Decision Science Letters 11 (2022) 419–430

Contents lists available at GrowingScience

Decision Science Letters

homepage: www.GrowingScience.com/dsl

Development of efficient strategies to optimize production efficiency: Evidence from Pine chemical industry

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C H R O N I C L E

Article history:
Received April 18, 2022
Received in revised format: June 18, 2022
Accepted July 3 2022
Available online July 3, 2022

Keywords:
Pine chemical products
Data envelopment analysis (DEA)
Efficiency/inefficiency
Dimension of operational capability
Analytic hierarchy process (AHP)

A B S T R A C T

A pine tree, namely Pinus merkusii is an indigenous species from Indonesia which grows extensively in the Island of Java, Sumatera, and Sulawesi. This plant produces both timber and non-timber forest products (TFP and NTFP). Resin or oleum pine resin, as the main NTFP of Pinus merkusii, becomes the raw material for the gum rosin and turpentine oil industry. Globally, Indonesia is ranked 3rd as a producer of pine products after China and Brazil, in which Perhutani as a State Owned Forestry Enterprise plays a major role in this industry. On average, Perhutani manufactures 65,000 tons of gum rosin and 14,000 turpentine oil per year. Entire volume of both pine products is produced by nine factories with various maximum capacities. Therefore, this research aims to measure efficiency and/or inefficiency score of each factory using data envelopment analysis (DEA) method, which is then complemented by a single bootstrap technique with 2.000 iterations to eliminate bias scores. Cost of raw material, labour, energy, and general affairs are employed as input variables, while the output variables are total revenue and production volume. As result, 27.3% inefficiency (efficiency score = 72.7%) is generally found in all Perhutani's pine chemical factories. To resolve this inefficiency issue, analytical hierarchy process (AHP) pairwise comparison questionnaire is distributed to 13 expert respondents to determine prioritized operational capability to focus on in optimizing efficiency of production performance. Dimensions of Cost, Quality, Flexibility, Innovation, and Sustainability are selected to construct the AHP questionnaires.

1. Introduction

Export activities play an important role in the dynamics of business in Indonesia, not only with respect to the foreign exchange earnings but also in increasing gross domestic product (GDP). In 2019, total value of Indonesia's exports was worth US$ 167,683 million, 92.97% or US$ 155,893.7 million was obtained from non-oil and gas and 7.03% or US$ 11,789.3 million from oil and gas commodities (BPS, 2020). One of the potential non-oil and gas export commodities comes from the forestry sector. Indonesian tropical rain forests provide high organism biodiversity, both of flora and fauna. Tropical rainforest also provides crucial ecosystem services such as raw materials, soil protection, timber source, medicinal plants, carbon sequestration, and watershed protection (Berry et al., 2010; Dent & Wright, 2009; Foody & Cutler, 2003; Rachel, 2014). Not only famous for their wood products, several non-timber products from Indonesia also dominate the world's export volume, one of which is gum rosin, a main non-volatile product yielded from raw pine resin processing. From the same process, a volatile material called turpentine oil is also produced (Riwayati, 2005). Both pine chemical products are widely used in the manufacture of soap, paints, waxes, adhesives, and various pharmaceutical products (Wang

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doi: 10.5267/dsl.2022.7.003

et al., 2018). Pine tree species that contributes to producing raw pine resin is called Pinus merkusii, an indigenous plant from Indonesia, planted extensively in the Island of Java, North Sumatera, and South Sulawesi (Corryanti & Rahmawati, 2015). Apart from Indonesia, Pinus merkusii also grows naturally in Vietnam, Cambodia, Thailand, Burma, India, and the Philippines (Sallata, 2013). Indonesia ranked third (9.2%) among the largest producers of gondorukem in the world after China (48.3%) and Brazil (20.7%) (Baumassy & Oy, 2019).

On the island of Java, a State Owned Forestry Enterprise named Perum Perhutani managed the 900,000 hectares area of Pinus merkusii în 2019 (Perhutani, 2020). Perum Perhutani is also known as the biggest pine products producer in Indonesia with an average volume of 65,000 tons of gum rosin and 14,000 tons of turpentine oil per year. (Perhutani, 2019; 2020). In 2019, the total sales value of NTFP (export and local market) contributed around 40% to Perhutani's total revenue, of which 33% revenue was generated from export trading of gum rosin and turpentine oil and 7% from domestic market (Perhutani, 2020). According to the law of mass transfer, pine resin processing produces an average of 70% gondorukem, 17% turpentine, and the remaining 13% consists of water and impurities (Riwayati, 2005). The yield of gondorukem, which is four times larger than turpentine, makes the sales of gondorukem a major contributor in achieving the revenue target from Perhutani's non-timber forest products (NTFPs). In fact, changes in the market price of gondorukem and turpentine are very volatile every year and China, as the largest producer, is still the main country determining market prices internationally (Fachrodji, 2009). **Fig. 1** shows the changes in sales value of gum rosin which was not synergistic with the changes in its volume. Total sales value kept decreasing from 2014 to 2019 despite the volume increasing (Perhutani, 2019; 2020).

