the manager in the sugar industry who responsible during plantation, processing, and marketing activities. Therefore, the supply chain relationship can be managed well in the form of collaboration. The result of empirical analysis suggests strategies to increase the efficiency score for each stakeholder. The result points out that sustainability has important roles in achieving high collaboration quality. Manager in each department has to pay attention to how to increase the revenue and social impacts while reducing the GHG emissions. Assistance and supervision to the farmers during the plantation has important roles to increase the yield and reduce the waste. It also enhances the positive relationship between farmers and the company. Then, during the production process, the manager has to maintain the process efficiency to optimise the total production. Marketing management has the main role to maintain the good relationship with the distributors and to bridge the information gaps between farmers and distributors in supply chain processes.

Furthermore, the integrated QFD-FANP-DEA method used in this case study demonstrated some advantages over the Supply Chain Collaboration Index (SSCI), which is a method commonly applied for evaluating collaboration quality in extant literature. Whilst SSCI only provides a highly-aggregated overall score for the whole collaboration system; the proposed method is capable of determining the efficiency score for each stakeholder. In such a way, this model has the ability to provide diagnostic

information for in-depth analysis on individual stakeholders and the related collaboration behaviour factors that need to be improved. It is also able to suggest ways for the supply chain to improve its collaboration quality both in part and overall. Therefore, in comparison with SSCI, the proposed method can provide more comprehensive and action-oriented assessment results.

Conclusion and future work

In this study, an integrated QFD-FANP and DEA to assess the collaboration quality in for supply chain has been presented. It captures the detailed assessment process that consists of analysis interdependence the importance weight of the collaboration system requirement by using the integration of QFD and FANP, and the analysis efficiency score of collaboration quality by using DEA. QFD helps to map the correlation and relationship among elements, while FANP helps to determine the importance weight to minimise the ambiguity of human judgement. DEA has a function to determine the relative efficiency of each stakeholder as well as the overall efficiency of collaboration among stakeholders. Using this model will help stakeholders to analyse the demands of business partners and identify problems that arise in the supply chain system and society, and then find solutions to keep them under control to minimise the negative impacts.

Overall, this study contributes to the knowledge by developing a method to assess the collaboration quality in supply chains. This model enables the combination of qualitative and quantitative data to effectively obtain the results that represent the impacts of collaboration behavioural factors and sustainability factors. Furthermore, the collaboration behavioural factors in this model are identified from broad literature of research on collaboration behaviour and associated factors in supply chains (as reported in Dania et al., 2018). Therefore, the application proposed model can be extended for different types of supply chains and industry sectors by adjusting and contextualising the stakeholder requirements respective to the characteristics of collaboration.

For future research, the quantitative analysis of the correlations between importance level of each factor and the level of collaboration needs to be further improved. Methods such as covariance-based structural equation modelling (CBSEM), partial least square (PLS), general structure component analysis (GSCA), and regression that can be applied in further studies. Also, different DEA approaches, such as Game Theory DEA, Stochastic DEA, Fuzzy DEA, and Hybrid DEA, can be investigated to compare the effectiveness of results and to further enhance the efficiency of the assessment model.

