

Design of a Lecturer Performance Evaluation Based on a Fuzzy Inference System with the Mamdani Method in the Field of Education and Teaching

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ABSTRACT

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Lecturer performance evaluation is an essential component in ensuring the quality of higher education. However, the complexity of the assessed aspects and the diversity of data types often make objective decision-making challenging. This study aims to develop a fuzzy logic-based lecturer performance evaluation system using the Mamdani method, which enables the simultaneous processing of qualitative and quantitative data. The model adopts a Multi Input Single Output (MISO) framework, with input variables representing several aspects of lecturer performance, including teaching, thesis supervision, and academic advising sourced from the Electronic Employee Performance Targets (e-EPT) of the Faculty of Teacher Training and Education, University of Trunodjoyo Madura. Data were collected through document analysis using a documentation guideline as the research instrument. Each variable is defined using triangular and trapezoidal membership functions. Through the fuzzification process, input data are transformed into degrees of membership, then processed using fuzzy inference rules, and finally converted into crisp values using centroid defuzzification, namely by determining the center of mass of the area under the curve. The centroid values are used to classify lecturer performance into four categories: Poor, Fair, Good, and Excellent. The proposed model was subsequently applied to the performance data of a lecturer as a case study and compared with the conventional method. The results showed that the conventional method produced an overall performance rating of Good, whereas the proposed the Fuzzy Inference System (FIS) with Mamdani method generated a centroid value of 81.6, corresponding to the Excellent category. In addition to producing the final performance category, the proposed FIS with Mamdani method provides information on the membership degrees of each assessment variable, rule activation strengths, and the contribution of each indicator to the final decision. These findings demonstrate that the proposed FIS with Mamdani method provides a more transparent, gradual, and comprehensive evaluation process than the conventional assessment method.



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A. INTRODUCTION

Lecturer performance evaluation is a crucial aspect in efforts to improve the quality of higher education. Such evaluations not only contribute to the professional development of academic staff but also serve as a foundation for policy decisions regarding career advancement, promotions, and performance-based remuneration (Kepmendikbudristek RI, 2024;

Permendikbudristek RI, 2020). However, in practice, lecturer performance evaluation has several limitations: (1) it often involves qualitative and subjective indicators, making it difficult to achieve fair and accurate assessments; (2) it tends to be rigid, rule-based, and reliant on fixed thresholds; (3) it simplifies lecturer performance into strict categories such as “meets” or “does not meet,” thereby failing to fully represent the complexity of academic activities; and (4) it has limitations in accommodating uncertainty and partial achievements, thus not fully reflecting the actual performance conditions of lecturers (Guruprasad et al., 2016; Abdulrahman et al., 2017; Manuja et al., 2018).

In the education and teaching domain, lecturer performance evaluation generally considers several key indicators that represent lecturers' academic responsibilities. This study focuses on three assessment variables: Teaching, Thesis Supervision, and Student Advising. Teaching reflects instructional responsibilities, including teaching workload and classroom activities (Keputusan Dirjen PT Kemendikbud, 2021). Thesis Supervision refers to lecturers' responsibilities in guiding students through the completion of their undergraduate theses (Keputusan Dirjen PT Kemendikbud, 2021), whereas Student Advising encompasses academic mentoring activities that support students' academic progress (Keputusan Dirjen PT Kemendikbud, 2021). These three assessment variables constitute essential components of the education and teaching domain because they directly reflect the quality of academic services provided by lecturers.

Lecturer performance evaluation has been implemented in many higher education institutions through the use of the Electronic Employee Performance Targets (e-EPT) system or similar performance assessment systems to support the evaluation of lecturers' academic performance. Nevertheless, conventional evaluation methods generally produce only an overall performance rating without explaining how each assessment variable contributes to the final decision. Furthermore, these methods rely on crisp thresholds, making them less capable of accommodating the gradual and uncertain nature of performance assessment. As a result, variations in lecturers' performance levels cannot be adequately represented. One promising approach to addressing these limitations is the Fuzzy Inference System (FIS), which models linguistic reasoning while effectively handling uncertainty in the decision-making process (Zadeh, 1965). Among various fuzzy inference techniques, the Mamdani method is widely adopted because it produces interpretable decisions through linguistic rule-based reasoning (Morales et al., 2008; Shukri & Isa, 2021).