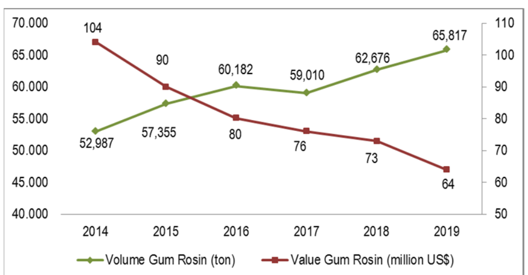

Fig. 1. Changes in total volume (ton) and value (million US$) of gum rosin from 2014 to 2019

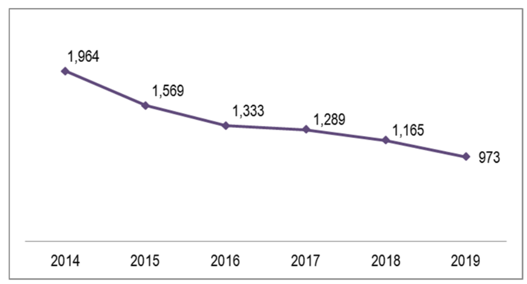

Fig. 2. Unit price changes of gum rosin from 2014 to 2019

The quotient of total revenue and sales volume can describe the average unit price of a product in a one year period of operation. Fig. 2 shows the unit price of gum rosin from 2014 to 2019 in US$ per ton. It continued to experience a significant decline at the price of US$ 1,964 per ton in 2014 falling to US$ 973 per ton kg in 2019 (Perhutani, 2019; 2020). Perhutani's unit price of gum rosin is notably influenced by the changes of demand volume in the market as well as the fluctuations of its global price. From a corporate point of view, it directly affects Perhutani's total profit (loss) with the existence of overheads and other fixed costs which are quite hard to reduce. In addition, Perhutani as a labor-intensive enterprise will not be able to compete vis-a-vis with private companies which can manage their total production costs more efficiently. They usually offer a more competitive selling price even though the total production volume is far below Perhutani as the market leader. Given these constraints, Perhutani is required to manage its pine chemical industry more efficiently in terms of minimizing production costs and optimizing production capacity, which will have a direct impact on the increase in total NTFP revenues and corporate profits in general.

Hence, this research aims to measure and analyze the efficiency of Perhutani's pine chemical factories using a non-parametric method namely data envelopment analysis (DEA) with the type of variable return-to-scale (VRS) and output oriented (Banker et al., 1984). Variables involved in the measurement are taken from production cost data from 2017 to 2019. All factories, 9 units in total, are distributed evenly on the island of Java, i.e. Garahan (GRHN), Sukun (SUKN), and Rejowinangun (RJWG) in East Java; Paninggaran (PNGR), Sapuran (SPRN), Winduaji (WNDJ), Cimanggu (CMGU), and Perhutani Pine Chemical Industry (PPCI) in Central Java; and Sindangwangi (SDWG) in West Java. As a comparison with the efficiency score obtained from DEA, the percentage of used capacity of each factory will also be calculated. An additional bootstrap technique is adopted to remove bias-score from the deterministic value. Therefore, the bias-corrected efficiency score, as the final result of the first analysis phase, reflects closer value to the actual data population (Simar & Wilson, 1998). The second phase of analysis employs multi-criteria decision-making techniques namely analytical hierarchy process (Saaty, 2008) in developing strategies to improve operational capabilities and reduce factors that can cause inefficient performance. In the preparation of the AHP questionnaire, several dimensions of operational capability based on the construction of operations management (Swink & Hegarty, 1998), namely operational innovation, operational improvement, and operational cooperation were used to fill the criteria level. Meanwhile, another concept of the operational capability dimension based on the concept of competitive advantage (Hilletofth & Sansone, 2018) is used to fill the alternative level. Responses were collected from 13 experts consisting of academics and practitioners. Finally, this research is expected to contribute to increasing the value of trade, especially exports of gum rosin and turpentine oil so that it can provide better financial benefits for the country and the company.

2. Literature Review

2.1 Data Envelopment Analysis (DEA)

DEA is well-known as a non-parametric approach to measure productivity and relative efficiency by instituting a production frontier line as its "efficient" benchmark (Zhu, 2003). In general, DEA evaluates and scores the efficiency of a company or unit called DMU (decision making unit) compared to other similar DMUs that have the best performance in the same industry. Thus, DEA is a relative measurement technique in which the efficiency score for each DMU is determined according to the input and output variables of entire samples (Coelli et al., 1998). DMU's relative efficiency is measured by estimating the output ratio for an input among the DMUs. A DMU with an efficiency score of 100% is considered efficient, while a DMU with a score below 100% is considered inefficient. The DEA method will identify a set of efficient DMUs, which will then be used as a benchmark to improve the efficiency of inefficient DMUs by optimizing output or reducing input values to become efficient (Zhu et al., 2014). Input and output variables must be homogenous among DMUs in DEA, which means that they utilize the same resources to produce the same output (Tsai et al., 2002). Technical efficiency can be measured from two orientations. First, the output-oriented DEA method calculates technical efficiency by maximizing the level of output at a fixed input, whereas input-oriented DEA calculates technical efficiency by minimizing the level of input at a fixed output. Efficient DMUs will form a frontier line as a reference for inefficient DMUs. All efficient DMUs (efficiency score equal to one) will fall exactly on this frontier line (Farrell, 1957).

There are two general DEA models to measure efficiency score. The first model was introduced by Charnes, Cooper and Rhodes (CCR) in 1978. This model operates under the assumption of constant return to scale (CRS). The CCR model determines efficiency by maximizing the weight of output to input based on the condition that there is an equal ratio for all DMUs and all firms operate at optimal scale. An increase in output will impact on an increase in input proportionally (Coelli et al., 1998). The second DEA model is known as BCC, proposed by Banker, Charnes and Cooper (1984), which is an extension of the CCR model. The BCC model assumes a variable return to scale (VRS) to identify the envelope surface in the form of a convex line covering the entire existing DMU. Cooper, Seiford and Tone (1999) stated the line that forms the frontier line leads to several characteristics, namely IRS (increasing return to scale) which occurs in the first solid line segment, DRS (decreasing return to scale) in the second solid line segment, and CRS (constant return to scale) which occurs at the point of transition from the first to the second segment. Unlike the CCR model, the BCC model is appropriate to use when firms are not operating at optimal or ideal scale.

