An Decision Making of Lecturer Assessment Model Using Combining Profile Matching and Fuzzy Logic Approach

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ABSTRACT
Lecturer performance appraisal plays a role in improving the quality of education in higher education. However, the performance appraisal process often experiences obstacles related to subjectivity and uncertainty in assessing various aspects of lecturer performance. This research applies a lecturer assessment decision-making model by combining Profile Matching and Fuzzy Logic methods to create a more objective and comprehensive system. The system uses six main criteria with five alternatives for selection, including teaching quality, research and publication, and community service, which are measured based on the fit between the ideal profile and the actual performance of the lecturer. The calculation results show that the weight value of the core factor and secondary factor greatly affects the ranking results, the final results show the value of alternatives on each criterion, the value of alternatives A1, A4 and A5 has a large value on criteria C1, C2 and C3. So that if the value of the core factor weight is greater on the C1, C2, C3 criteria, it tends to make alternatives that have a large value on the C1, C2 and C3 criteria superior to other alternatives

Keywords: Profile Matching, Fuzzy Logic, Lecturer Performance Appraisal, Decision Making.

INTRODUCTION

Lecturer performance appraisal has an important role in maintaining the quality of education in higher education. This assessment is not only useful for the university to assess teaching performance, but also as a reflection material for the lecturers themselves to continue to improve their competence (Sopian et al., 2023). However, in practice, the lecturer performance assessment process often faces obstacles such as the subjectivity of the assessor, lack of transparency, and unclear weighting of each aspect assessed. Inaccuracy in giving this assessment can have an impact on the motivation of lecturers and ultimately the quality of learning provided to students (Sudipa et al., 2021; Warta et al., 2023).

Performance appraisal systems in higher education are still largely quantitative and manual-based, utilizing questionnaires filled out by students and direct supervisors. Although this approach has been applied in recent years, the evaluation results are often seen as less valid because not all aspects are assessed equally and objectively. Therefore, there is a need for a system that is more comprehensive, structured, and able to accommodate various dimensions of assessment.

The existing assessment system still relies heavily on subjective opinions and does not consider more measurable factors, such as the lecturer's ability to manage the class, interaction with students, and contribution to curriculum development(Karuru et al., 2023). Some of the main problems that are often faced are subjectivity of assessment, inconsistent assessment criteria and lack of objectivity in determining decision making(Aristamy et al., 2021; Kraugusteeliana & Violin, 2024; Wijaya et al., 2024).

One potential approach to solving this problem is to use a combination of Profile Matching and Fuzzy Logic methods. Profile Matching is a technique used to match a person's profile with an expected profile, thus enabling a more structured evaluation(Rony et al., 2023; Saputra et al., 2024; Sudipa et al., 2020). On the other hand, Fuzzy Logic has the advantage of handling uncertainty and subjective data, so that it can provide decisions that are more flexible and closer to reality (Hartono et al., 2010; Prieto et al., 2020; Zadeh, 2023). Combining these two methods can make a model in the lecturer assessment system, so that the assessment can be more objective by considering multiple assessment criteria.

This research is very important to do considering the increasingly complex demands on the quality of higher education. With global competition between universities, universities need to ensure that their lecturers are of high quality and that their performance evaluations are conducted fairly and objectively. The combination of Profile Matching and Fuzzy Logic provides an opportunity to create a better assessment system by reducing subjectivity and taking into account various aspects that were previously difficult to measure. The results of this research are expected to make a real contribution to the development of a lecturer performance appraisal system. The resulting system can also be used in making decisions related to promotion, training, and development of lecturers, thus ultimately improving the quality of education in higher education.

LITERATURE REVIEW

The assessment of lecturer performance is a critical component in enhancing educational quality and ensuring effective teaching methodologies. Recent advancements in decision-making models, particularly those integrating Profile Matching and Fuzzy Logic approaches, have emerged as significant methodologies in this domain. These models facilitate a nuanced evaluation of lecturer performance by considering multiple criteria and the inherent uncertainties associated with qualitative assessments.

One prominent model is the Rank Order Centroid (ROC) method, which has been utilized to prioritize attributes and criteria in lecturer performance assessments(Wahidin et al., 2024). This method allows decision-makers to establish a priority order for various criteria(Santika et al., 2022), subsequently generating weights for these criteria through computational methods. Such an approach enhances the objectivity of the evaluation process, as highlighted by (Usanto et al., 2023). Furthermore, the Analytic Network Process (ANP) method, as discussed by (Purwani, 2022; Widjaja et al., 2024), complements this by examining interdependencies among performance factors, thereby providing a comprehensive framework for lecturer evaluation.

