

IMPLEMENTATION OF THE FUZZY ANALYTICAL HIERARCHY PROCESS AND DATA ENVELOPMENT ANALYSES FOR ASSESSMENT OF THE CAPABILITY OF FARMER GROUPS IN INDONESIA

ONI SOESANTO¹, YUSI TYRONI MURSITYO², EKO DARMANTO³, ZURAIDAH⁴, NINIK WAHJU HIDAJATI⁵, SAMINGUN HANDOYO^{6,7}

¹Study Program of Mathematics, Lambung Mangkurat University, Banjarbaru 71213,, Indonesia

²Department of Information Systems, Brawijaya University, Malang 65145, Indonesia

³Department of Information Systems, Muria Kudus University, Kudus 59532, Indonesia

⁴Study Program of Islamic Banking, State Islamic Institute of Kediri, Kediri 64127, Indonesia

⁵Department of Civil Engineering, Universitas Negeri Surabaya, Surabaya 60232,, Indonesia

⁶Department of Statistics, Brawijaya University, Malang 65145, Indonesia

⁷Department of Electrical Engineering and Computer Science-IGP, National Yang Ming Chiao Tung University, Hsinchu 30010, Taiwan

E-mail: ¹osoesanto@ulm.ac.id, ²yusi_tyro@ub.ac.id, ³eko.darmanto@umk.ac.id
⁴zuraidahmalang@iainkediri.ac.id, ⁵ninikwahju@unesa.ac.id, ^{6,7}samistat@ub.ac.id

ABSTRACT

Farmer Groups are one of the forums for farmers to increase resources and production of agricultural products. Strong farmer groups will greatly contribute to improving the welfare of the Indonesian people. This study aims to rank farmer groups and evaluate their performance efficiency so that they are in accordance with the priority interests of each criterion unit to support the task of decision-makers in fostering farmer groups in an appropriate manner. Fuzzy Analytical Hierarchy Process (FAHP) Model - Data Envelopment Analysis (DEA) is a ranking method based on preference data in the form of fuzzy numbers. In this study, the AHP-DEA fuzzy method was modified to become AHP-DEA-CCR fuzzy (Charnes, Cooper, and Rhodes). The modification was carried out by weighting using entropy-based fuzzy AHP on the input and output models. The FAHP-DEA model developed successfully mapped 15 farmer groups into 3 groups based on 3 criteria, namely learning vehicles, cooperation vehicles, and production units. Based on performance efficiency in the 3 criteria, 2 strategies are obtained to increase their abilities. One scenario is to provide training to increase production units to farmer groups with DMU IDs 1, 2, 6, 4, and 3, provide counseling and training to increase the use of learning vehicles and provide training to increase the use of cooperation vehicles to farmer groups 10,11, 12, 14, and 15. The varying decision risk into 0.2 (pessimistic), 0.5 (moderate), and 0.8 (optimistic) do not have a significant effect on the decision maker's choice.

Keywords: *Decision Making, Efficiency Performance, Fuzzy AHP-DEA, Important Criteria, Decision Risk.*

1. INTRODUCTION

In general, modeling with a machine learning approach is categorized into 3 types, namely regression, classification, and description model. A model having a numerical target variable is known as regression [1], a model with a categorical target variable is called classification [2], while a model

without a target variable is a descriptive model [3]. Recently, Nugroho et al [4] developed ridge regression and MLP neural networks on the multi-target variable. While classification models based on a sigmoid function as the decision boundary in binary classes are done in [5-7] and Widodo et al [8] developed a classification model based on the probability density function. In addition, a

description model to evaluate a correlation between self-efficacy and hope is carried out by Utami et al [9], and another type of description model (clustering based on fuzzy sets) is conducted by Handoyo et al [10]. The main job of a decision maker is to make a decision by choosing the best of some alternative decision. A description model that can give a ranking from a list of decision choices is very needed to make fairness in decision-making. The Analytical Hierarchical Process AHP) is a popular method as a tool for handling ranking tasks.

The definition and concept of AHP had been given by Saaty in Liu et al [11]. He defined AHP as a method of supporting decision-making to solve complex and unstructured problems that are divided into some number of groups, then organize the groups into a hierarchical arrangement. A AHP process starts with considering subjective individual perception by comparing preferences between two elements called criteria. Preference criteria are transformed into numerical values and finally, using a synthesis method to obtain the highest priority criteria [12]. Some examples of AHP implementation are conducted by Purwanto et al [13] chose the starting lineup of soccer players, and Abrahamsen et al [14] selected the prioritizing investments in safety measures in the chemical industry. If there are many criteria involved and each criterion has a different degree of preference, lead to the decision-maker will face difficulty.