An additional method called single bootstrap is also employed to remove bias on DEA efficiency score (Simar & Wilson, 1998). The conventional or deterministic DEA method does not involve the possibility of random errors in its mathematical formula. In other words, DEA assumes that the distance between the observations and the frontier line simply reflects inefficiency. However, in reality, this gap reflects not only inefficiency but also statistical noise. Therefore, it is necessary to determine the statistical properties of conventional DEA scores for the purposes of interpretation and inference analysis. Bootstrap can be defined as an iterative simulation of the data generation process through resampling. This method is applied on the conventional DEA measurement of each simulated sample so that the final bias-corrected efficiency score can mimic distribution of the original population (Simar & Wilson, 1998, 2000).

2.2 Gum rosin and turpentine oil as two main Perhutani's commercial NTFPs

Perusahaan Umum Kehutanan Negara (abbreviated as Perhutani) is a State-Owned Enterprise of the Republic of Indonesia that is engaged in the forestry-based-activities sector. Referring to Annual Report 2019, Perhutani's main business covers activities of forest governance and management plans, utilization of forest service and products (timber and non-timber), forest products trade, forest rehabilitation and reclamation, forest protection and conservation, forest education and training, forest research and development, and agroforestry expansion. According to the Annual Report 2019, Perhutani distinguishes its business line into three main groups, namely TFP (timber forest product), NTFP (non-timber forest product), and Agroforestry-Ecotourism. Revenue contribution of each business line from 2017 to 2019 is tabulated Table 1 and visually shown in Fig. 3.

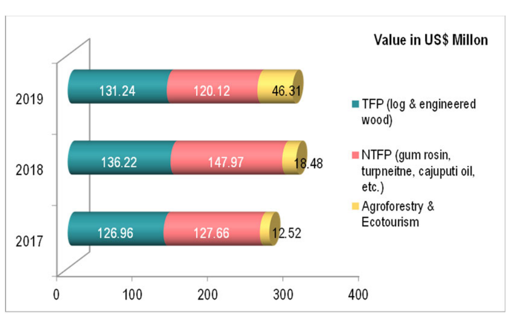

Fig. 3. Chart of Perhutani Revenue Stream by Line of Business fro 2017 to 2019

Tabel 1
Perhutani Revenue Stream by Line of Business & Each Contribution from 2017 to 2019

Business Line	Value of Revenue (US$ Million)					
	2017		2018		2019	
TFP (log & engineered wood)	126.96	47.5%	136.22	45.0%	131.24	44.1%
NTFP (gum rosin, turpneitne, cajuputi oil, etc.)	127.66	47.8%	147.97	48.9%	120.12	40.4%
Agroforestry & Ecotourism	12.52	4.7%	18.48	6.1%	46.31	15.6%
Total Pendapatan per Tahun	**267.13**	**100%**	**302.67**	**100%**	**297.67**	**100%**

Around 90% of total NTFP (non-timber forest product) revenue comes from gum rosin and turpentine trades. In 2019, these two products contributed about 35% of Perhutani's total revenue. Mostly (78.35%) are intended for export activities, and the rest (21.65%) is produced to fulfil domestic needs (Perhutani, 2020).

Perhutani has a total of 9 pine chemical factories, evenly distributed along the Island of Java. The average production volume of gum rosin is 65,000 tons per year, while 14,000 tons per year for the turpentine oil (Perhutani, 2020). Both products are produced from the distillation process of oleum pine resin (oleoresin) with 70-80% yields for gum rosin and 15-25% for the turpentine oil (Riwayati, 2005). Quality grades of gum rosin are determined based on standards of color and clarity. The international reference used to measure gum rosin's color, namely Gardner Color standard (ASTM 6166) was reissued by the American Society for Testing and Materials in 2016. The lower the Gardner value, the higher the quality of gum rosin and the price is more expensive (Riwayati, 2005).

2.2 Dimensions of Operational Capability

Operational capability is one of the particular components of organizational capability. According to the resource-based view (RBV) approach (Wernerfelt, 1984), an organization has different levels of capability in resource exploitation to achieve its desired goals (Amit & Schoemaker, 1993; Peteraf, 1993). Resources can be tangible (financial and building), intangible (technology, reputation, and culture), or human (special skills and knowledge, communication, and motivation). On the other hand, organizational capabilities represent a distinctive and superior way of distributing, allocating, and coordinating resources (Amit & Schoemaker, 1993; Cavusgil et al., 2007; Schreyogg & Kliesch-Eberl, 2007).

The development of operational capabilities is very important to create a sustainable competitive advantage in a dynamic market environment (Corbett & Claridge 2002; Sansone et al., 2017). Operational capability is the company's ability to leverage resources into the operating system, developed over time through the implementation of competencies on competitive priorities (Corbett & Claridge 2002; Koufteros et al., 2002; Prester et al., 2016). A key element of an operational strategy is to adapt operational capabilities to meet the demands and needs of an ever-changing market (Grobler & Grubner 2006). Operational capability determines operational strategy and its performance. It is conceptualized as a firm's competitive strength (Grobler & Grubner 2006; Hallgren 2007; Liu & Liang 2015). In order for companies to anticipate market changes, operational capabilities should be dynamic and able to transform quickly to win a superior position over its competitors (Cruz & Rodriguez 2008; Liu & Liang 2015). Several contexts of operational capability dimensions have become the topic of discussion by several previous researchers. Hilletofth & Sansone (2018) defined multidimensional operations strategy, namely cost, quality, delivery, flexibility, service, innovation, and sustainability. Meanwhile, Swink and Hegarty (1998) focused more on operations management which is described as operational improvement, operational innovation, operational customization, operational cooperation, operational responsiveness, and operational reconfiguration.

