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Multi-criteria Fuzzy Regression Model for Evaluating Oil Palm Grading

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Abstract **- Measurement of quality is an important task in the evaluation of agricultural products. A higher quality of raw input material produces a higher quantity and quality of end products. Therefore, in the palm oil production, the quality inspection process of fruits needs to be conducted properly to ensure that high-quality fruit bunches are selected. Additionally, human subjective judgments during the evaluation make the fruit grading inexact. Thus, the objectives of this paper is to build a fuzzy multi-criteria evaluation model that characterises the criteria of oil palm fruits to decide the fuzzy weights of these criteria based on a fuzzy regression model. A numerical example is included to illustrate the computational process of the proposed model.**

Keywords **– Multi-criteria evaluation, fuzzy regression analysis, oil palm fruit grading**

I. Introduction

A good quality of oil palm fruits plays an influential and significant role in improving the quality and quantity of palm oil products in palm oil industry. Since fresh fruit bunches are the starting input for crude palm oil production, therefore, it is necessary that only high-quality fruit bunches be selected and processed [1], [2]. Oil palm fruits are inspected and graded by expert inspectors at a mill who have capabilities and experiences in grading fresh fruit bunches and who judge quality by looking individually at the product [1]. Basically, the grading practice involves the inspection of bunch quality, and the estimation of basic extraction rates and graded extraction rates.

Fruit bunches are typically evaluated using visual examination based on several criterias such as colour, number of detached or attached fruitlets, physical appearance and surface form. Each criterion carries a different weight of importance in the evaluation. These weights are necessary and can be used to decide the most important criterion during the fruit evaluation. Since several factors were considered in the evaluation, these situations should be represented as multi-criteria problems.

Currently, human graders are involved directly in the evaluation and grading process in the mills. Numerous studies [1], [3], [4], [5], [6] have been published regarding automating the grading process to accelerate sorting and evaluation. However, that kind of technology is still not implemented in Malaysian palm oil mills. For that reason, human grading still remains the most suitable method due to the high cost of advanced machine implementation.

In practice, grading experts, whose capability and experience are needed to adequately grade fresh fruit bunches, inspect and grade oil palm fruits at a mill. The skill and experience of human graders are important, as the grading process involves expert visual evaluation. Consequently, accumulated knowledge is useful in the grading process, even though the evaluation is based on several quantitative and qualitative criteria that are influenced by the grader's experiences and knowledge [7]. Thus, the evaluation involves both accurate and inexact information, since the fruit grading evaluation depends upon subjective human judgments.

The objective of this paper is to provide an estimation of weights of criteria by means of fuzzy regression. Moreover, this paper introduces a fuzzy multi-criteria evaluation model to assist and improve the quality inspection process as well as to support the decision-making process in the palm oil industry. The remainder of this paper is organised as follows. Section II explains two widely used methods, namely, AHP and TOPSIS, for comparison with our proposed method using real data. Section III and Section IV describes the fuzzy multi-criteria evaluation model and fuzzy regression model respectively. Section V discusses fuzzy multi-criteria evaluation decision-making based on our model. Section VI presents a real application of the model in the evaluation of oil palm grading, and Section VII concludes this paper with some additional remarks.

II. Decision Making and Evaluation

A multi-criteria decision-making problem usually requires decision makers to provide qualitative assessments of the performance of each alternative considering various criteria and to find the best solution among all feasible options. There are several techniques available to evaluate the alternatives based on numerous available data samples. Among these, the Analytic Hierarchy Process known as AHP [8] is the most frequently used method because of its ability to evaluate complex multi-criteria alternatives and become a practical tool of multi-criteria decision analysis. There has been extensive research in this area that has been successfully applied in real situations [9].

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is also one of the most popular of the ideal point methods and is one of the best-known multi-criteria decisions making methods [10]. While the AHP concentrates on pairwise comparison judgment, the TOPSIS method is based on an aggregating function, which represents the closeness of the evaluation to the ideal solution. However, the evaluation conducted by the traditional AHP and TOPSIS methods does not consider the interval or fuzzy value.