Numerous studies have applied the Fuzzy Inference System (FIS) to support performance evaluation and decision-making because of its ability to model linguistic reasoning while accommodating uncertainty. One of the most widely used approaches is the Mamdani method, which generates decisions through linguistic rule-based reasoning. Herpratiwi et al. (2022) applied the Mamdani method to evaluate teachers' success in online learning using three fuzzy sets: teacher, score, and success rate. The results demonstrated that the Mamdani method could be used to determine teachers' success in delivering online instruction. In the context of higher education, several studies have also applied the Mamdani method to evaluate lecturer performance. Makwana et al. (2023) developed a lecturer performance evaluation model based on five groups of academic indicators comprising fifteen assessment variables. The findings indicated that the proposed model could be used to support the design of training programs,

annual reward schemes, and salary increment decisions for lecturers. Umam & Wibawa (2020) developed FIS to evaluate lecturer performance quality based on the Lecturer Achievement Index (LAI) using nine performance indicators mapped into three quality categories through membership functions and fuzzy rules. Meanwhile, Nugroho et al. (2019) evaluated lecturer performance using the Mamdani method based on the four lecturer competencies mandated by the Law of the Republic of Indonesia No. 14 of 2005 on Teachers and Lecturers (UU RI, 2005) and further reinforced by the Regulation of the Minister of Education, Culture, Research, and Technology No. 44 of 2024, namely pedagogical, professional, personality, and social competencies (Permendikbudristek RI, 2024). The scores for each competency were processed using a Fuzzy Inference System (FIS) to generate an overall lecturer performance category. Taken together, these studies indicate that the Mamdani method has considerable potential to support performance evaluation in the education sector for both teachers and lecturers across various assessment frameworks. Nevertheless, previous studies on lecturer performance evaluation have employed diverse assessment frameworks, including lecturer competencies, institution-specific academic indicators, and LAI. The diversity of these assessment frameworks indicates that a standardized approach to evaluating lecturer performance using FIS has not yet been established.

Despite the successful application of FIS with Mamdani method in various studies, the assessment frameworks employed remain diverse, ranging from teacher success rates and institution-specific academic indicators to the LAI and the four lecturer competencies. These frameworks primarily emphasize competency-based assessment or institution-specific evaluation systems. Studies that specifically evaluate lecturer performance based on activities in the Education and Teaching domain as one of the pillars of the Tri Dharma of Higher Education remain limited. Furthermore, previous studies have generally focused on developing FIS models to generate performance scores or categories without comparing fuzzy-based evaluation results with the conventional assessment mechanisms implemented in higher education institutions. Such comparisons are important for demonstrating the extent to which FIS can provide a more comprehensive evaluation than conventional assessment methods currently in use.

To address these gaps, this study develops FIS with Mamdani method for lecturer performance evaluation using indicators that represent activities in the Education and Teaching domain, namely Teaching, Thesis Supervision, and Student Advising. In addition to generating fuzzy-based performance scores, the proposed model compares the evaluation results with those obtained using the conventional assessment mechanism employed by higher education institutions. Academically, this study extends the application of FIS with Mamdani method to activity-based lecturer performance evaluation in the Education and Teaching domain. Practically, the proposed model offers an alternative evaluation mechanism that is more comprehensive, transparent, and capable of accommodating uncertainty in the lecturer performance assessment process.