An AHP method is based on the psychological and assessment theory. However, another approach called Data Envelopment Analysis (DEA) does not base on assessment and psychological theory [15]. It is A prominent technique to make decisions and improve alternatives of decision choice based on non-parametric modeling and ratio calculations. However, an obvious difficulty to use the method is how to obtain accurate input and output data in real applications [16]. The application of the DEA method has been used as performance measurement in various scientific disciplines and various operational activities, including the evaluation of retail industry performance abilities, carried out by Rouyendegh et al. [17], analysis of group decision-making with interval multiplicative preference relations carried out by Liu et al. [18]. An idea to make a hybrid approach that accommodates the advantages of both AHP and DEA methods is a smart breakthrough in innovating a more powerful ranking method.

The use of craps set which treats each entity as a member of a set is deemed less fulfilling of objectivity elements. A fuzzy approach that also

includes the degree of membership of an entity in the set is deemed capable of providing further information and also fulfilling elements of fairness [19-21]. Applications of the fuzzy approach in artificial intelligence include optimization methods for parameter estimation [22-23] which are able to produce a small bias, regression modeling to predict a numerical value [24-25], and classification modeling to predict a label from a class. entities [26-28]. Models based on the fuzzy approach are able to produce a better model in accuracy performance both in regression and classification modeling.

Practitioners and researchers have developed many hybrid ranking models involving the fuzzy concept including the fuzzy multi-criteria decision-making (FMCDM) to select the supplier for vendor-managed inventory which was conducted by Sumrit [29], the FMCDM for Sustainable risk management strategy selection was done by Edjossan-Sossou et al [30], the fuzzy AHP to measure the quantify vulnerabilities of web applications were conducted by Shojaeshafiei et al [31], and the fuzzy AHP-DEA for measuring the efficiency of freight transport railway were undertaken by Blagojević et al [32]. Hybrid models involving the fuzzy AHP have proven in yielded very satisfactory performances.

A farmer group is an organization that cannot be separated in achieving success in the agricultural sector development of a country. Guidance and empowerment of farmer groups are carried out continuously. The efforts to increase the capabilities of farmer groups to carry out their functions well and to develop farming businesses must be supported by baseline information on their profiles. Because the existing profile of farmer groups was obtained through a survey with questionnaire, the data is a craps numbers that do not represent actual preferences given by most of the respondents. The fuzzy numbers can handle unfair perspectives of respondent preferences. The research aims to rank and evaluate the performance efficiency of 15 farmer groups in the South Kalimantan province of Indonesia by the implementation of the fuzzy AHP-DEA method. The ranked capability yielded fairly will give the profile information mapped well that it can help the government to guide and empower them in the future.

2. PROPOSED METHOD

In the fuzzy AHP method, The Triangular Fuzzy Number (TFN) is used to represent the judgment of the decision maker in a pairwise comparison matrix. TFN is represented by $\tilde{A} = (a_1, a_2, a_3)$, where $a_1 \leq$

$a_2 \leq a_3$ and a_1 is the lowest value, a_2 is the middle value, a_3 is the top value. The values a_1 and a_3 represent the uncertain range that may exist in the decisions made by the decision maker which can be seen in Table 1 below [33]:

Table 1: The scale of Triangular Fuzzy Number (TFN)

Fuzzy Number	Triangular Fuzzy Number scale	Reciprocal Scale	Linguistic Scale
1	(1,1,1): diagonal (1,1,3): other	(1,1,1):diagonal (1/3,1,1): other	Same importance
3	(1,3,5)	(1/5,1/3,1)	little more importance
5	(3,5,7)	(1/7,1/5,1/3)	More important
7	(5,7,9)	(1/9,1/7,1/5)	Very Important
9	(7,9,9)	(1/9,1/9,1/7)	Absolutly Important

Table 1. Furthermore, it is used to form a pairwise comparison matrix in the FAHP which describes the level of importance for each criterion and sub-criteria for each input-output unit. Data Envelopment Analysis (DEA) is basically a method for determining the optimal weight so that a production unit or Decision Making Unit (DMU) becomes efficient, namely reaching a value of 1. However, in its application, DEA is used for DMU assessments to obtain an efficiency value. AHP-based entropy fuzzy method is used to generate criteria weights from the importance of each criterion which it will be used in DEA to obtain the efficiency value of the DMU [34].