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Appendix A

Table A.1 DEA results and improvement suggested

DMU	F-C-D Benchmarking				F-D Benchmarking				F/D Benchmarking			
	Total revenue (%)	GHG Emissions (%)	Social Impact (%)	Technical Efficiency (%)	Total revenue (%)	GHG Emissions (%)	Social Impact (%)	Technical Efficiency (%)	Total revenue (%)	GHG Emissions (%)	Social Impact (%)	Technical Efficiency (%)
F1	95.52	59.29	66.64	93.4	95.47	59.16	66.64	69.4	83.28	4.62	68.05	99.4
F2	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F3	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F4	69.76	10.48	0.95	98.8	57.72	7.04	3.92	95.1	4.99	0.20	4.58	99.8
F5	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F6	93.99	40.59	3.47	95.4	91.94	30.61	14.16	81.9	73.50	1.68	33.31	99.5
F7	9.65	3.74	24.48	99.5	0.00	3.81	24.48	97.3	28.26	1.95	24.94	99.5
F8	94.49	36.47	3.05	95.9	92.73	27.50	13.16	83.2	35.63	1.89	31.32	99.5
F9	98.36	50.49	3.85	94.3	96.90	40.06	16.54	77.2	47.47	1.25	37.83	99.5
F10	69.86	18.53	1.62	97.8	66.94	16.21	8.38	89.2	24.38	3.03	20.32	99.5
F11	73.71	15.75	1.42	98.1	66.58	11.94	6.61	91.8	17.51	3.16	15.51	99.5
F12	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F13	9.61	0.00	25.05	99.9	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F14	81.52	65.75	4.95	92.9	78.16	55.42	20.90	71.7	27.91	1.32	21.02	99.7
F15	85.92	50.02	3.85	94.5	79.89	42.51	17.36	76.1	0.00	0.01	0.00	100
F16	88.51	52.41	4.03	94.3	86.20	43.48	17.09	76.4	26.74	1.40	21.02	99.8
F17	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F18	78.72	17.93	1.54	98	71.38	12.46	6.71	91.8	10.66	0.40	9.15	99.8
F19	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F20	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F21	92.66	26.43	2.15	97	90.67	20.53	9.10	87	10.15	3.00	10.56	99.6
F22	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F23	86.59	17.77	1.62	97.9	85.28	15.68	7.88	89.7	36.70	1.81	33.11	99.6
F24	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100

F25	67.91	55.37	4.03	94.1	62.78	47.99	18.04	75.3	0.00	0.00	0.00	100
F26	97.91	23.31	1.91	97.4	97.60	19.66	9.13	88.1	47.88	0.54	6.98	99.9
F27	69.88	7.70	0.60	99.2	65.47	5.78	3.14	96.1	0.00	0.00	0.00	100
F28	94.89	12.63	1.07	98.6	93.52	9.30	4.80	94	0.00	0.00	0.00	100
F29	95.16	15.54	1.48	98.2	93.35	11.10	6.02	92.9	74.84	0.74	10.40	99.9
F30	95.13	25.48	1.96	97	94.83	23.69	10.24	85.4	42.48	2.44	38.89	99.6
F31	88.41	47.69	4.03	94.7	84.72	36.15	16.53	79.2	30.55	1.01	25.98	99.6
F32	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F33	95.50	25.01	2.06	97.3	94.73	19.89	9.38	87.9	7.59	0.59	7.75	99.9
F34	48.19	20.20	1.58	97.7	41.54	18.61	8.09	88.5	0.00	0.00	0.00	100
F35	96.88	16.35	1.58	98.2	95.86	11.28	6.19	92.7	86.69	1.33	14.31	99.8
F36	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F37	8.10	7.70	0.71	99.1	0.00	6.88	1.19	98.4	0.00	0.00	0.00	100
F38	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F39	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F40	97.41	64.46	4.76	93.2	96.87	53.65	20.01	72.8	17.45	1.25	21.02	99.8
F41	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F42	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F43	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F44	0.00	1.91	0.15	99.8	19.34	1.38	0.74	99	19.79	0.60	9.50	99.8
F45	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F46	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F47	90.59	30.11	2.49	96.8	90.63	21.01	9.75	87.4	0.00	0.00	0.00	100
F48	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F49	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F50	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F51	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F52	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F53	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F54	92.46	13.60	1.19	98.5	90.34	9.78	5.01	93.7	0.00	0.00	0.00	100
F55	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F56	89.61	57.04	4.85	93.7	86.20	43.24	19.16	76	41.46	2.00	36.31	99.5
F57	92.98	57.04	4.85	93.6	90.68	43.40	19.35	75.8	45.96	4.18	41.61	99.5
F58	74.25	20.96	1.88	97.6	63.20	14.34	7.54	90.7	12.96	0.57	11.28	99.8
F59	67.60	20.96	1.88	97.7	53.69	14.18	7.44	90.9	11.56	0.55	9.84	99.8
F60	78.84	21.71	1.88	97.6	68.92	14.70	7.75	90.5	16.19	0.65	14.38	99.7
F61	0.00	0.00	0.00	100	0.00	0.00	0.00	100	15.05	0.89	0.00	100
F62	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F63	20.89	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F64	78.09	21.71	1.88	97.6	67.81	14.89	7.85	90.4	18.71	0.76	16.61	99.7
F65	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F66	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F67	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F68	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F69	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F70	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F71	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F72	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F73	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F74	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F75	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F76	4.25	25.73	2.34	97.1	12.14	19.30	9.74	88	0.00	0.00	0.00	100
F77	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F78	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F79	78.51	11.43	1.07	98.7	70.57	7.06	3.92	95.1	44.14	0.26	5.44	99.8
F80	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F81	74.22	19.82	1.62	97.8	31.56	11.56	5.93	92.3	0.00	0.00	0.00	100
F82	94.16	24.05	1.96	97.2	93.79	22.51	9.59	86.4	20.99	1.48	25.05	99.8