Therefore, in this paper, we selected to evaluate the alternatives and compare the results produced by fuzzy multi-criteria evaluation method (FMEM) with interval values for evaluation.

A. Analytic Hierarchy Process

The AHP value using a direct rating evaluation is computed as follows:

$$R_j = \sum_{i=1}^{K} a_{ji} w_i , \text{ for } j = 1,2,..., m \tag{1}$$

where R_j is the sample for the j th alternative, m is the number of alternatives, and K is the number of criterion; a_{ji} denotes the score of the j th alternative related to the i th criteria; and w_i denotes the weight of the i th criterion.

B. The Technique for Order Preference by Similarity to an Ideal Solution

The steps in the general TOPSIS process are as follows:

Step 1: Establish a normalised decision matrix for the ranking. Assume A_j is the sample for the j th alternative, $j = 1,2,..., n$; F_i represents the i th criterion, $i = 1,2,..., k$, and f_{ji} is a value indicating the performance rating of each alternative solution with respect to each criterion F_i. The structure of the matrix can be expressed as follows:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{matrix} F_1 & F_2 & \cdots & F_n \end{matrix} \\ \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{k1} & f_{k2} & \cdots & f_{kn} \end{bmatrix} \end{array}$$

The normalised value r_{ji} is calculated as:

$$r_{ji} = \frac{f_{ji}}{\sqrt{\sum_{i=1}^{n} f_{ji}^2}} , \tag{2}$$

where $j = 1,2,..., n$; $i = 1,2,..., k$

Step 2: Calculate the weighted normalised decision matrix by multiplying the normalised decision matrix by its weights. Let w_{ji} denote the weight of the i th criterion. The weighted normalised value V_{ji} is calculated as follows:

$$v_j = w_{ji} r_{ji} . \tag{3}$$

Step 3: Determine the positive ideal solution V^+ and the negative ideal solution V^-, respectively:

$$V^+ = \max\{v_j^+ ,..., v_n^+\},$$
$$V^- = \min\{v_j^- ,..., v_n^-\} \tag{4}$$

where $j = 1,2,..., n.$

Step 4: Find the separation measure using the dimensional Euclidean distance. D^+ denotes the separation from the positive ideal, and D^- is the separation from the negative ideal. The separation measures D^+ and D^- of each alternative are given as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ji} - v_j^+)^2} , \quad i = 1,..., k \tag{5}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ji} - v_j^-)^2} , \quad i = 1,..., k \tag{6}$$

Step 5: Calculate the relative closeness of the i th alternative to the ideal solution and rank the alternatives in descending order. The relative closeness of the alternative A_j is defined as follows:

$$C_i = \frac{D_i^-}{D_i^+ - D_i^-} , \quad 0 \le C_i \le 1, \quad i = 1,..., k \tag{7}$$

All alternatives are compared with the positive ideal solution and the negative ideal solution. Larger index values indicate better performance of the alternatives.

III. Fuzzy Multi-Criteria Evaluation Model

The fuzzy multi-criteria evaluation model (FMEM) is constructed on the same basis as conventional AHP, except for the assumption that pairwise comparisons are decided by the ratio between weights [11]. We do not employ this assumption in our scoring and ranking method. Also, straightforward judgment is used instead of pairwise comparison. Ordinary AHP uses a 5 to 9-point scale for the level of importance to compare the criterion with each other. Meanwhile, triangular fuzzy numbers are used instead of crisp numbers to describe the fuzzy importance level. A triangular fuzzy number is denoted by $A = (a, h)$, using central value a and width h . Table I shows the intensity of an importance scale for a crisp number [12] and a fuzzy number.

A combination of crisp and fuzzy numbers is used based on the appropriateness for the criteria of the problem, and is assigned to the alternatives to measure their performance against each criterion. The mixture of crisp and fuzzy numbers can give flexibility and extension to an evaluation process, where a suitable judgment scale can be made that corresponds to the criteria.