Consider Fuzzy judgment matrix \tilde{V} (input paired comparison matrix) and fuzzy judgment matrix \tilde{U} (output paired comparison matrix), namely:

$$\tilde{V} = \begin{bmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \dots & \tilde{v}_{1n} \\ \tilde{v}_{21} & \tilde{v}_{22} & \dots & \tilde{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{n1} & \tilde{v}_{n2} & \dots & \tilde{v}_{nn} \end{bmatrix} \text{ and}$$

$$\tilde{U} = \begin{bmatrix} \tilde{u}_{11} & \tilde{u}_{12} & \dots & \tilde{u}_{1m} \\ \tilde{u}_{21} & \tilde{u}_{22} & \dots & \tilde{u}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{u}_{m1} & \tilde{u}_{m2} & \dots & \tilde{u}_{mm} \end{bmatrix} \quad (1)$$

Fuzzy subjective weight vector \tilde{W}_v for each column of fuzzy judgment matrix \tilde{V} and fuzzy subjective weight vector \tilde{W}_u for each column of fuzzy judgment matrix \tilde{U} , namely [35]

$$\tilde{W}_v = [\tilde{w}_{v_1} \quad \tilde{w}_{v_2} \quad \dots \quad \tilde{w}_{v_n}] \text{ and}$$

$$\tilde{W}_u = [\tilde{w}_{u_1} \quad \tilde{w}_{u_2} \quad \dots \quad \tilde{w}_{u_m}] \quad (2)$$

The confidence interval is determined by multiplying the subjective weight vector \tilde{W}_v to the corresponding column of the fuzzy judgment matrix

\tilde{V} and the subjective weight vector \tilde{W}_u to the corresponding column of the fuzzy judgment matrix \tilde{U} . The yielded confidence interval is presented in Equation (3) as the following [36]:

$$\tilde{T} = \begin{bmatrix} \tilde{w}_{v_1} \otimes \tilde{v}_{11} & \tilde{w}_{v_2} \otimes \tilde{v}_{12} & \dots & \tilde{w}_{v_n} \otimes \tilde{v}_{1n} \\ \tilde{w}_{v_1} \otimes \tilde{v}_{21} & \tilde{w}_{v_2} \otimes \tilde{v}_{22} & \dots & \tilde{w}_{v_n} \otimes \tilde{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{w}_{v_1} \otimes \tilde{v}_{n1} & \tilde{w}_{v_2} \otimes \tilde{v}_{n2} & \dots & \tilde{w}_{v_n} \otimes \tilde{v}_{nn} \end{bmatrix} \text{ and}$$

$$\tilde{Z} = \begin{bmatrix} \tilde{w}_{u_1} \otimes \tilde{u}_{11} & \tilde{w}_{u_2} \otimes \tilde{u}_{12} & \dots & \tilde{w}_{u_m} \otimes \tilde{u}_{1m} \\ \tilde{w}_{u_1} \otimes \tilde{u}_{21} & \tilde{w}_{u_2} \otimes \tilde{u}_{22} & \dots & \tilde{w}_{u_m} \otimes \tilde{u}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{w}_{u_1} \otimes \tilde{u}_{m1} & \tilde{w}_{u_2} \otimes \tilde{u}_{m2} & \dots & \tilde{w}_{u_m} \otimes \tilde{u}_{mm} \end{bmatrix} \quad (3)$$

The multiplication operation on fuzzy numbers and the confidence interval yielded the following results:

$$v_{11} = (v_1, v_2, v_3) \text{ with } \alpha \in [0,1] \text{ and}$$

$$\tilde{v}_{11}^\alpha = [(v_2 - v_1)\alpha + v_1, -(v_3 - v_2)\alpha + v_3] = [v_1^\alpha, v_3^\alpha]$$

$$\tilde{w}_{v_1} = (w_1, w_2, w_3) \text{ with } \alpha \in [0,1] \text{ and then}$$

$$\tilde{w}_{v_1}^\alpha = [(w_2 - w_1)\alpha + w_1, -(w_3 - w_2)\alpha + w_3] = [w_1^\alpha, w_3^\alpha]$$

By considering Equation (3), $\tilde{w}_{v_1}^\alpha \otimes \tilde{v}_{11}^\alpha$ and the results of the multiplication operation on the fuzzy numbers, then an interval of confidence that is stated as the following

$$\tilde{w}_{v_1}^\alpha \otimes \tilde{v}_{11}^\alpha = [w_1^\alpha, w_3^\alpha] \otimes [v_1^\alpha, v_3^\alpha] = [w_1^\alpha v_1^\alpha, w_3^\alpha v_3^\alpha]$$