F83	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F84	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F85	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F86	96.75	30.49	2.68	96.6	95.60	22.64	11.28	86.2	29.66	1.94	28.48	99.8
F87	63.28	16.20	1.48	98.2	47.75	11.20	6.19	92.7	0.00	0.00	0.00	100
F88	78.18	17.15	1.58	98.1	69.19	11.66	6.37	92.5	13.36	0.96	12.13	99.8
F89	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F90	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
F91	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
D1	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
D2	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
D3	47.30	91.41	12.58	77.6	70.66	70.51	54.77	29.2	49.77	76.96	42.86	100
D4	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
D5	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
D6	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
D7	90.90	54.44	1.48	96.8	90.48	50.56	6.71	87.1	90.47	50.47	6.89	100
D8	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
D9	0.00	0.00	0.00	100	0.00	0.00	0.00	100	0.00	0.00	0.00	100
C1	0.00	0.00	0.00	100								

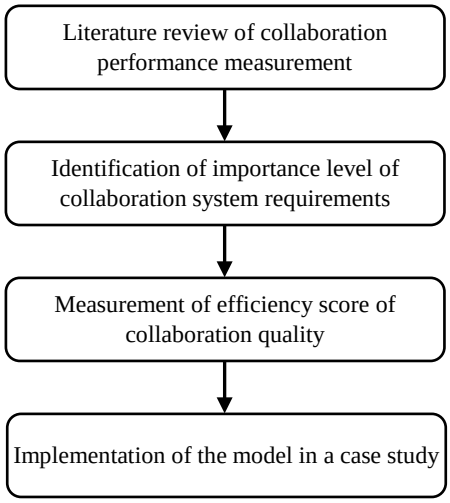


Figure 1. Research Methodology

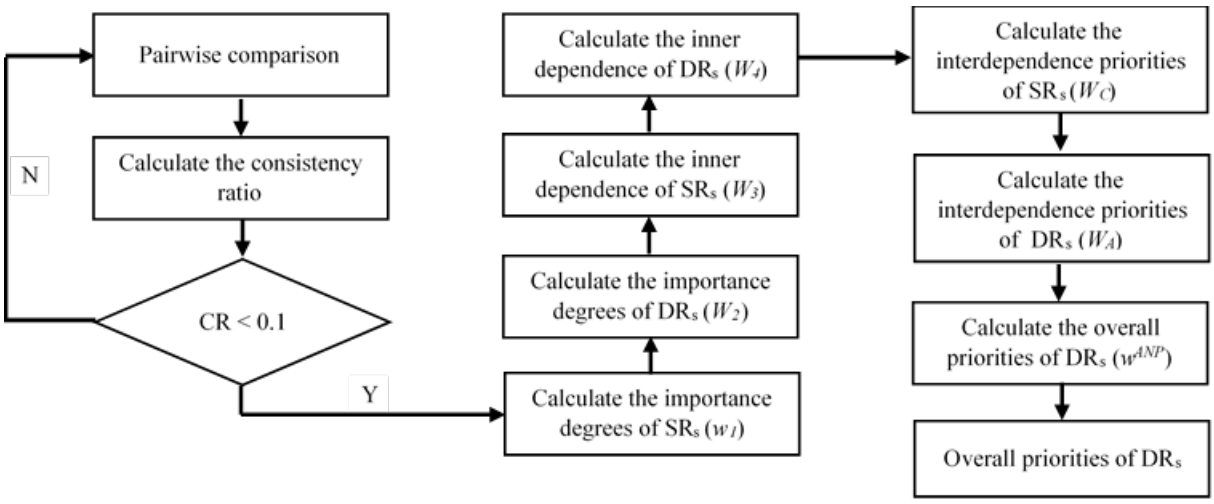


Figure 2. Flow diagram of identifying importance level of collaboration system requirements