Assume we have K criteria and n samples. Let i indicate a criterion number and j as a sample number. In order to build the multi-criteria evaluation model, let us through the extension principle denote a judgment matrix by

$\mathbf{A} = [a_{ji}]_{n\times K}$ and a fuzzy weight vector of criteria selection by $\mathbf{W} = [W_i]_{1\times K}$.

TABLE I
INTENSITY OF IMPORTANCE SCALE

Intensity of Importance			Definition
Crisp value	Fuzzy value: Notation	Fuzzy value: Membership Function $A=(a,h)$	
1	$\tilde{1}$	(1,1)	Equal importance
2	$\tilde{2}$	(2,1)	Equal to moderately importance
3	$\tilde{3}$	(3,1)	Moderate importance
4	$\tilde{4}$	(4,1)	Moderate to strong importance
5	$\tilde{5}$	(5,1)	Strong importance
6	$\tilde{6}$	(6,1)	Strong to very strong importance
7	$\tilde{7}$	(7,1)	Very strong importance
8	$\tilde{8}$	(8,1)	Very to extremely strong importance
9	$\tilde{9}$	(9,1)	Extreme importance

Using Equation (1), the total score vector $\mathbf{R} = [r_j]_{n\times 1}$ of alternatives can be calculated with the following expressions:

$$\mathbf{R} = [r_j] = \mathbf{A}\cdot\mathbf{W}^T$$
$$\mathbf{R}_j = \sum_{i=1}^{K}\left(a_{ji}\cdot w_i\right), \qquad (8)$$

where T is the transpose of matrix or vector. Let us denote A, B, C and D fuzzy numbers. We then have the following relations:

$$\mu_{AB+CD}(t) = \vee_{t=u+v}\, \mu_{AB}(u)\wedge\mu_{CD}(v),$$
$$\text{and } \mu_{AB}(t) = \vee_{t=uv}\, \mu_A(u)\wedge\mu_B(v). \qquad (9)$$

IV. FUZZY REGRESSION MODEL

A fuzzy regression model is built in terms of fuzzy numbers and all observed values expressing uncertainty in the system. Thus, a fuzzy regression model can also be called a possibilistic regression model ([13]; [14]; [15]; [16]; [17]). In other words, the fuzzy regression model aims to build a model that contains all observed data within the estimated fuzzy numbers.

The fuzzy regression is written as follows:

$$\mathrm{Y} = [Y_j] = [A_1 x_{j1} + A_2 x_{j2} + \cdots + A_K x_{jk}] = \mathbf{A}\mathbf{x}_j^T$$
$$x_{j1} = 1;\ j = 1,2,\cdots n \qquad (10)$$

where regression coefficient A_i is a triangular-shaped fuzzy number $A_i = (a_i, h_i)$ with centre $a_i = [a_1, a_2, ..., a_K]$ and width $h_i = [h_1, h_2, ..., h_K]$. In equation (10), $\mathbf{x}_j$ is a value vector of all criteria for the *j*-th sample.

According to the extension principle, Equation (10) is rewritten as follows:

$$Y_j = \mathbf{A}\mathbf{x}_j^T = (\mathbf{a}\mathbf{x}_j^T, \mathbf{h}\,|\,\mathbf{x}_j\,|^T) \qquad (11)$$

where $|\,\mathbf{x}_j\,| = (|\,x_{j1}\,|, |\,x_{j2}\,|, \cdots, |\,x_{jK}\,|)$. The output of the fuzzy regression (10), whose coefficients are fuzzy numbers, results in a fuzzy number.

The regression model with fuzzy coefficients can be described using the lower boundary $\mathbf{a}\mathbf{x}_j^T - \mathbf{h}\,|\,\mathbf{x}_j\,|^T$, centre $\mathbf{a}\mathbf{x}_j^T$ and upper boundary $\mathbf{a}\mathbf{x}_j^T + \mathbf{h}\,|\,\mathbf{x}_j\,|^T$. A sample $(y_j, \mathbf{x}_j)$ $(j = 1,2,\cdots,n)$ is defined for the total evaluation with centre y_j, width d_j as a fuzzy number (y_j, d_j), and a value vector of all criteria $\mathbf{x}_j$, where the template membership function of fuzzy coefficients is set to $L(\alpha)$, and membership grade is α, which extends to a sample included in the regression model.