Finally, it is obtained

$$\tilde{T}_\alpha = \begin{bmatrix} t_{11b}^\alpha, t_{11u}^\alpha & \dots & t_{1nl}^\alpha, t_{1nu}^\alpha \\ \vdots & \ddots & \vdots \\ t_{1b}^\alpha, t_{n1u}^\alpha & \dots & t_{nml}^\alpha, t_{nnu}^\alpha \end{bmatrix} \text{ and}$$

$$\tilde{Z}_\alpha = \begin{bmatrix} z_{11l}^\alpha, z_{11u}^\alpha & \dots & z_{1ml}^\alpha, z_{1mu}^\alpha \\ \vdots & \ddots & \vdots \\ z_{m1l}^\alpha, z_{m1u}^\alpha & \dots & z_{mml}^\alpha, z_{mmu}^\alpha \end{bmatrix}$$

with the α value is given. Furthermore, the optimization index will be calculated depends on the decision maker attitude toward a decision risk called the optimism degree (λ). Where the optimization index is given as the following:

$$t_{ij}^\alpha = (1 - \lambda)t_{ijl}^\alpha + \lambda t_{iju}^\alpha, \forall \lambda \in [0,1] \quad (4)$$

Where

$$\hat{T} = \begin{bmatrix} \hat{t}_{11}^\alpha & \hat{t}_{12}^\alpha & \dots & \hat{t}_{1n}^\alpha \\ \hat{t}_{21}^\alpha & \hat{t}_{22}^\alpha & \dots & \hat{t}_{2n}^\alpha \\ \vdots & \vdots & \ddots & \vdots \\ \hat{t}_{n1}^\alpha & \hat{t}_{n2}^\alpha & \dots & \hat{t}_{nn}^\alpha \end{bmatrix} \text{ and}$$

$$\hat{Z} = \begin{bmatrix} \hat{z}_{11}^\alpha & \hat{z}_{12}^\alpha & \dots & \hat{z}_{1m}^\alpha \\ \hat{z}_{21}^\alpha & \hat{z}_{22}^\alpha & \dots & \hat{z}_{2m}^\alpha \\ \vdots & \vdots & \ddots & \vdots \\ \hat{z}_{m1}^\alpha & \hat{z}_{m2}^\alpha & \dots & \hat{z}_{mm}^\alpha \end{bmatrix} \quad (5)$$

After obtaining the results from the optimization index, a relative frequency matrix will be formed [37].

$$F = \begin{bmatrix} f_{11} & f_{12} & \dots & f_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \dots & f_{nn} \end{bmatrix} \text{ and}$$

$$G = \begin{bmatrix} g_{11} & g_{12} & \dots & g_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m1} & g_{m2} & \dots & g_{mm} \end{bmatrix} \quad (6)$$

Where

$$f_{ij} = \frac{i_{ij}^\alpha}{s_{ti}} \text{ and } g_{ij} = \frac{z_{ij}^\alpha}{s_{zi}} \text{ for all } i, j$$

$$s_{ti} = \sum_{i=1}^n \hat{t}_{ki}^\alpha \text{ and } s_{zi} = \sum_{r=1}^m \hat{z}_{kr}^\alpha \text{ for row } k$$

Furthermore, the calculating of *entropy* value and the *entropy* weight use the equation (7) as follows [38]:

$$V_n = -\sum_{i=1}^n (f_{ni}) \log_2(f_{ni}) \text{ and}$$

$$U_m = -\sum_{r=1}^m (g_{mr}) \log_2(g_{mr}) \quad (7)$$

where V_i is the i th input entropy value and the r th output entropy value. For the entropy weights can be determined by equation (8) as follows:

$$W_{V_i} = \frac{V_i}{\sum_{i=1}^n V_i} \text{ and}$$

$$W_{U_r} = \frac{U_r}{\sum_{r=1}^m U_r}, \quad i, r = 1, 2, \dots, m \quad (8)$$

This entropy weight will be used in calculating the DEA efficiency of the CCR model. The calculation of efficiency uses the following equation

$$\max \theta_p = \frac{\sum_{r=1}^n w_{ur} y_{rp}}{\sum_{i=1}^m w_{vi} x_{ip}} \quad (9)$$

with

$$\frac{\sum_{r=1}^n w_{ur} y_{rj}}{\sum_{i=1}^m w_{vi} x_{ij}} \leq 1, W_{U_r} \geq 0, W_{V_i} \geq 0,$$

$$x_{ij} > 0, y_{rj} > 0$$

Where,

- θ_p = efficiency of the p^{th} DMU
- W_{u_r} = entropy weight of the r^{th} output
($r = 1, 2, \dots, n$)
- W_{v_i} = entropy weight of the i^{th} input
($i = 1, 2, \dots, m$)
- y_{rj} = the r^{th} output of the j^{th} DMU
($j = 1, 2, \dots, d$)
- x_{ij} = the i^{th} input of the j^{th} DMU
($j = 1, 2, \dots, d$)