2.3 Multi-criteria decision making of prioritized operational capability through analytic hierarchy process (AHP)

The Analytic Hierarchy Process (AHP) method was developed by Thomas L. Saaty in the 1970s for decision making by taking into account the factors of perception, preference, experience and intuition. AHP combines personal judgments and values into one logical way. Analytic Hierarchy Process (AHP) can solve complex multi-criteria problems into a hierarchy. Complex problems can be interpreted that the criteria for a problem are so many (multi-criteria), the structure of the problem is not clear, the opinion of the decision maker is uncertain, the decision maker is more than one person, as well as the inaccuracies of the available data. According to Saaty (2008), hierarchy is defined as a representation of a complex problem in a multi-level structure where the first level is the goal, followed by the level of factors, criteria, sub-criteria, and so on down to the last level of alternatives. With a hierarchy, a complex problem can be broken down into groups which are then arranged into a hierarchical form so that the problem will appear more structured and systematic.

Supriadi et al., (2018) stated that as its advantages, AHP can simplify complex and unstructured problems into an easy to understand and flexible model. AHP can solve problems with independent elements which do not have any linear correlation. AHP groups elements into a hierarchical structure at different levels where human natural thinking also does the same thing. AHP provides a scale of measurement for prioritizing decisions, and advances logical consistency in judgments to make priorities. Meanwhile, this method also has several shortcomings, including the assessment given by the

AHP model is highly dependent on the subjectivity and perception of each respondent. AHP also does not have statistical testing. Hence, there is no level of confidence as a benchmark for the correctness of the hierarchical model.

3. Methodology

3.1 Study design and sampling strategy

The object of this study is Perum Perhutani, a State-Owned Forestry Enterprise of the Republic of Indonesia. Scope of this research is limited only in gum rosin and turpentine oil or pine products business line in general. Both, primary and secondary data collection techniques are employed. In the first stage, main secondary data (i.e., Production Cost Reports from 2017 to 2019) are obtained to measure efficiency scores of all pine chemical factories using DEA variable return-to-scale method (Banker et al., 1984). Bias score measurement is included following Simar & Wilson's (1998) single bootstrap technique. Nine pine chemical factories of Perhutani are selected as DMU population for DEA, namely Garahan (GRHN), Sukun (SUKN), Rejowinangun (RJWG), Paninggaran (PNGR), Sapuran (SPRN), Winduaji (WNDJ), Cimanggu (CMGU), Perhutani Pine Chemical Industry (PPCI), and Sindangwangi (SDWG). Cost of raw material, labour cost, cost of energy, and general affair cost are chosen as input variables, whreas total revenue and total production volume as output variables. Cost grouping (direct material, direct labour, and factory overhead) is made following the study of Charles T. Horngren (2008). Other supporting secondary data are also used, e.g., Annual Report 2019 (Perhutani, 2020) and Statistics Book 2014-2018 (Perhutani, 2019). Next, the second stage of analysis employs primary data collection through focus group discussion (FGD) by administering AHP hierarchical questionnaires on the pairwise comparison matrix (Saaty, 2008). Goal of the AHP matrix in this research is to develop strategies based on prioritized operational capability to optimize efficiency or to reduce inefficient performance of Perhutani pine chemical factories.

3.2 Questionnaire development

The AHP questionnaire is constructed in a set of pairwise comparison matrices. Each element in an upper level is used to compare the elements in the level immediately below with respect to it. A scale of numbers is used to indicate how many times more important one element is over another element. According to intensity of importance, scale numbers are divided from 1=equally importance to 9=extreme importance (2=weak or slight; 3=moderate importance; 4=moderate plus; 5=strong importance; 6=strong plus; 7=very strong or demonstrated importance; 8=very, very strong) (Saaty, 2008). Hierarchical structures, in which the constituent elements are utilized to construct the AHP questionnaire, are shown in the Table 2.

Table 2
Hierarchical Structures in AHP Questionnaire Pairwise Comparison

Goal	Developing strategies in optimizing production efficiency of Perhutani's pine chemical factories
Criterions	1) Product development capability; 2) Process & technology capability; 3) Cooperation capability
Factors	1) Operational improvement; 2) Operational innovation; 3) Operational cooperation
Alternatives	1) Cost efficiency; 2) Flow efficiency; 3) Product quality; 4) Process quality; 5) Delivery flexibility; 6) Employee flexibility; 7) Product innovation; 8) Process innovation; 9) Product sustainability; 10) Process sustainability

Criterion level is selected with regard to a study conducted by Huang and Chen (2003) about capability analysis for a multi-process product. Factor level is filled with the elements composed by Hilletofth & Sansone (2018) in which their research framework defined capability from operation strategies point of view. Lastly, elements of Alternative level are constituted with respect to a comprehensive multiple-case study about competitive strategy of operational capability by Hilletofth & Sansone (2018).

3.3 Data Analysis

With regard to the DEA method, selected input and output variables are processed using software called R-statistics to produce a deterministic efficiency score as well as scale efficiency score. Simar & Wilson's (1998) bootstrap techniques are employed as an extensive technique to result in bias-corrected efficiency scores of each factory. The DEA variables which cause inefficiencies are further analyzed using AHP method to determine the strategies development in optimizing factory performance. Collected primary data in the arrangement of pairwise comparison matrix is analyzed using software called Expert Choice™ to summarize the most prioritized alternative of operational capability dimension to work and focus on. A total of 13 expert respondents which consist of some of Perhutani's top management responsible for pine chemical business operation, private entrepreneur from similar business line, buyer of pine products, and academic. Expert Choice™ software will combine entire respondents' answers. There will be one collated chart with eigenvectors for each alternative.

4. Result

This section consists of two parts. First, the DEA method will result in an efficiency score, both deterministic and bias-corrected, as well as the scale efficiency score of Perhutani's pine chemical factory. Second, the AHP method will result in prioritized dimension operational, obtained and calculated collectively from all consistent responses.