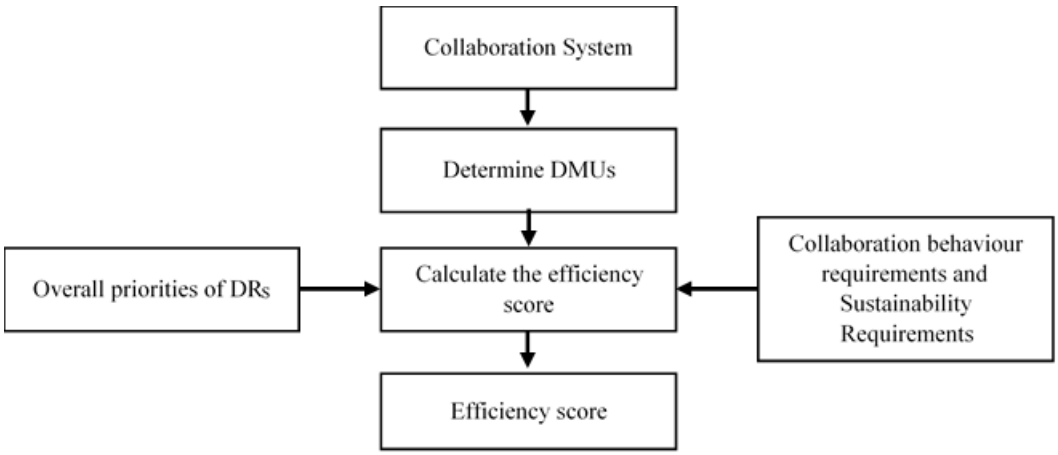


Figure 3. Measuring efficiency score of collaboration quality

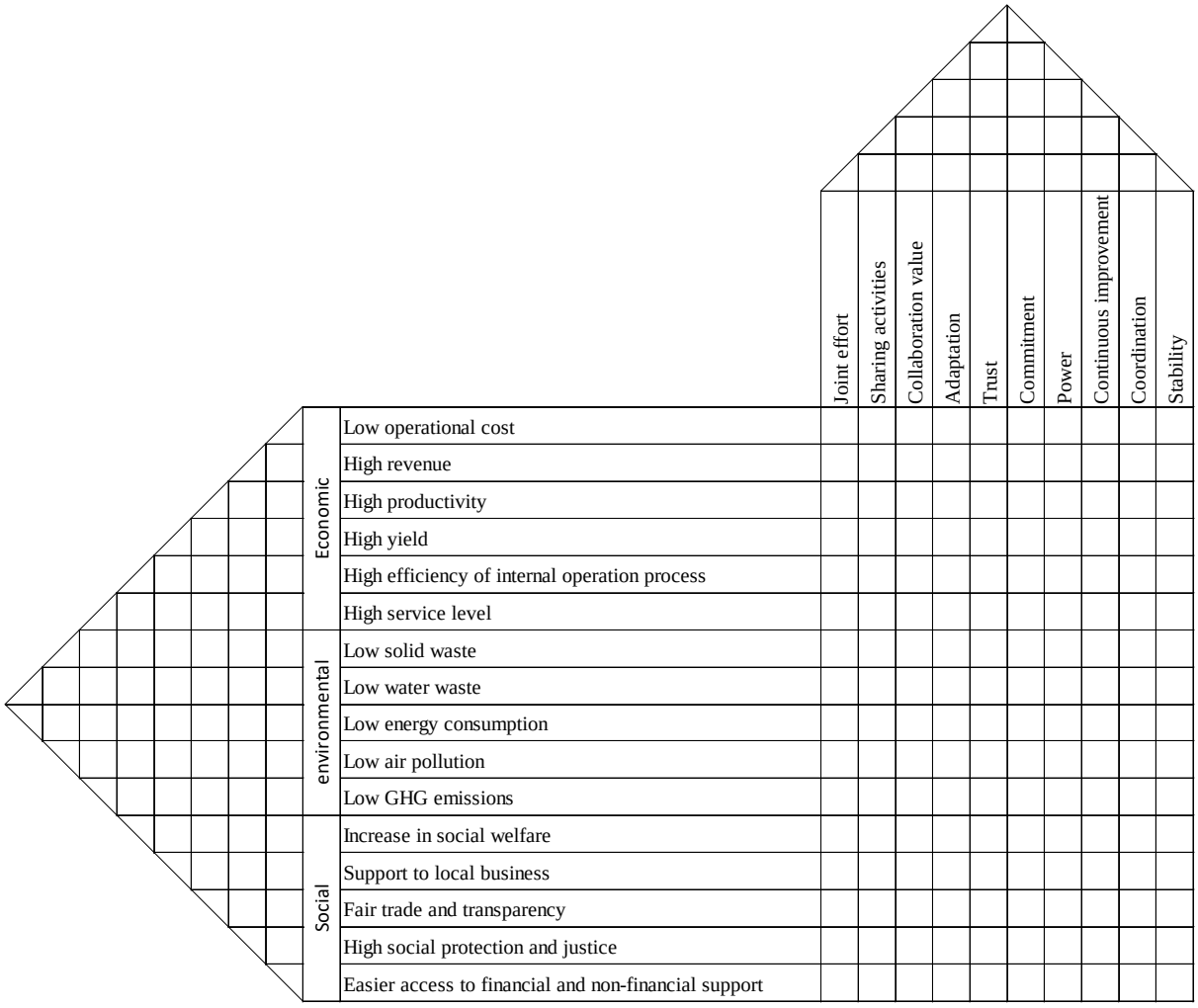


Figure 4. House of Quality (*HoQ*) of collaboration quality assessment

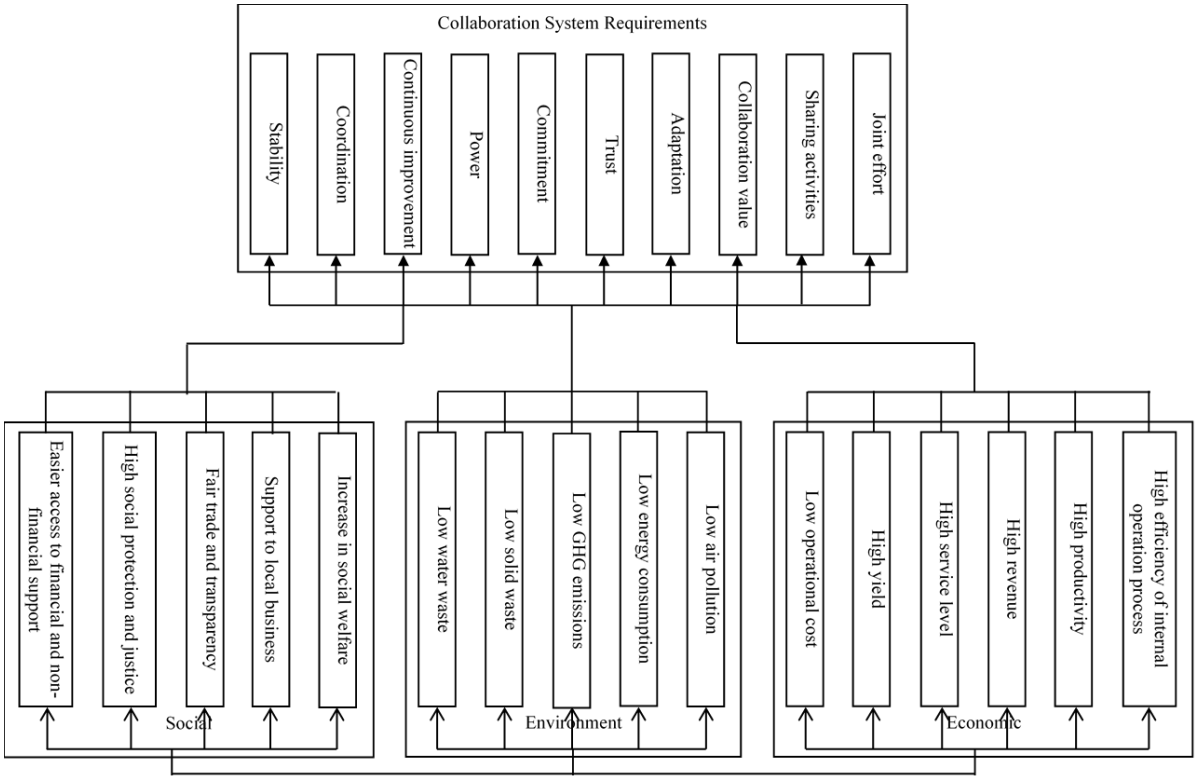


Figure 5. ANP network diagram

								0.074	0.091	0.090	0.098	0.085	0.101	0.096	0.103	0.097	0.086				
								0.078	0.076	0.092	0.098	0.097	0.079	0.093	0.097	0.099	0.097				
								0.105	0.101	0.101	0.099	0.088	0.098	0.096	0.100	0.097	0.097				
								0.093	0.093	0.086	0.099	0.074	0.058	0.094	0.096	0.100	0.097				
								0.114	0.116	0.126	0.103	0.133	0.137	0.100	0.099	0.103	0.103				
								0.123	0.127	0.120	0.107	0.121	0.135	0.102	0.102	0.108	0.108				
								0.095	0.095	0.078	0.093	0.064	0.092	0.101	0.091	0.087	0.092				
								0.108	0.107	0.103	0.098	0.119	0.095	0.096	0.102	0.103	0.103				
								0.099	0.095	0.106	0.111	0.123	0.096	0.106	0.103	0.105	0.107				
								0.110	0.098	0.098	0.095	0.096	0.109	0.116	0.107	0.101	0.112				
								Joint effort	Sharing activities	Collaboration value	Adaptation	Trust	Commitment	Power	Continuous improvement	Coordination	Stability				