Incorporating fuzzy logic into these models addresses the vagueness and subjectivity often present in performance evaluations. Fuzzy logic allows for the representation of uncertainty in the assessment criteria, enabling a more flexible and realistic evaluation framework. (Do et al., 2020; Sudipa et al., 2024) emphasize the importance of integrating quantitative assessments with multi-criteria decision-making models, which can effectively capture the complexities of lecturer performance across various dimensions, including self, peer, and student evaluations. This integration is crucial in distinguishing between a lecturer's potential and their actual teaching effectiveness.

Moreover, the development of a web-based information system for lecturer performance appraisal, as explored by (Rakhmadani & Adhinata, 2021; Wijanarko et al., 2024), illustrates the practical application of these decision-making models. By employing gamification concepts and rating scale methods, this system enhances engagement and provides a structured approach to performance evaluation. Such systems can leverage fuzzy logic to interpret qualitative feedback, thereby enriching the assessment process.

The sustainability of lecturer performance evaluation models is also a significant consideration. Research by (Retnowati et al., 2021) propose a model that encompasses various aspects of lecturer performance, including teaching, research, and community service. This holistic approach ensures that evaluations are not only comprehensive but also aligned with the broader goals of educational institutions. Furthermore, the use of formative assessments, as indicated in their study, supports continuous improvement in teaching practices.

In summarize, the integration of Profile Matching and Fuzzy Logic approaches in lecturer performance assessment models represents a significant advancement in educational evaluation methodologies. These models not only enhance the objectivity and comprehensiveness of assessments but also address the complexities and uncertainties inherent in evaluating teaching effectiveness. Future research should continue to explore the application of these models across diverse educational contexts to further refine and validate their effectiveness.

RESEARCH METHOD

Fuzzy Logic

Analyzing the set of criteria in the form of crisp numbers which are transformed into fuzzy to gain membership degrees (fuzzification) helps one to determine the gap from fuzzy data and create a solution in the form of the proper decision. Theory of fuzzy sets is significantly influenced by the degree of membership function(Prieto et al., 2021). The membership function shows and clarifies for an attribute the degree of proximity and membership of an object (x)(Adeyi et al., 2021). Classical set theory is based on exact integers; fuzzy set theory is otherwise. Odd numbers indicate the presence of an element in the set (A), where the element has the chance of becoming a member, namely either joining A or not joining A.This work intends to merge approaches between fuzzy logic and profile matching, aiming to handle fuzzy data in the form of sets utilizing linear ascending fuzzy curves.

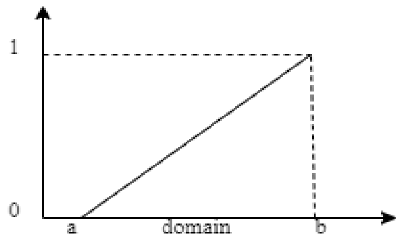

Figure 1: Representation of an Ascending Linear Curve

Membership Function:

$$\mu\,(x) = \left\{ \begin{array}{c} 0; \quad x \leq a \\ \frac{x-a}{b-a}; \quad a \leq x \leq b \\ 1; \quad x \geq b \end{array} \right\} \tag{1}$$

Profile Matching Method

The basic mechanism in profile matching is the identification of the necessary competencies (abilities) to maximize results from numerous criteria. These skills or competencies have to be either totally fulfilled or near to the choice of a lecturer. Usually, the profile matching procedure (also known as GAP) matches the student profile with the necessary criteria so that the difference can be known(Rodriguez & Chavez, 2019). The weight value increases with decreasing the gap generated. Completing the Profile Matching technique follows these steps(Cinelli et al., 2022):

1. Competency GAP Calculation

After determining the students to be assessed, then determine the calculation of competency gap mapping where what is meant by the gap here is the difference between the student profile and the ideal profile or can be shown by Equation (3) below:

GAP = Alternative Profile - Ideal Profile

2. Determine GAP Calculation (2)

After obtaining the GAP of each modified alternative value, each alternative profile is given a weighted value according to the provisions in the modified GAP value weight table.

Table 1. Modified GAP Value Weights

No.	GAP Differences	Weight Value	Description
1	0	11	Competency as needed
2	0,1	10,5	Individual competence exceeds 0.1
3	-0,1	10	Individual competency deficiency 0.1
4	0,2	9,5	Individual competence exceeds 0.2
5	-0,2	9	Individual competency deficiency 0.2
6	0,3	8,5	Individual competence exceeds 0.3
7	-0,3	8	Individual competency deficiency 0.3
8	0,4	7,5	Individual competence exceeds 0.4
9	-0,4	7	Individual competency deficiency 0.4
10	0,5	6,5	Individual competence exceeds 0.5
11	-0,5	6	Individual competency deficiency 0.5
12	0,6	5,5	Individual competence exceeds 0.6
13	-0,6	5	Individual competency deficiency 0.6
14	0,7	4,5	Individual competence exceeds 0.7
15	-0,7	4	Individual competency deficiency 0.7

3. Calculation and Grouping of Core and Secondary Factors

After determining the weight of the gap value in the same way, each aspect is grouped into two groups, namely Core Factor (NCF) and Secondary Factor (NSF).