4.1 DEA efficiency scores of Perhutani's pine chemical factories

In the measurement of DEA efficiency score, this study employs an output-oriented variable-return-to-scale approach (Banker et al., 1984). The bias score contained in the deterministic model is then corrected by the bootstrap technique (Simar & Wilson, 1998) with 2,000 iterations in this study. Average efficiency score, both deterministic and bias-corrected, for each factory per year from 2017 to 2019 is shown in Table 3. The measurement of scale efficiency scores is also carried out. Hence, the tendency of the return-to-scale, either increasing (IRS) or decreasing (DRS), can be revealed (Seiford & Zhu, 1999).

Table 3

Efficiency Score & RTS Type of Each Pine Chemical Factory

No	Factory	Deterministic Efficiency Score	Bias-Corrected Efficiency Score	Bias Score	Scale Efficiency Score	Σ Lambda	RTS
1	GRHN	0.683	0.652	-0.032	0.959	1.025	DRS
2	SUKN	0.732	0.697	-0.034	0.968	0.984	IRS
3	RJWG	0.818	0.747	-0.070	0.951	0.902	IRS
4	PNGR	0.868	0.779	-0.089	0.935	0.528	IRS
5	SPRN	0.835	0.788	-0.047	0.990	0.734	IRS
6	WNDJ	0.833	0.785	-0.048	0.992	0.756	IRS
7	CMGU	0.809	0.773	-0.036	0.988	0.813	IRS
8	PPCI	0.596	0.563	-0.033	0.950	1.159	DRS
9	SDWG	0.802	0.756	-0.046	0.918	1.490	DRS
Average Score		**0.775**	**0.727**	**-0.048**	**0.961**	**0.932**	**DRS**

According tobias-corrected technique (Simar & Wilson, 1998), the top three factorieswith the highest efficiency score are SPRN (0.788), WNDJ (0.785), and PNGR(0.779). This rank can be different with the deterministic model (Banker etal., 1984) depending on the score of bias that is removed. Besides the resultingefficiency score, DEA software, namely R-statistics is also able to project the target of each inefficient variable so that DMUs could perform more efficiently(Ibrahim et al., 2020). Target models that accommodate predefined desiredoutput targets or predefined available inputs during efficiency improvement are shown in Table 4.

Table 4

General Improvement Target of Each Operational Variable (Input & Output)

Type	Variables	Unit	Average Initial Value*	Average Target Value*	Improvement	
					%	Sign
Input	Raw Material Cost	US$ Thousand	628.33	564.87	10.1%	-
	Labour Cost	US$ Thousand	6.80	4.25	37.6%	-
	Energy Cost	US$ Thousand	26.71	19.15	28.3%	-
	General Affair Cost	US$ Thousand	2.76	1.87	32.3%	-
Output	Total Revenue	US$ Thousand	1,198.31	1,582.84	32.1%	+
	Total Production Volume	Ton	789.50	934.16	21.7%	+

*Stated in value per month; calculated on average from 2017 to 2019

For the input variable, the average initial value is always greater than the target. It shows that inefficiency does exist, thus production cost reduction is expected. On the contrary, greater target value of output variable denotes that revenue or production volume should be increased to be more efficient. Of the total 6 variables used in this research, raw material cost has the lowest inefficiency score. The other variables should be improved or optimized obviously because of its slightly high inefficiency scores (above 20%). Improvement percentage per variable input or output for every factory is shown in Table 5.

Table 5

Improvement Target for Each Pine Chemical Factory per Operational Variable (Input & Output)

No	Factory	Raw Material Cost	Labour Cost	Energy Cost	General Affair Cost	Total Revenue	Total Production Volume
1	GRHN	-6,5%	-18,9%	-24,8%	-22,7%	+47,7%	+38,1%
2	SUKN	-6,4%	-13,0%	-25,0%	-20,7%	+43,6%	+29,5%
3	RJWG	-12,6%	-17,7%	-27,7%	-31,5%	+26,8%	11.10%
4	PNGR	-0,6%	-6,3%	-10,2%	-13,9%	+35,2%	+16,1%
5	SPRN	-8,0%	-19,4%	-8,9%	-17,1%	+18,4%	+10,1%
6	WNDJ	-14,9%	-15,5%	-26,4%	-29,1%	+23,6%	+2,3%
7	CMGU	-13,8%	-19,8%	-26,4%	-31,9%	+25,6%	+5,5%
8	PPCI	-2,9%	-68,9%	-46,1%	-29,2%	+87,1%	+76,7%
9	SDWG	-15,9%	-46,3%	-31,2%	-44,0%	+10,9%	+6,4%

Respondents filled out AHP questionnaires using the Expert Choice™ application through a focus group discussion (FGD). Hence, each respondent is expected to have the same perception of the question items. The facilitator will immediately enter the respondent's answers into the application for each statement of pairwise comparison while ensuring that inconsistencies of entire questionnaire sections are less than 10%. A section with inconsistency more than 10% is reconfirmed by reasking the respondent to revise and adjust the answer until it meets the acceptability limit for consistency. The synthesis of the Eigenvector combination which is obtained from a total of 13 respondents is shown in Table 6 and Fig. 4.