B. METHODS

This study employs a quantitative-descriptive approach based on FIS to evaluate lecturer performance in carrying out the Tri Dharma of Higher Education in the domain of education and teaching, as mandated by Law of the Republic Indonesia No. 12 of 2012 on Higher Education (UU RI, 2012). The lecturer performance assessment model is developed based on Electronic Employee Performance Targets (e-EPT) implemented within the Faculty of Teacher Training and Education at University of Trunodjoyo Madura. This system incorporates several main variables—each comprising supporting sub-variables—and performance indicators used to evaluate lecturers in carrying out the Tri Dharma of Higher Education. One of the main variables analyzed in this study is the education and teaching component.

The membership function parameters were established based on the assessment intervals defined in the lecturer performance evaluation guidelines. These intervals were then transformed into linguistic categories and represented using fuzzy membership functions to construct FIS. The sample supporting variables within the main variable—hereafter referred to as linguistic variables in the FIS—analyzed in this study are: (1) teaching, (2) thesis supervision, and (3) academic advising. These three variables were selected because they directly reflect lecturers' involvement in the learning process and academic services for students, and they possess clear quantifiable elements suitable for analysis using the fuzzy system. Each variable is accompanied by specific indicators, as detailed in Table 1 below.

Table 1. Supporting Variables and Indicators within the Main Variable of Education and Teaching

Supporting Variable	Aspect	Indicator
Teaching		Regular teaching credit load
		Teaching integrated with research or community service
		Teaching that implements innovative learning methods
Thesis Supervision	Quantity	Proportion between the number of students who graduated in one academic year and the total number of supervised students
	Quality	Supervision frequency
		Academic supervision quality
Student Advising	Quantity	Number of students advised
	Quality	Frequency of academic advising sessions
		Quality of academic advising supervision

Data analysis in this study employs the Mamdani method, which is widely recognized in fuzzy-based decision-making systems for its ability to accommodate subjective assessments through linguistic rules (Mamdani & Assilian, 1975; Ross, 2010). The structure of the system is designed using the Multi Input Single Output (MISO) model, a configuration involving multiple input variables and a single output variable (Zimmermann, 1996; Nwobi-okoye et al., 2016).

The FIS model in this study is developed through four main stages, namely: (1) fuzzification, transforming crisp input values (e.g., assessment scores ranging from 1 to 4) into fuzzy values based on linguistic membership functions; (2) fuzzy rule base construction, defining linguistic IF-THEN rules that link input variables (performance indicators) to the assessment output; (3) fuzzy inference, processing the rules using the Mamdani method, which combines multiple rules into a single fuzzy conclusion; and (4) defuzzification, converting the resulting fuzzy output into a crisp value to produce a final decision, using the centroid method as the

defuzzification technique (Zadeh, 1975; Ross, 2010; Jang et al., 1997). Microsoft Excel is used as the analytical tool in this process. Figure 1 illustrates the stages of the FIS.

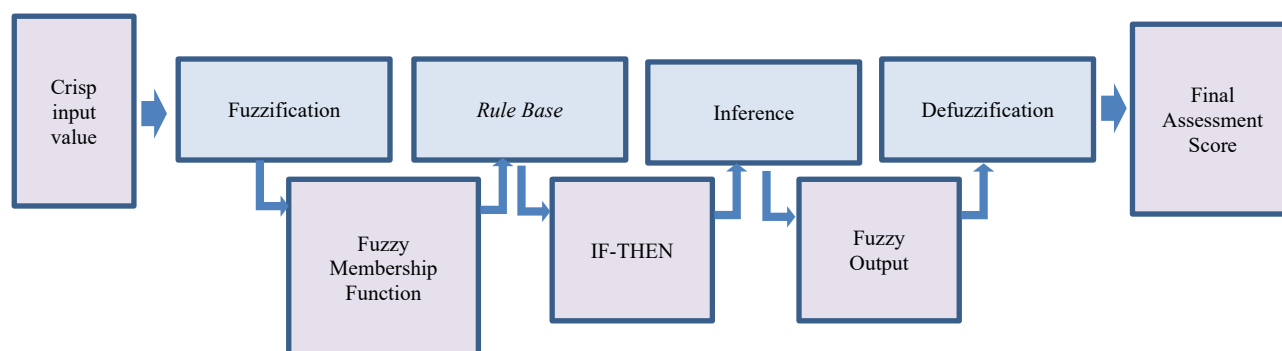


Figure 1. Stages of the Fuzzy Inference System (FIS)