The inclusion relation between the model and the samples should be written as follows:

$$y_j + L^{-1}(\alpha)d_j \le \mathbf{a}\mathbf{x}_j^T + L^{-1}(\alpha)\mathbf{h}\,|\,\mathbf{x}_j\,|^T$$
$$y_j - L^{-1}(\alpha)d_j \ge \mathbf{a}\mathbf{x}_j^T - L^{-1}(\alpha)\mathbf{h}\,|\,\mathbf{x}_j\,|^T \qquad (12)$$

In other words, the fuzzy regression model is built to contain all samples in the model. This problem results in a linear program.

Using the notations of observed data $(y_j, \mathbf{x}_j)$, $y_j = (y_j, d_j)$, $\mathbf{x}_j = [x_{j1}, x_{j2}, \cdots, x_{jK}]$ for $j = 1,2,\cdots,n$ and fuzzy coefficients $\mathbf{A}_i = (\mathbf{a}_i, \mathbf{h}_i)$ for $i = 1,2,\cdots,K$, the regression model can be mathematically written as the following linear program problem:

$$\min_{\mathbf{a},\mathbf{h}} \sum_{j=1}^{n} \mathbf{h}\,|\,\mathbf{x}_j\,|^T$$
$$\textit{subject to}$$
$$y_j + L^{-1}(\alpha)d_j \le \mathbf{a}\mathbf{x}_j^T + L^{-1}(a)\mathbf{h}\,|\,\mathbf{x}_j\,|^T$$
$$y_j - L^{-1}(\alpha)d_j \ge \mathbf{a}\mathbf{x}_j^T - L^{-1}(a)\mathbf{h}\,|\,\mathbf{x}_j\,|^T \qquad (13)$$
$$(j = 1,2,\cdots,n),$$
$$\mathbf{h} \ge 0.$$

Solving the linear programming problem mentioned above, we have a fuzzy regression. This fuzzy regression contains all samples in its width and results in an expression of all possibilities that the samples embody, which the treated system should contain. It is possible in the formulation of the fuzzy regression model to treat non-fuzzy data with no width by setting the width h_j to 0 in the above equations.

V. FUZZY MULTI-CRITERIA DECISION MAKING

In this study, the general decision process of oil palm fruit grading is enhanced using a multi-criteria and fuzzy regression method. The initial step in the decision framework is to review related references to accumulate the key pieces of knowledge in the study domain. The findings from this step are useful for determining and decomposing the problem. This kind of information gathering process is rather similar to a knowledge acquisition step in the expert system methodology.

The preliminary study about oil palm grading process was conducted by reviewing and extracting knowledge from published references consisting of process guide books, research papers, surveys and reports, on oil palm fruit grading, which provided secondary information for this project. The information gathered was then represented using an appropriate knowledge model. The basic acquisition procedure consisted of locating each criterion for the grading process within the deterministic tables that contain key pieces of knowledge useful for the next process in this study.

TABLE II
DESCRIPTIVE CRITERIA USED IN OIL PALM FRUIT GRADING

Criteria	**Description**
c_1 : Color	Color of the fruitlets
c_2 : Attached Fruitlets	Number or percentage of attached fruitlets from the fruit bunch
c_3 : Detached Fruitlets	Number or percentage of detached fruitlets from the fruit bunch
c_4 : Surface	External surface of the fruit bunch
c_5 : Condition	Fruit bunch condition as a whole