Table 6
Synthesis of Eigenvector Combination

Alternative	Eigenvector	Operational Capability Dimension	Mean Eigenvector
Product Quality	0.140	**Quality**	0.132
Process Quality	0.124		
Process Sustainablity	0.118	**Sustainability**	0.118
Product Sustainability	0.117		
Process Innovation	0.106	**Innovation**	0.105
Product Innovation	0.103		
Cost Efficiency	0.087	**Cost**	0.077
Flow Efficiency	0.067		
Employee Flexibility	0.074	**Flexibility**	0.069
Delivery Flexibility	0.064		

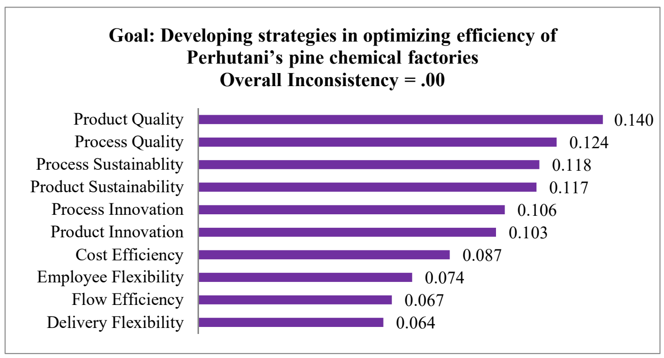

Fig. 4. Eigenvector for each alternative of operational capability dimensions

Based on the rating of all respondents, dimension of quality is found to have the highest Eigenvector. It consists of two alternatives, i.e., product quality and process quality. In the second position, dimension of sustainability takes place, followed by innovation, cost, and flexibility. Flexibility is considered as the least influential operational dimension because basically Perhutani pine products cannot be customized according to the buyer's specifications. Prompt delivery is always made using finished goods which have already been listed as inventory. Therefore, the discussion on the next section in developing strategies to optimize Perhutani's pine chemical factories will focus only on quality improvement, for both product and process.

5. Discussion

Pine chemical products, well known as gum rosin and turpentine oil, are traded worldwide and become the mainstays of non-timber forest products (NTFP) originated from Indonesia (Fachrodji et al., 2009). Based on the total production volume by country, Indonesia (9.2%) ranks third after China (48.3%) and Brazil (20.7%). Perum Perhutani is the largest producer in Indonesia with gum rosin production of 65,170 tons and turpentine oil of 14,293 tons in 2019 (Perhutani, 2020). Total national production of gum rosin is around 90,000 tons per year (Baumassy & Oy, 2019). Thus, around 25,000 tons of gum rosin is produced by private companies spread across the islands of Java, Sumatra and Sulawesi. Most Indonesian gum rosin and turpentine oil, (±90%) are exported to various countries in the world, while the remaining (±10%) is used for domestic consumption. Referring to Indonesia Foreign Trade Statistics, three main export destinations of Indonesian pine chemical products are China, India, and Japan (BPS, 2020).

Refer to the data issued by Indonesia Central Bureau of Statistics (acronym: BPS) in 2019 and 2020, top countries of export destination based on foreign trading-volume and value of Indonesia Gum Rosin (HS Code: 38061000) and Turpentine Oil (HS Code: 38051000) can be discovered. According to recapitulation of average trading volume from 2017 to 2019, China (36.26%), India (22.29%), Taiwan (6.19%), Japan (5.02%), and Pakistan (4.39%) became the top 5 countries of export destination of Indonesia gum rosin. From another product line, India took most of Indonesia's turpentine oil export trading (87.67%), while China (7.97%) and Japan (1.75%) are in second and third place (BPS, 2019; 2020).

Perhutani, as a State-Owned Forestry Enterprise, has main businesses in the production and commerce of timber (TFP) and non-timber forest products (NTFP). The revenue generated from NTFP is greater than 40% annually. Revenue obtained from gum rosin and turpentine oil export activities itself contributed to 29.88%, while domestic sales accounts for 3.30% to the company's total revenue in 2019 (Perhutani, 2020). Annually, Perhutani produces around 65,000 ton gum rosin and

14,000 ton turpentine oil on average (Perhutani, 2019). This gum rosin volume is estimated to have reached 81% of total national production, while the remaining 19% volume is produced by several private companies, medium to small enterprises (Baumassy & Oy, 2019). All pine chemical products of Perhutani are manufactured by 9 factories, spread evenly through the island of Java from west to east, and located close to raw material sources namely oleum pine resin which are tapped from pine trees.

Referring to Table 3, average efficiency score of 9 (nine) Perhutani pine chemical factories are 0.727 0r 72.7%. In other words, 0.273 or 27.3% inefficiency does exist. In general, the type of RTS is still decreasing. It means that the operation scale is too exaggerated, thus downsizing action is suggested. This condition is also proven by the excessive some input value (Table 4) which requires reduction significantly, i.e. labour cost (-37.6%), energy cost (-28.3%), and general affair cost (-32.3%), as well as increase in output value i.e. total revenue (+32.1%) and total production volume (+21.7%).

Based on operation scale in manufacturing gum rosin and turpentine oil, Perhutani pine chemical factories are still facing DRS (decreasing return-to-scale) in general. If a DMU wants to maintain its BCC efficiency, DRS recommends downsizing due to lower disproportionality. Conversely, IRS should upsize its production as any increasing inputs result in disproportionally higher increase of outputs. Therefore, each DMU pursues two objectives to improve efficiency and rescale the unit operation either for upsizing or downsizing production (Rodder, et al., 2018). To determine the target for downscaling, if required, the Board of Directors should consider one or more units with the lowest efficiency score. In this research, PPCI will be the first main target. PPCI yields the greatest inefficiency of 43.7%. PPCI mandatorily requires major improvements to increase total revenue by 87.1% and total production volume by 76.7%, as well as to reduce labour cost by 68.9%, energy cost by 46.1%, and general affair by 29.2%. Two other factories with DRS type are GRHN and SDWG. GRHN is required to grow the outputs majorly by 47.7% of total revenue and 38.1% of total production volume. Meanwhile SDWG requires to reduce the inputs majorly by 15.9% of raw material cost, 46.3% of labour cost, 31.2% of energy cost, and 44.0% of general affair cost. To avoid the downsizing of any factory's operational unit, those particular projected targets at each factory should be approached at optimum speed.