C. RESULT AND DISCUSSION

1. Input Variable Assessment Rubric

Before implementing FIS to evaluate lecturer performance, the initial step undertaken was the development of a performance scoring rubric. This rubric was designed to ensure that each indicator within the teaching variable (such as Semester Credit Hours (SCH)), undergraduate thesis supervision, and academic advising responsibilities—has clear, measurable, and consistent assessment descriptors. Before applying the FIS to evaluate lecturer performance, the initial step involves the development of a performance scoring rubric. This rubric is designed to ensure that each indicator within the teaching variable—such as Semester Credit Hours (SCH), thesis supervision, and academic advising—has a clear, measurable, and consistent assessment description.

a. Teaching

The first indicator within the lecturer teaching variable is the regular teaching credit load carried out in one semester. In lecturer performance assessment systems, particularly within the teaching variable, workload is measured in terms of SCH. However, not all lecturers have the same teaching responsibilities. Lecturers who hold structural positions—such as dean, head of study program, or head of a research or study center—have additional responsibilities beyond the Tri Dharma of Higher Education, namely managerial and administrative duties. Therefore, their teaching load is generally limited to a maximum of 12 SCH per semester, as commonly practiced across higher education institutions in Indonesia. Any teaching load exceeding this limit is allocated to structural activities and is not included in the assessment of teaching performance. In contrast, lecturers who do not hold structural positions have a maximum teaching load of 16 SCH per semester. This principle is consistent with performance assessment theories that emphasize the importance of considering task context and individual roles within assessment systems to avoid structural bias (Healey, 2007; Wibowo, 2016).

To support the flexibility of fuzzy-based assessment, the categories for the number of SCU and the corresponding scores are designed to be linear and proportional. The score range is set from 1 (very low) to 4 (excellent), based on the degree to which a lecturer's

SCU workload meets the minimum and maximum thresholds according to their academic or structural position. This linear model was chosen to facilitate its transformation into a fuzzy logic system (fuzzification), making it easier to map onto membership functions and define the rule base within the fuzzy inference system. This approach aligns with the fundamental principles of fuzzy logic, which emphasize the gradual representation of values rather than discrete classifications when dealing with uncertainty and variability in performance (Zadeh, 1975; Zimmermann, 1996). The teaching assessment guidelines are presented in Table 2.

Table 2. Supporting Variables and Indicators within the Main Variable of Education and Teaching

Lecturer Status	SCH Load	Score	Category
With Structural Role	< 3	1	Poor
	3 – 5	2	Fair
	6 – 8	3	Good
	9 – 12	4	Excellent
	> 12	4	Excellent
Without Structural Role	< 6	1	Poor
	6 – 8	2	Fair
	9 – 12	3	Good
	13 – 16	4	Excellent
	> 16	4	Excellent

The second indicator in the assessment of lecturer teaching performance is teaching activities that integrate research or community service. This integration reflects the alignment of the three pillars of higher education (Tri Dharma) and reinforces the connection between scientific knowledge, research, and societal contributions—substantively providing students with academic experiences grounded in scholarly practice. This approach aligns with the view that lecturer performance indicators should be applicable and contextual in order to effectively promote the tangible integration of the Tri Dharma within teaching practice (Boyer, 1990; Brew, 2006). Within the Faculty of Teacher Training and Education at Universitas Trunodjoyo Madura, it has been established that lecturers are required to teach a minimum of 2 SCH per semester that are based on research or community service as a means of fulfilling the standard for Tri Dharma integration. The determination of the 2 SCH threshold also takes into account the faculty's curriculum structure, in which there are no research or community service based courses with a weight of 1 SCH. Generally, both regular courses and those based on research or community service carry a minimum weight of 2 SCH; therefore, the assessment criteria must be realistic and aligned with actual academic implementation. The weighting of indicators positions regular teaching as the lecturer's primary responsibility, while research/community service integration and teaching innovation are regarded as factors that strengthen the quality of the learning process. This strategy is consistent with higher education quality enhancement policies that emphasize a balance between the execution of core teaching duties and the continuous improvement