Calculation of Core Factor Value (NCF):

$$NCF = \frac{\sum NC}{\sum IC} \quad (3)$$

Information:

NCF : Average Core Factor
Ni :Total score of Core Factors
IC :Number of items

Calculation of Secondary Factor (NSF) Value:

$$NSF = \frac{\sum NS}{\sum IC} \quad (4)$$

Information:

NSF : Average Secondary Factor
Ni :Total number of Secondary Factor scores
IC :Number of items

4. Total Value Calculation

The end result of the profile matching process is a ranking of customers who are eligible for credit. The ranking refers to the results of certain calculations. The total value is calculated based on the core and secondary percentages, which are estimated to affect the customer profile. The calculation can be seen in Equation (6) below:

$$(x)\%\ NCF + (x)\%\ NSF = N \quad (5)$$

Description:

NCF : Average value of core factors
NSF : Average secondary factor
N : Total Value
(X)% : Percentage of input value

First determine the percent value, namely the core factor of 70% and the secondary factor of 30%. Then the core factor and secondary factor values are summed according to the formula.

RESULT AND DISCUSSION

Criteria and Alternative Data Analysis

The lecturer performance assessment system developed in this study uses several main criteria that reflect various important aspects of lecturer performance, determining the criteria based on a literature review of related research that has been done. The main criteria used in this assessment system are Teaching Quality (C1), Research and Publication (C2), Community Service Activities (C3), Involvement in Curriculum Development (C4), Academic Leadership (C5), Evaluation Questionnaire Value from Students (C6). In determining the assessment of each criterion, it uses a value scale of 0-100 on each criterion. Alternative data uses 6 alternative data in the calculation process of the lecturer selection model.

Determining the Ideal Profile Value Criteria

The ideal profile value is obtained from the results of interviews with decision makers. The ideal profile is determined first to produce a GAP score with an alternative lecturer score. The ideal profile values for criteria C1 to C6 are based on values from 0 to 100, so the conversion of fuzzy values uses an ascending linear curve. The conversion process into fuzzy values is needed to make the assessment process more objective and each value can be converted through a fuzzy curve.

Calculation of fuzzy value conversion for criteria C1 to criteria C6 using an ascending linear curve

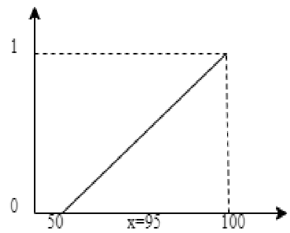

Figure 5. Fuzzy Graph for Criteria

$\mu_{\text{nilai C1 Criteria}}(97) = \frac{98-50}{100-50} = = 0{,}96$ $\mu_{\text{nilai C4}}(95) = \frac{95-50}{100-50} = = 0{,}9$

$\mu_{\text{nilai C2 Criteria}}(97) = \frac{98-50}{100-50} = = 0{,}96$ $\mu_{\text{nilai C5}}(95) = \frac{95-50}{100-50} = = 0{,}9$

$\mu_{\text{nilai C3 Criteria}}(97) = \frac{98-50}{100-50} = = 0{,}96$ $\mu_{\text{nilai C6}}(95) = \frac{95-50}{100-50} = = 0{,}9$

Table 2. Ideal Value Profile Criteria

Criteria	Criteria Name	Ideal Profile	Fuzzy Value Conversion
C1	Teaching quality	98	0,96
C2	Publications and Research	98	0,96
C3	Community Service Activities	98	0,96
C4	Involvement in Curriculum Development	95	0,9
C5	Academic Leadership	95	0,9
C6	Evaluation Questionnaire Value from Students	95	0,9

Alternative Value

The following alternative student scores for science olympiad candidates on each assessment criteria can be seen in Table 4 below:

Table 3. Alternative Values

Alternative	Alternative Value on Criteria					
	C1	C2	C3	C4	C5	C6
A1	67	98	80	77	90	79
A2	98	65	70	90	88	90
A3	80	80	80	80	80	77
A4	70	90	90	90	70	70
A5	59	98	98	68	68	80

The alternative value of each criterion is then converted into a decreasing fuzzy curve function value using Equation (1). The fuzzy conversion results can be seen in Table 5 below:

Table 4. Fuzzy Conversion Results

Alternative	Alternative Value on Criteria					
	C1	C2	C3	C4	C5	C6
A1	0,34	0,96	0,6	0,54	0,8	0,58
A2	0,96	0,3	0,4	0,8	0,76	0,8
A3	0,6	0,6	0,6	0,6	0,6	0,54
A4	0,4	0,8	0,8	0,8	0,4	0,4
A5	0,18	0,96	0,96	0,36	0,36	0,6

Competency GAP Calculation

The Competency Gap is calculated by Equation (2), with the benchmark ideal profile value in Table (2) and the alternative value in Table (3). Then the difference in GAP values is calculated which can be seen in Table 6 below:

Table 5. Competency GAP Score

Alternative	Alternative Value on Criteria					
	C1	C2	C3	C4	C5	C6
A1	0,34	0,96	0,6	0,54	0,8	0,58
A2	0,96	0,3	0,4	0,8	0,76	0,8
A3	0,6	0,6	0,6	0,6	0,6	0,54
A4	0,4	0,8	0,8	0,8	0,4	0,4
A5	0,18	0,96	0,96	0,36	0,36	0,6
Ideal Value	0,96	0,96	0,96	0,9	0,9	0,9
A1	-0,62	0	-0,36	-0,36	-0,1	-0,32

A2	0	-0,66	-0,56	-0,1	-0,14	-0,1
A3	-0,36	-0,36	-0,36	-0,3	-0,3	-0,36
A4	-0,56	-0,16	-0,16	-0,1	-0,5	-0,5
A5	-0,78	0	0	-0,54	-0,54	-0,3

Calculation of Core Factor and Secondary Factor

After the fuzzy conversion value is obtained, then the value is converted into the Modified GAP Value Weight in table 1. The Core Factor (NCF) value uses equation (3) and the calculation of the secondary factor (NSF) value uses equation (4). In this study there are groups of criteria that are core factors, namely C1, C2 and C3. Meanwhile, the secondary factor criteria groups are C4, C5, and C6. So the next step is to determine the value of NCF and NSF.

Table 7. Core Factor and Secondary Factor values

Alternative	C1	C2	C3	C4	C5	C6	NCF	NSF
A1	5	11	8	8	10	8	8	8,666667
A2	11	5	6	10	10	10	7,333333	10
A3	8	8	8	8	8	8	8	8
A4	6	10	10	10	6	6	8,666667	7,333333
A5	4	11	11	6	6	10	8,666667	7,333333

Final Score Calculation and Ranking

The NCF and NSF values of each alternative are then calculated with equation 6 so as to obtain the final alternative value, namely the value of Ni, the core factor weight value of 70% and the secondary factor weight value of 30%. The final alternative score results can be seen in table 8 below:

Table 8. Total Competency Score

Alternative	NFC (70%)	NSC(30%)	Ni
A1	8	8,66667	8,2
A2	7,33333	10	8,1
A3	8	8	8
A4	8,66667	7,33333	8,3
A5	8,66667	7,33333	8,3

From table 8, the final value of each alternative is obtained, then proceed with ranking based on Ni values from largest to smallest. The final results selected the three best alternatives, namely A1 and A4 and A5 with a value of 8.3 and A1 with a value of 8.2 so that the three selected alternatives become the best lecturer based on 6 selection criteria.

The analysis that can be given from the ranking results is that the weight value of the core factor and secondary factor greatly affects the ranking results, if reviewed on the value of alternatives on each criterion (Table 4), the value of alternatives A1, A4 and A5 has a large value on the criteria C1, C2 and C3. So that if the value of the core factor weight is greater on the C1, C2, C3 criteria, it tends to make alternatives that have a large value on the C1, C2 and C3 criteria superior to other alternatives.

CONCLUSION

This research successfully developed a decision-making model for lecturer performance appraisal by combining Profile Matching and Fuzzy Logic methods. This model offers a more objective and comprehensive approach by reducing the influence of subjectivity in lecturer performance evaluation. From the calculation results, the system is able to measure the suitability between the ideal profile and the actual performance of lecturers based on six main criteria: teaching quality, research and publication, community service, curriculum development, academic leadership, and student evaluation. Each criterion is measured using predetermined weights, where core criteria such as teaching quality, research, and community service get higher weights. The analysis conducted shows that alternatives with the highest scores on the core criteria (C1, C2, C3) have an advantage in the ranking process. The final result of the calculation shows that lecturers A4 and A5 are the best alternatives with a score of 83, followed by A1 with a score of 82. This system can be a reference for universities in making decisions related to promotion, career development, and improving the quality of education.

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