On another side, factories with IRS type are suggested to expand its operation scale by increasing the inputs. According to the percentage of inefficiency score for each variable in Table 4, increasing inputs should focus on adding raw material only while maintaining the other costs at the same level. In reality, escalating pine resin tapping volume becomes a difficult thing to do with the principle of sustainability forest management. Sustainable forest management plays an important role in enhancing forest protection, ensuring sustainable use of forest products and forest ecosystem services to improve human wellbeing (Bhandari & Lamichhane, 2020). Therefore, if adding raw material is less possible to carry out, strategies to reduce other operational costs (labour, energy, and general affair) or raise the unit price become considerable options to improve efficiency of operational performance.

5.1 Strategies in enhancing product and process quality to overcome inefficiency of Perhutani's pine chemical factories

According to synthesized results of priority alternatives from 13 expert respondents, the Product Quality ranks first with the highest eigenvector of 0.140. The next position is occupied by Process Quality ($\omega = 0.124$), Process Sustainability ($\omega = 0.118$), and Product Sustainability ($\omega = 0.117$). The dimension of Quality becomes the main priority operational capability dimension followed by the dimension of Sustainability in this research.

In general, Perhutani only produces 2 types of product specifications called X and WW. The basic difference is in the color specifications, where X has a lighter color than WW. It causes the unit selling price of X to be slightly higher than WW. The complete specification differences of X and WW is shown in Table 7.

Tabel 7
Technical Data Sheet (TDS) Gum Rosin Garde X & WW

Specification	Produk Quality		Testing Instrument/Method
	X	WW	
Softening Point	≥ 78ºC	≥ 78ºC	Ring and Ball
Gardner Colour)	5 - 6	6 - 7	S.W. Gardner
Impurity	≤ 0,02%	≤ 0,05%	Gooch Filter G-3
Acid Number	160 - 190	160 - 190	Titrimetry
Saponification Number	170 - 220	170 - 220	Titrimetry
Iodine Number	5 - 25	5 - 25	Titrimetry
Ash Content	≤ 0,02%	≤ 0,04%	Furnace Heraeus
Residual Turpentine	≤ 2%	≤ 2%	Oven Memmert

Expert respondents assess the business model of gondorukem and turpentine commerce in a holistic way or as an end-to-end process which its quality must be guaranteed or assured from the initial supply of raw materials, manufacture, and delivery until the product is well received by end buyers in each country of export destination. Marketing employees are also responsible for conveying any information related to buyer's order to the factory as manufacturer appropriately and correctly. Specification of product quality will be re-checked upon the arrival at the buyer's factory. Perhutani as producer is still in charge to ensure that the result does not deviate from the value written on the Certificate of Analysis (COA). Incompliance with the COA will have the potential to bring complaints to Perhutani. Buyer complaints granted by Perhutani will impact on financial losses due to free replacement of goods, as well as non-financial loss of buyer trust (customer loyalty).

High product quality can only be achieved if it is supported by good process quality and correct production procedures. For example, gum rosin is not allowed to pass quality control (QC) checks if the softening point is found below 78ºC. In terms of product stability, gum rosin is rather sensitive to high environmental temperature. It will easily soften if the condition of the container is too hot while being shipped to the buyer's destination country. The softened gum rosin can seep out of the drum packaging so that it can contaminate the container floor which the shipping company will also claim for cleaning costs to Perhutani. In contrast to turpentine, the product is in a liquid phase and is more stable as long as the packaging is tightly closed. The complexity of the supply chain, starting from pine resin tapping, product manufacturing, and distribution makes the Quality dimension a top priority in optimizing the efficiency of Perhutani's pine chemical factories. Therefore, determination of strategies involving quality assurance of the product and process must be prioritized and implemented first.

Operation management strategy of a company should always be improved to result in higher productivity due to a more efficient manufacturing process, thus yielding better quality of the end products. Given the limitations of the product life cycle, companies must always be able to research and develop new products to design and to market. Strong communication is mandatorily required between manufacturers, suppliers and customers. A company's product strategy will determine the number of marketable product lines with their respective life cycles, size of the market share, and amount of investment in the process. In relation to product and process strategies, Heizer and Reinder (2006) classify operations management strategies into product design and process transformation (simulation, lean manufacturing, facility layout). Those strategies will be strongly recommended to implement with regard to the suitability of the responses given by the expert respondents from fulfillment semi-quantitative AHP questionnaires.

Product design is a strategy to develop characteristics and functions of a new product in accordance with the needs of buyers. Final product design should be adapted into the production stage. It is necessary to standardize the end product to minimize discrepancies. Product design strategy will affect other operating strategies, such as costs, quality, and human resources. In other words, a product design will determine the capability to produce at high or low cost, general or premium quality, with the number of employees adjusted to the layout and production facilities (Anderson & Zeithaml, 1984; Fullerton et al., 2003; Meenaghan & Turnbull, 1981; Yoo, 2009).

Process transformation or process design is a strategy to manufacture end products according to quality specification, cost limit, and other operational management requirements. Selected process design will have a long-term impact on operating efficiency, flexibility, cost, and product quality which binds the company to the use of technology, utilization of human resources, and specific maintenance. The investment model in the process design will contribute to determining the company's basic cost structure (Kadim, 2017). Based on some previous literature review, there are three methods to optimize the process production system. The first method is simulation. This method reproduces the behavior of a complex system to be tested and evaluated with a simpler model of analysis. Simulation can be applied to design new facilities or optimize existing ones (Guban et al., 2017; Merkuryev et al., 2009). The second method is lean manufacturing. Lean-manufacturing requires the principles of continuous improvement and elimination of process waste, such as over-production, over-processing, defective products, unnecessary transportation and displacement (Fawaz & Jayant, 2007; Fullerton et al., 2003; Holweg, 2007). The third method is facility layout. This method focuses on regulating machine, material and human flow to minimize total flow or travel distance, material handling costs, and time spent in the manufacturing system (Riyad et al., 2014; Telek, 2013).