0.196	0.189	0.192	0.219	0.191	0.166	Low operational cost	0.100	0.102	0.097	0.091	0.099	0.112	0.107	0.072	0.108	0.108	0.103	0.115			
0.164	0.176	0.207	0.153	0.160	0.166	High revenue	0.099	0.102	0.095	0.092	0.096	0.104	0.110	0.067	0.124	0.105	0.106	0.102			
0.164	0.155	0.226	0.152	0.135	0.144	High productivity	0.100	0.104	0.106	0.099	0.100	0.105	0.115	0.049	0.116	0.105	0.100	0.097			
0.156	0.160	0.193	0.219	0.164	0.175	High yield	0.099	0.110	0.103	0.096	0.094	0.101	0.115	0.058	0.127	0.101	0.094	0.106			
0.166	0.168	0.156	0.150	0.186	0.172	High efficiency of internal operation process	0.101	0.091	0.094	0.103	0.080	0.101	0.122	0.073	0.121	0.112	0.102	0.100			
0.154	0.152	0.026	0.108	0.164	0.178	High service level	0.099	0.095	0.072	0.100	0.101	0.138	0.116	0.039	0.121	0.111	0.107	0.078			
0.000	0.215	0.202	0.073	0.182	0.141	Low solid waste	0.027	0.098	0.073	0.105	0.082	0.094	0.128	0.074	0.129	0.129	0.088	0.022			
0.000	0.207	0.198	0.149	0.172	0.008	Low water waste	0.027	0.089	0.077	0.099	0.078	0.097	0.129	0.076	0.149	0.117	0.089	0.020			
0.000	0.193	0.203	0.303	0.193	0.240	Low energy consumption	0.027	0.098	0.080	0.090	0.078	0.094	0.124	0.089	0.138	0.099	0.109	0.031			