3. COLLECTING DATA AND RESEARCH STAGES

The assessment of the capability of farmer groups is formulated and compiled with an approach to management aspects and leadership aspects. They include the input criteria, namely planning, organizing, implementation, and the output criteria,

namely controlling, reporting, and developing. A farmer group leadership (Panca Ability of Farmers Groups / PAKEM POKTAN) from functions of farmer groups as learning centers (14 inputs and 18 outputs), cooperation forums (17 inputs and 16 outputs), and Production Units (19 inputs and 16 outputs) [39]. Before the assessment is carried out, the decision maker (agricultural extension agent) determines the priority scale between the criteria and sub-criteria based on his subjective view, and a table of interests between criteria and deeper sub-criteria is obtained for each input-output pair unit. Based on the table of interests, fuzzy synthesis is then performed to obtain the entropy weight for each criterion and sub-criterion. Performance appraisal is given by the decision maker by providing a subjective assessment of each farmer group based on an assessment instrument that refers to the 2011 Farmer Groups Capability Assessment Guidelines by the Jakarta Agricultural Extension Centre.

Data collection was carried out through interviewed with the Barito Kuala Regency Agriculture Office of the South Kalimantan Province of Indonesia, which was the decision maker through the Central Extension Centre, which in this case was represented by agricultural extension officers to provide an assessment of their respective farmer groups. Criteria and sub criteria compiled by the Agricultural Extension and Human Resources Development Agency, Ministry of Agriculture of the Republic of Indonesia.

The criteria for assessing the capability of farmer groups are formulated and compiled with an approach that considers aspects of management and leadership. They include planning, organizing, implementing, controlling, and reporting, as well as leadership development. The considering input variable is the function of farmer groups as vehicles for learning, cooperation, and production unit. To make a simple representation, an uppercase letter is used as a variable symbol. They represent planning activities (A), organizing activities (B), and the capability to carry out activities (C). While the output variables in vehicles of learning, cooperating, and production units are the capability to control and report activities (D) and the capability to develop group leadership (E).

Each of the criteria in learning vehicles, cooperation vehicles, and production units has their respective sub-criteria and deeper sub-criteria. They are based on the function and role of farmer groups as learning classes, vehicles for cooperation, and production units in developing farms that are

continuously structured in assessing the capability of farmer groups.

The following are the steps for fuzzy AHP with the weighting entropy method on the Data Envelopment Analysis (DEA) with the Charnes, Cooper, and Rhodes (CCR) model:

- a. Construct a hierarchical structure of criteria for input and output variables
- b. Determine the Fuzzy Judgment Matrix.
- c. Determine the Fuzzy Subjective Weight Vector.
- d. Determine the Interval of Confidence.
- e. Calculate the Optimization Index.
- f. Construct a Relative Frequency matrix.
- g. Calculate the entropy values and entropy weights.

4. RESULTS AND DISCUSION

In this study, the computation process of the proposed method is given step by step in detail following Eq. 1 to Eq. 9 and the numerical results are presented in efficient ways. The learning vehicle of farmer groups is used as an example in the computation process in detail.

The entropy weights for the criteria and sub-criteria from the input are calculated using the fuzzy AHP which consists of steps that the results are given in Table 2 to Table 6 for the learning vehicles criteria. They will be used as weighting for the DEA of framer groups. An example of the calculation of the Entropy Weight on the Input Criteria namely the learning vehicles presented in Table 2, and entropy weights are given at the Output Criteria for the learning vehicles in Table 7. The same calculations are also carried out in input-output criteria for the cooperation vehicles, and Production Units (calculate similar Table 2 to Table 7 for criteria cooperation vehicles and production units). The same process is carried out for each sub-criteria and sub-sub-criteria of the cooperation vehicles and production units so that the results are similar to as shown in Table 2 to Table 6 and the weighting is then carried out on the criteria, sub-criteria, and sub-sub-criteria, the results are similar to as in Table 7 below:

Table 2: The Pairwise Comparison matrix between criteria

C ri.	Criteria								
	A			B			C		
A	1.00	1.00	1.00	1.00	3.00	5.00	3.00	5.00	7.00

B	0.20	0.33	1.00	1.00	1.00	1.00	1.00	3.00	5.00
C	0.14	0.20	0.33	0.20	0.33	1.00	1.00	1.00	1.00

Table 3: The Confidence Interval of the alpha=0.8

Cri.	Criteria					
	A		B		C	
A	1.000	1.000	2.600	3.400	4.600	5.400
B	0.307	0.467	1.000	1.000	2.600	3.400
C	0.189	0.227	0.307	0.467	1.000	1.000
W	2.600	3.400	8.600	9.000	1.000	1.400