TABLE III
DATA SAMPLES AND TOTAL EVALUATION

Sample	(y_j, d_j)	c_1	c_2	c_3	c_4	c_5
A1	(9,0.2)	9	5	9	5	5
A2	(9,0.1)	9	5	8	6	6
A3	(8,0.2)	8	8	5	4	4
A4	(5,0.1)	3	8	4	4	5
A5	(6,0.1)	5	8	4	6	7
A6	(7,0.2)	6	5	8	3	6
A7	(8,0.2)	7	7	2	3	3
A8	(8,0.1)	7	6	3	3	2
A9	(6,0.1)	5	7	3	5	5
A10	(5,0.1)	5	5	7	6	8
A11	(8,0.2)	7	5	7	5	3
A12	(7,0.1)	6	5	3	3	6
A13	(5,0.1)	4	8	3	6	6
A14	(5,0.1)	4	5	7	8	8
A15	(6,0.1)	5	3	6	4	8
A16	(7,0.2)	6	4	7	5	5
A17	(4,0.1)	3	3	8	6	6
A18	(5,0.1)	4	4	4	3	3
A19	(6,0.1)	5	3	7	5	2
A20	(8,0.1)	7	5	8	2	8

The multi-criteria evaluation model in this system consists of total evaluation, criteria, and alternatives to be evaluated. The main objective was to select a standard quality of oil palm fruit bunches. Several criteria were considered during the process of inspection for quality.

Fuzzy regression analysis was used to model an expert evaluation structure. A fuzzy weight value for each criterion was used to build the fuzzy multi-criteria structure for the total evaluation of oil palm fruits. Table II shows the weights and details of each criterion. In this case study, 20 sample alternatives were used for the weights against each criterion. To simplify the calculation, the weights against each criterion were assigned in a straightforward manner instead of by manual comparison using matrix. The final score R were calculated during the implementation.

TABLE IV
WEIGHTS OF CRITERIA

weight	width
$a_1 = 0.925$	$h_1 = 0.000$
$a_2 = 0.000$	$h_2 = 0.224$
$a_3 = 0.075$	$h_3 = 0.040$
$a_4 = 0.000$	$h_4 = 0.000$
$a_5 = 0.000$	$h_5 = 0.014$

TABLE V
RESULT COMPARISON

Sample	Expert Evaluation, (y_j, d_j)	Total Evaluation by FMEM, $(\tilde{y}_j, d_j)$
A1	(9,0.2)	(8.999, 1.48)
A2	(9,0.1)	(8.924, 1.44)
A3	(8,0.2)	(7.774, 1.99)
A4	(5,0.1)	(3.075, 1.95)
A5	(6,0.1)	(4.925, 1.95)
A6	(7,0.2)	(6.149, 1.44)
A7	(8,0.2)	(6.624, 1.65)
A8	(8,0.1)	(6.699, 1.46)
A9	(6,0.1)	(4.850, 1.69)
A10	(5,0.1)	(5.150, 1.40)
A11	(8,0.2)	(6.999, 1.40)
A12	(7,0.1)	(5.774, 1.24)
A13	(5,0.1)	(3.925, 1.91)
A14	(5,0.1)	(4.225, 1.40)
A15	(6,0.1)	(5.075, 0.91)
A16	(7,0.2)	(6.074, 1.18)
A17	(4,0.1)	(3.375, 0.99)
A18	(5,0.1)	(4.000, 1.06)
A19	(6,0.1)	(5.150, 0.95)
A20	(8,0.1)	(7.074, 1.44)

VI. ILLUSTRATIVE EXAMPLE AND DISCUSSION

This section shows an example of FMEM. The data sample and total evaluation are as tabulated in Table III. The values for each criterion were assigned in a straightforward manner based on an intensity of importance scale, stated in Table I. For example, criterion c_1 for sample A1 is assigned to 9 which represents that A1 has an extremely good color.

The regression model (13) was applied to the dataset and the weight obtained as shown in Table IV where a_i and h_i denote a weight and its width of criteria c_i. The evaluations c_1 to c_5 in Table III are the ones of criteria obtained from the experts. From Table IV, the result shows that in the expert judgment, Color, Attached Fruitlet and Detached Fruitlet criteria are evaluated important ones, followed by (0.925,0.000), (0.000, 0.224), and (0.075, 0.040), respectively.