0.000	0.195	0.201	0.242	0.248	0.314	Low air pollution	0.028	0.086	0.068	0.099	0.081	0.076	0.137	0.082	0.149	0.137	0.086	0.033			
0.000	0.190	0.196	0.233	0.205	0.297	Low GHG emissions	0.028	0.097	0.053	0.099	0.066	0.106	0.147	0.040	0.173	0.120	0.100	0.031			
0.000	0.398	0.196	0.190	0.101	0.224	Increase in social welfare	0.053	0.083	0.069	0.115	0.093	0.119	0.127	0.015	0.134	0.131	0.115	0.059			
0.000	0.173	0.206	0.191	0.136	0.198	Support to local business	0.052	0.075	0.049	0.103	0.061	0.129	0.134	0.056	0.151	0.125	0.118	0.048			
0.000	0.161	0.200	0.248	0.222	0.131	Fair trade and transparency	0.053	0.075	0.062	0.077	0.060	0.139	0.148	0.069	0.126	0.111	0.134	0.051			
0.000	0.098	0.200	0.179	0.274	0.204	High social protection and justice	0.054	0.086	0.070	0.079	0.077	0.135	0.147	0.003	0.153	0.112	0.138	0.051			
0.000	0.170	0.198	0.192	0.267	0.244	Easier access to financial and non-financial support	0.053	0.066	0.063	0.107	0.054	0.150	0.133	0.080	0.111	0.117	0.119	0.057			
								0.092	0.091	0.098	0.089	0.114	0.116	0.088	0.104	0.105	0.104				
								0.092	0.091	0.098	0.089	0.114	0.115	0.088	0.104	0.105	0.104				