Table 4: The Confidence Interval of the lambda=0=0.5

Cri.	Criteria					
	A		B		C	
A	2.600	3.400	22.360	30.600	4.600	7.560
B	0.797	1.587	8.600	9.000	2.600	4.760
C	0.490	0.771	2.637	4.200	1.000	1.400

Table 5. The obtained Entropy Criteria

Criteria	Entropy	
	Value	Weight
A	1.0534	0.2979
B	1.2257	0.3466
C	1.2569	0.3555

Table 6. Entropy weights on the Learning Vehicles input criteria

Criteria	Sub criteria	Sub-Sub criteria	Final Entropy weight (W _{v_i})
A (0.2979)	A1 (0.4981)	A11	0.0737
		A12	0.0743
	A2 (0.5019)	A21	0.0447
		A22	0.0520
B (0.3466)	B1 (1.0000)	B11	0.1710
		B12	0.1300
		B13	0.0460
C (0.3555)	C1 (0.4981)	C11	0.0580
		C12	0.0720
		C13	0.0470
	C2 (0.5019)	C21	0.0300
		C22	0.0640
		C23	0.0840

Total of Entropy weight	1.0000
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Table 7. Entropy weights on the Learning Vehicles Output criteria

Criteria	Sub criteria	Sub-sub criteria.	Final Entropy weight (W_{v_i})
D (0.4981)	D1 (0.2759)	D11	0.0369
		D12	0.0316
		D13	0.0296
		D14	0.0228
		D15	0.0165
	D2 (0.2501)		0.1246
	D3 (0.2357)	D31	0.0187
		D32	0.0172
		D33	0.0150
		D34	0.0198
		D35	0.0133
		D36	0.0139
	D37	0.0195	
D4 (0.2382)		0.1186	
E (0.5019)	E1 (0.3488)		0.1750
	E2 (0.3128)		0.1570
	E3 (0.3385)	E31	0.0898
		E32	0.0802
Total of Entropy weight			1.0000

The input criteria of the learning Vehicles in Table 6 shows that the highest importance weight is on criterion C (Implementation) and on the output criteria of the highest importance on the criteria for

the development of farmer group leadership (E), in the same way, it can be seen that the weight of importance for the sub-criteria and the sub-sub criteria for each other unit, namely the Cooperation vehicles and the Production units.

The DMU used in this study was 15 farmer groups. The efficiency of the farmer groups in Table 4 is calculated and ranked to determine the results of the performance of the farmer groups. The total value obtained from the subjective assessment results of the decision maker for each DMU on each criterion and sub-criteria and the efficiency value of the entropy weight for each criterion is given on the Table 8. The efficiency calculation in the DEA model uses the formula as follows:

$$\theta_1 = \frac{W_{u_1}y_{11} + W_{u_2}y_{21} + \dots + W_{u_{17}}y_{171} + W_{u_{18}}y_{181}}{W_{v_1}x_{11} + W_{v_2}x_{21} + \dots + W_{v_{13}}x_{131} + W_{v_{14}}x_{141}}$$

$$\theta_{15} = \frac{W_{u_1}y_{115} + W_{u_2}y_{215} + \dots + W_{u_{17}}y_{1715} + W_{u_{18}}y_{1815}}{W_{v_1}x_{115} + W_{v_2}x_{215} + \dots + W_{v_{13}}x_{1315} + W_{v_{14}}x_{1415}}$$

Where θ_1 is the efficiency of the DMU_1 , and $y_{11}, y_{21}, \dots, y_{181}$ shows the output value 1, 2, ..., 181 of the DMU_1 and $x_{11}, x_{21}, \dots, x_{141}$ indicates the input value 1, 2, ..., 14 of the DMU_1 , as well as the both of $W_{u_1}, W_{u_2}, \dots, W_{u_{18}}$ and $W_{v_1}, W_{v_2}, \dots, W_{v_{14}}$ denote the input and output entropy weights, respectively. With the terms of efficiency $\theta_1, \theta_2, \dots, \theta_{15}$ has a value greater than 0 or less than 1. So that the calculation results are obtained in Table 8 as follows

Table 8: The Fuzzy AHP-DEA CCR on the Learning, Cooperation, and Production unit vehicles