Other criteria of fruit characteristics are not strongly considered. The Attached Fruitlet indicates that this criterion is also important and provides the flexibility covering from 0 to 0.224. Therefore, the result indicates that experts should place stress also for decision of attached fruitlet judgment. If, instead, the attached fruitlet showed a weak dominance, then the other criteria might represent a strong dominance in the total evaluation. The weight value yielded from the fuzzy regression model is helpful for assisting the grading process with minimal monitoring by human experts.

From the results, a model for the total expert evaluation was obtained. After the weight value for each criterion was derived by means of fuzzy regression, all the fuzzy weights were used to estimate the total evaluation based on the fuzzy multi-criteria evaluation model described in Section III. The estimated results showed that this model produces values highly similar to the expert evaluation values. Table V shows the tabulated results for actual and estimated values.

TABLE VI
EVALUATION RESULTS OBTAINED USING THREE METHOD

Ranking	AHP		TOPSIS		FMEM	
	Sample	Preference (P_j)	Sample	Preference (P_j)	Sample	Preference (P_j)
1	A1	0.078	A1	1.000	A1	(8.999, 1.48)
2	A2	0.078	A2	0.987	A2	(8.924, 1.44)
3	A3	0.068	A3	0.827	A3	(7.774, 1.99)
4	A20	0.062	A20	0.668	A20	(7.074, 1.44)
5	A11	0.061	A11	0.667	A11	(6.999, 1.40)
6	A8	0.058	A8	0.660	A8	(6.699, 1.46)
7	A7	0.058	A7	0.658	A7	(6.624, 1.65)
8	A6	0.054	A6	0.503	A6	(6.149, 1.44)
9	A16	0.053	A16	0.502	A16	(6.074, 1.18)
10	A12	0.050	A12	0.497	A12	(5.774, 1.24)
11	A10	0.045	A10	0.338	A10	(5.150, 1.40)
12	A19	0.045	A19	0.338	A19	(5.150, 0.95)
13	A15	0.044	A15	0.336	A15	(5.075, 0.91)
14	A5	0.043	A5	0.333	A5	(4.925, 1.95)
15	A9	0.042	A9	0.332	A9	(4.850, 1.69)
16	A14	0.037	A14	0.177	A14	(4.225, 1.40)
17	A18	0.035	A18	0.168	A18	(4.000, 1.06)
18	A13	0.034	A13	0.166	A13	(3.925, 1.91)
19	A17	0.029	A17	0.075	A17	(3.375, 0.99)
20	A4	0.027	A4	0.026	A4	(3.075, 1.95)

Table VI shows the evaluation result of the FMEM method compared with the AHP and TOPSIS methods. Let P_i (for $i = 1,2,\ldots,n$) represent the final preference of alternative A_i when all decision criteria are considered. We obtain the top four final ranking scores of alternatives using the FMEM method, as $Fmem_{A1} \succ Fmem_{A2} \succ Fmem_{A3} \succ Fmem_{A20}$. Meanwhile, the AHP method produces $ahp_{A1} \succ ahp_{A2} \succ ahp_{A3} \succ ahp_{A20}$ and the TOPSIS method gives $topsis_{A1} \succ topsis_{A2} \succ topsis_{A3} \succ topsis_{A20}$.

All the comparable methods use the same weight of criteria produced by Eq. (13). From the comparison, we see that the FMEM method achieves the same ranking of results as the AHP and TOPSIS methods. However, the ranking results obtained by the FMEM method show added flexibility with the introduction of the width to the evaluation. The width in this evaluation is important as it reflects natural human judgment, which tends to evaluate in interval or fuzzy values rather than crisp and precise judgments.

VII. CONCLUSIONS

While human expertise involved in decision-making, the judgment experience and knowledge of these experts is unique to each person. However, better understanding of this judgment knowledge, which can be represented by weights of criteria during a decision-making process, can be useful for facilitating the decision-making process with minimal evaluation input from human experts. Moreover, the fuzzy multi-criteria structure is also capable of considering uncertain values in the judgment evaluation. This uncertainty element is important, as the judgment evaluation strongly involves individual human preferences. The work described in this paper reveals that fuzzy evaluation in a multi-criteria situation can be effectively used to better facilitate the decision making process during the inspection of oil palm fruit bunch quality.

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