								0.092	0.090	0.098	0.088	0.114	0.116	0.088	0.104	0.105	0.104				
								0.092	0.090	0.099	0.088	0.114	0.116	0.088	0.104	0.105	0.104				
								0.093	0.091	0.098	0.088	0.114	0.116	0.088	0.103	0.105	0.104				
								0.092	0.091	0.098	0.088	0.115	0.116	0.087	0.104	0.106	0.103				
								0.093	0.091	0.098	0.088	0.114	0.115	0.088	0.103	0.105	0.104				
								0.093	0.091	0.098	0.088	0.114	0.115	0.088	0.103	0.105	0.104				
								0.093	0.091	0.098	0.088	0.113	0.115	0.089	0.103	0.105	0.105				
								0.094	0.091	0.098	0.088	0.113	0.115	0.089	0.103	0.105	0.105				
								0.093	0.091	0.098	0.087	0.114	0.116	0.088	0.103	0.105	0.104				
								0.093	0.091	0.098	0.088	0.115	0.116	0.087	0.104	0.106	0.103				
								0.093	0.092	0.098	0.087	0.114	0.115	0.087	0.104	0.106	0.104				
								0.093	0.091	0.098	0.087	0.115	0.116	0.087	0.104	0.106	0.105				
								0.092	0.091	0.098	0.087	0.115	0.116	0.087	0.104	0.106	0.104				
								0.092	0.091	0.097	0.087	0.115	0.116	0.087	0.104	0.106	0.104				
								0.092	**0.091**	**0.098**	**0.088**	**0.114**	**0.116**	**0.088**	**0.104**	**0.105**	**0.104**				