DMU _j	Class	Learning Vehicles			Cooperation Vehicles			Production Unit		
		Total	Efficiency	Ranking	Total	Efficiency	Ranking	Total	Efficiency	Ranking
1	Advance	359	0.8820	1	359	0.2661	9	359	0.3397	9
2	Advance	297	0.5680	2	297	0.8081	2	297	0.5355	6
3	Advance	317	0.4509	5	317	0.5011	4	317	0.5181	5
4	Advance	311	0.4603	4	311	0.6891	3	311	0.3970	8
5	Beginer	241	0.2949	8	241	0.3255	8	241	0.6411	3
6	Beginer	173	0.4666	3	173	0.3015	7	173	0.5297	7
7	Beginer	141	0.4010	6	141	0.3958	6	141	0.6688	2
8	Beginer	108	0.3654	7	108	0.9230	1	108	0.8036	1
9	Beginer	113	0.2421	9	113	0.4371	5	113	0.6089	4
10	Advance	295	0.0222	15	295	0.0212	14	295	0.0245	11
11	Advance	325	0.0228	13	325	0.0180	15	325	0.0271	10
12	Advance	314	0.0222	14	314	0.0212	13	314	0.0237	14
13	Advance	271	0.0253	12	271	0.0249	10	271	0.0219	15
14	Advance	286	0.0250	11	286	0.0240	11	286	0.0248	12
15	Advance	288	0.0250	10	288	0.0227	12	288	0.0237	13

By using Table 8, the rankings for each group on learning vehicles, collaboration vehicles and

production units are obtained based on the DEA CCR model. The first place for the learning vehicle

criteria is the 1st farmer group with a relative efficiency of 0.882 and includes advanced classes. From Table 8, it can be seen that there are two farmer groups with the same relative efficiency (0.025), namely the 13th, the 14th and the 15th farmer groups. These three groups are also in the same class with slightly different total values which are 271, 286, and 288 respectively. Likewise, the 10th farmer group and the 12 farmer group with the same relative efficiency of 0.022, and their total values are 295 and 314 respectively.

In the cooperation vehicles based on the DEA CCR model, namely the 8th farmer group in the first place with a relative efficiency of 0.923 and including the beginner class. From Table 8, it can be seen that there are two farmer groups with the same relative efficiency of 0.021, namely the 10th farmer group and the 12th farmer group. These two groups are also in the same class with slightly different total scores which are 295 and 314 for farmer groups of the 10th and the 12th respectively.

In the production unit based on the fuzzy AHP-DEA CCR model, namely the 8th farmer group in the first place with a relative efficiency of 0.804 and including the beginner class. From the results of calculations on the Learning Center, Cooperation Forum, and Production Unit, there are farmer groups with the highest efficiency values. This farmer group can become a reference for other farmer groups in order to they can achieve improvement or greater efficiency values than the previous ones. For farmer groups that have low or insufficient efficiency values, they can re-evaluate which parts are still not optimal or need improvement.

Farmer groups (DMU) can be mapped according to their ranking in each criterion. The first 5 best for the creation of learning vehicles are the DMU with IDs 1, 2, 6, 4, and 3 where they have efficiency values of 0.8820, 0.5680, 0.4666, 0.4603, and

0.4509 respectively. The efficiency value gap between the first and second rankings is too large. For the cooperation vehicles criterion, DMUs ranking orders are the DMU with IDs 8, 2, 4, 3, and 9. The DMU 2nd, 3rd, and 4th because they have been included in the top 5 ranks of the learning vehicles criterion are substituted by the DMU with IDs 7, 5, and 13. The first 5 DMUs for the cooperation vehicles criterion are DMU with IDs 8, 9, 7, 5, and 13 where their efficiencies on the cooperation vehicles criterion are 0.9230, 0.4371, 0.3958, 0.3255, and 0.0249. The remaining DMUs i.e. the DMU with IDs 10, 11, 12, 14, and 15 also obtained unsatisfactory ranks on the production unit criterion.

There are 2 scenarios for agricultural extension workers in conducting training and coaching farmer groups. Scenario 1 is to carry out counseling and training on learning vehicles at DMUs with IDs 10, 11, 12, 14, and 15. Counseling and coaching of production units are given to the DMUs with IDs 8, 9, 7, 5, and 13, then counseling to improve cooperation vehicles are given to DMUs with IDs 1, 2, 6, 4, and 3. While scenario 2, cooperation vehicles training and counseling are given to DMUs with IDs 10, 11, 12, 14, and 15, and Counseling and coaching production units are given to the DMUs with IDs 1, 2, 6, 4, and 3. furthermore, counseling and training on learning vehicles were given to the DMUs with IDs 8, 9, 7, 5, and 13.