Perhutani as the market leader of pine chemical products in Indonesia and in the world should be able to develop its pine products into derivatives. For example, gum rosin that is obtained from heating and evaporation of pine resin can be modified into some derivatives product, such as maleic modified rosin (MMR) and glycerol rosin ester (GRE) by adding reactions of oxidation, hydrogenation, dehydrogenation, isomerization, Diels-Alder couplings, esterification, saponification with formaldehyde and phenol. MMR and GRE have better and more specific functions compared to gum rosin only. MMR is widely used as durable road mark, while GRE is known as food-grade rosin and commonly used in beverages and pharmaceutical industries (Gandini & Lacerda, 2015; Kumooka, 2008; Llevot et al., 2015; Rodriguez-Gracia et al., 2016; Yadav et al., 2016; Yao & Tang, 2013). Product design strategies are mandatorily needed to preserve Perhtiani's competitive advantages in facing more and more competitors. On the other hand, process design is also necessary especially to improve the production system of existing Perhutani's pine chemical factories. With regard to year of establishment, whole pine chemical factories were built before 2000 except PPCI in 2012 (Perhutani, 2020). Paninggaran (PNGR) was established in 1968; Sukun (SUKN) was established in 1976; Sapuran (SPRN), Cimanggu (CMGU), Winduaji (WNDJ), and Garahan (GRHN) were established in 1980s; Rejowinangun (RJWG) and Sindangwangi (SDWG) were established in 1990s. Therefore, without consistent continuous improvement, the technology used might be outdated which in the long-term will affect cost consumption due to less efficient processes or production systems. In their research about sustainable energy systems, Chu et al., (2020) stated that recent advances in technology will always put energy security as the first and top priority. Utilization of renewable energy sources has become more important and imperative for many countries (Eroglu, 2021). These attitudes have promoted the application of energy saving and energy storage, as well as pollutant (CO_2) emission reduction (Jin, 2020). In the near future, Perhutani is expected to adopt these principles of sustainable development in its pine chemical industries which are not only able to enhance environmental protection in the short term, but also support strategic cost reduction (Shields & Young, 1992) to increase company's profitability in the long-term.

6. Conclusion

Pine chemical products, well known as gum rosin and turpentine oil, are traded worldwide and become the mainstays of non-timber forest products (NTFP) originated from Indonesia (Fachrodji et al., 2009). Based on the total production volume by country, Indonesia (9.2%) ranks third after China (48.3%) and Brazil (20.7%) (Baumassy & Oy, 2019). Perum Perhutani is the largest producer in Indonesia with gum rosin production of 65,170 tons and turpentine oil of 14,293 tons in 2019 (Perhutani, 2020). To preserve its competitive advantages in the market, Perhutani must have optimum production performance which is measurable by calculating the efficiency score of all factories. In total, nine pine chemical factories are selected as decision making units (DMUs) for data envelopment analysis (DEA) method, namely Garahan (GRHN), Sukun (SUKN), Rejowinangun (RJWG), Paninggaran (PNGR), Sapuran (SPRN), Winduaji (WNDJ), Cimanggu (CMGU), Perhutani Pine Chemical Industry (PPCI), and Sindangwangi (SDWG). In the measurement of DEA efficiency score, this study employs an output-oriented variable-return-to-scale approach (Banker et al., 1984). The bias score contained in the deterministic model is then corrected by the bootstrap technique (Simar & Wilson, 1998). As a result, the top three factories with the highest efficiency score are SPRN (0.788), WNDJ (0.785), and PNGR (0.779).

On average, the efficiency score of 9 (nine) Perhutani pine chemical factories are 0.727 or 72.7%. In other words, 0.273 or 27.3% inefficiency does exist. In general, the type of RTS is still decreasing (DRS). It means that the operation scale is too exaggerated, thus downsizing action is suggested. Therefore, several strategies to reduce operational production costs (labour, energy, and general affair) or raise the selling price become considerable options to improve efficiency of operational performance. Referring to the study of Shields and Young (1992), increase in profitability can be achieved by employing the advances in technology and human resource management to reduce production cost progressively, in long-term and coordinated ways, not as an instantaneous action.

According to synthesized results of priority alternatives from 13 expert respondents, dimension of Quality has the highest eigenvectors ($\omega_{\text{Product Quality}} = 0.140$; $\omega_{\text{Process Quality}} = 0.118$). Hence, Quality dimension (product and process quality) becomes a top priority in optimizing the efficiency of Perhutani's pine chemical factories. Render (2009) stated that the operation management strategy of a company should always be improved to result in higher productivity due to a more efficient manufacturing process, thus yielding better quality of the end products. Heizer and Reinder (1985) classify operations management strategies into product design and process transformation (simulation, lean manufacturing, facility layout). Those strategies will be strongly recommended to implement with regard to the suitability of the responses given by the expert respondents from fulfillment semi-quantitative AHP questionnaires. Using appropriate product and process design, Perhutani may enhance its capability to produce at lower cost, premium quality, with the suitable number of employees adjusted to the layout and production facilities.

This study has a number of limitations that can be used as consideration to conduct further research. In the analysis of factory efficiency using the DEA method, data of all DMUs from January 2017 to December 2019 are treated in a cross-sectional manner and not in a time series, so that the factors causing productivity growth, or stated in Malmquist index to reflect total factor productivity (Malmquist, 1953), cannot be identified. In addition, the future research is also suggested to include environmental factors besides company's operational variables in constructing a holistic mathematical model. In relation to efficiency scores, the double bootstrap truncated-regression method (Simar & Wilson, 2007) can be used as an approach. Lastly, the findings of this research are expected to contribute to the development of science and operation management. Practically, the company's top management also can reveal that improving and resolving quality issues can promote the success of strategic cost reduction as long-term and coordinated strategies to boost up and maintain the company's profitability.

Acknowledgement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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