Figure 6. HoQ of Case Study

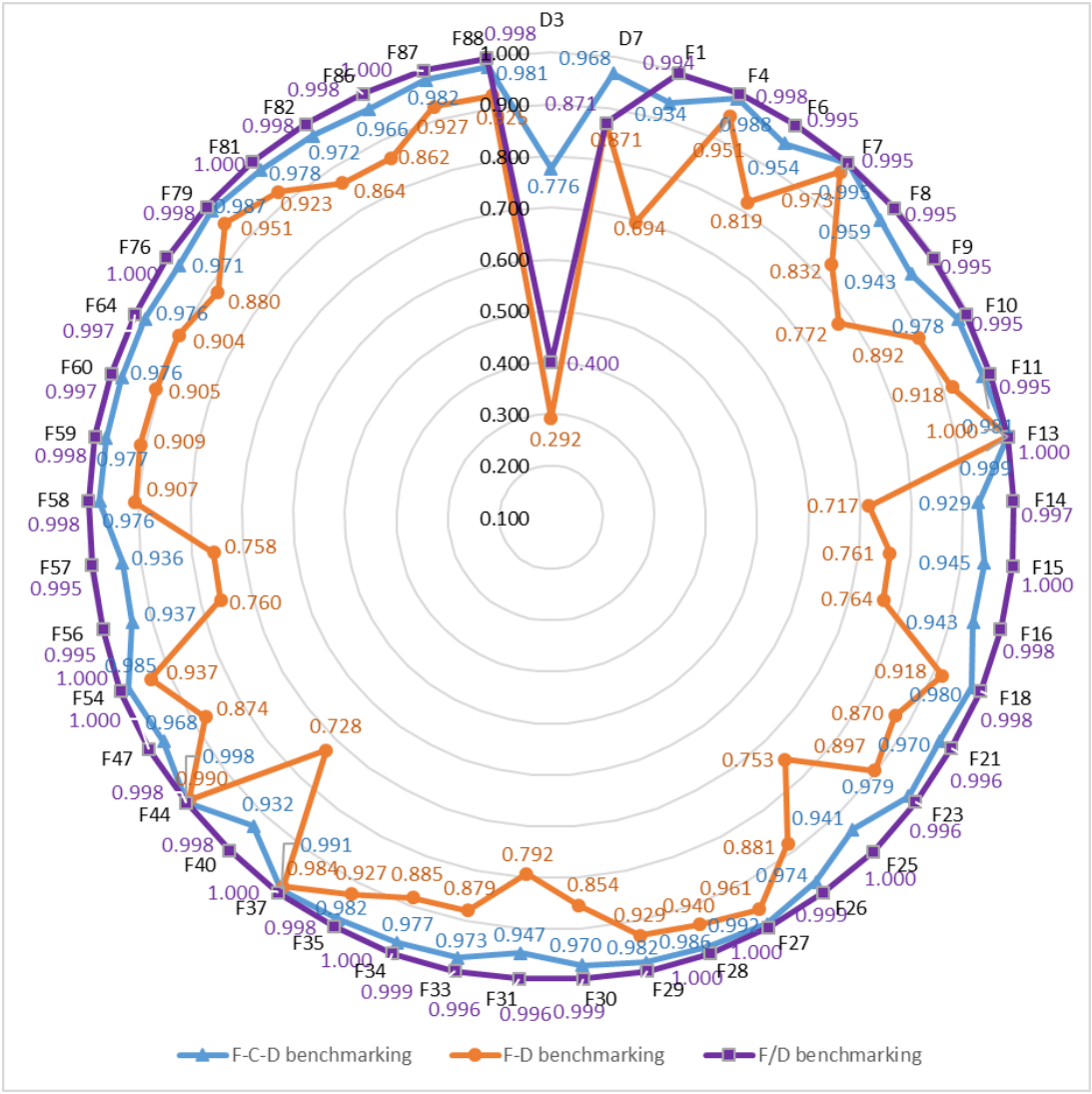


Figure 7. Efficiency score of inefficient DMUs in sugar supply chain