The limitation of farmer groups in the above area lead to a small size of the sample involved in the research. The condition causes various ranking methods that need a hypothesis test can not be applied due to the violation of the normality assumption. Another issue is there are some important characteristics described in the capability of farmer groups that did not consider in the research

Table 9: The Efficiency performance of the Fuzzy AHP-DEA-CCR

DMU _j	$\lambda = 0.2$ (Pessimistic)			$\lambda = 0.5$ (Moderate)			$\lambda = 0.8$ (Optimistic)		
	Learning vehicles	Cooper. Vehicles	Product. Unit	Learning vehicles	Cooper. Vehicles	Product. Unit	Learning vehicles	Cooper. Vehicles	Product. Unit
1	0.9467	0.276	0.3424	0.9057	0.2697	0.339	0.8820	0.2661	0.3397
2	0.5681	0.806	0.5318	0.5697	0.8066	0.534	0.5680	0.8081	0.5355
3	0.5019	0.502	0.5365	0.4739	0.5021	0.523	0.4509	0.5011	0.5181
4	0.4984	0.706	0.4178	0.4784	0.6956	0.402	0.4603	0.6891	0.3970
5	0.2935	0.329	0.6603	0.2916	0.3228	0.649	0.2949	0.3255	0.6411
6	0.4749	0.326	0.5718	0.4678	0.3095	0.541	0.4666	0.3015	0.5297
7	0.4034	0.428	0.6664	0.3995	0.4061	0.667	0.4010	0.3958	0.6688
8	0.3743	0.970	0.7946	0.3708	0.9407	0.796	0.3654	0.9230	0.8036

9	0.2504	0.471	0.6124	0.2455	0.4478	0.611	0.2421	0.4371	0.6089
10	0.0201	0.019	0.0222	0.0213	0.0204	0.023	0.0222	0.0212	0.0245
11	0.0208	0.016	0.0244	0.0219	0.0174	0.025	0.0228	0.0180	0.0271
12	0.0201	0.019	0.0216	0.0213	0.0204	0.022	0.0222	0.0212	0.0237
13	0.0230	0.022	0.0198	0.0243	0.0238	0.020	0.0253	0.0249	0.0219
14	0.0229	0.021	0.0225	0.0241	0.0229	0.023	0.0250	0.0240	0.0248
15	0.0229	0.020	0.0216	0.0241	0.0217	0.022	0.0250	0.0227	0.0237

The level of performance efficiency of each DMU for each criterion at $\lambda = 0.8$ (Optimistic). As a comparison in decision making, a combination of $\lambda = 0.2$ (Pessimistic) and $\lambda = 0.5$ (Moderate) can be used as an alternative to the decision maker as illustrated in Table 9

Based on Table 9, it can be seen that by considering the decision variation $\lambda = 0.2$ (Pessimistic), $\lambda = 0.5$ (Moderate) and $\lambda = 0.8$ (Optimistic) have yielded not much different decision patterns. Thus the decision maker can choose just one variation in the performance appraisal process of farmer groups.

The proposed method offers an alternative scenario for stakeholders in conducting training for farmer groups. This should have an immediate impact, namely the scheduling of extension officers can be adjusted to the needs of farmer groups according to the factual conditions in the field. This could not be explored clearly in similar previous research as in [31-32].

5. CONCLUSION

The fuzzy AHP-DEA (modified fuzzy AHP-DEA CCR) model has been implemented to analyze the performance of farmer groups in the South Kalimantan province of Indonesia. The results provide recommendations to decision-makers (government) to be able to prioritize specific interests in the region. Thus the performance efficiency of each farmer group from an area can be known according to the actual conditions. Based on the weights obtained in the analysis, the fuzzy AHP-DEA model can describe in detail the efficiency of each criterion, sub-criterion, sub-sub-criterion, and the total performance efficiency of each group. Based on the performance efficiency, farmer groups with IDs 1, 2, 6, 4, and 3 are the first 5 rank for the learning vehicles criterion, farmer groups with IDs 8, 9, 7, 5, and 13 are the first 5 rank for the cooperation vehicles criterion. In addition, farmer groups with IDs 10, 11, 12, 14, and 15 have unsatisfactory in efficiency performance in all criteria. The results can make easily for decision-

makers to determine priority steps in fostering (giving appropriate counseling and training) farmer groups in the area in the future. The proposed method gives a baseline insight into the deployment of fuzzy numbers as an observed value of categorical attributes in the survey of respondents' preferences toward issues in the improvement of farmer groups' capability. In future works, an increasing number of farmer groups as interviewing respondents and adding the input-output of criteria, sub-criteria, and sub-sub criteria will lead to better profiling of farmer groups.

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