of learning quality through research and pedagogical innovation (Dirjen PT Kemdikbud, 2020; OECD, 2019).

Research/community service based teaching may take the form of: 1) courses based on the lecturer's own research findings, 2) student projects directly linked to the lecturer's research programs, 3) learning activities that address real-world issues derived from community service initiatives, and 4) field-based or collaborative learning involving external partners. In the scoring system, lecturers who teach 2 SCH are categorized as having met the minimum standard and are assigned a score at the "adequate" or "good" level, depending on the study program's policy context. Meanwhile, lecturers who do not teach any research- or community service-based SCH are categorized at the "low" level. Conversely, lecturers who teach more than 2 SCH (e.g., 4 or 6 SCH) are awarded higher scores as a form of recognition for a stronger commitment to integrating the Tri Dharma. To ensure the quality and relevance of learning activities, a minimum standard of 2 SKS per semester based on research or community service is established. The scoring guidelines are presented in Table 3.

Table 3. Teaching Assessment Guidelines for Research/Community-Based and Innovative Learning

SCH Amount	Score	Category
0	1	Poor
2 - 3	3	Fair or Good
> 4	4	Excellent

The third indicator in the teaching performance component assessment is the extent to which lecturers implement innovative teaching methods in their instructional activities. Innovation in teaching is a key indicator for improving the quality of higher education, in line with the principles of student centered learning and the Merdeka Belajar-Kampus Merdeka (MBKM) initiative. Innovative teaching methods may include, but are not limited to: (1) project-based learning, problem-based learning, and case-based learning (Bistari et al, 2024); (2) interactive digital technology-based learning (Adiyono et al., 2024); (3) cross-disciplinary collaborative learning (Farooq, 2024); and (4) the integration of learning with MBKM activities such as internships, research, and independent studies (Rifanti et al., 2023). As with the second indicator, the third indicator also sets a minimum standard of 2 SCU per semester to be delivered using innovative teaching methods. Therefore, the scoring guidelines follow the same structure as the second indicator, as presented in Table 3.

Subsequently, the three scores from the three teaching indicators are summed to obtain a combined score for the teaching component. Each of the three indicators plays a distinct role in reflecting the quality of a lecturer's teaching performance. Therefore, the combination of the three scores is not carried out using an equal weighting approach, but rather through proportional weighting based on the relative importance of each task. The regular teaching aspect, which represents the core responsibility of lecturers, carries the highest weight at 50%. Meanwhile, the other two aspects—teaching integrated with research or community service, and teaching using innovative

methods—are each assigned a weight of 25%. From the teaching component, a minimum score of 1 and a maximum score of 4 can be obtained.

The assessment of the regular teaching credit load indicator is based on official teaching assignment letters issued by the institution, as these documents represent formally recognized teaching responsibilities and serve as the primary administrative basis for the implementation of lecturers' teaching duties. This approach is consistent with higher education quality assurance practices that regard official assignment documents as the main reference in evaluating lecturer performance in the teaching domain (BAN PT, 2020; Suryadi, 2014). In contrast, the assessment of research/community service based teaching and teaching that applies innovative learning methods cannot be determined solely by teaching credit load; instead, it must be grounded in the Semester Learning Plan or other supporting documents that explicitly demonstrate the integration of research and/or community service activities into course content, as well as the use of innovative instructional strategies.

The Learning Plan is regarded as a key pedagogical document that reflects instructional design, methodological approaches, and intended learning outcomes, making it a relevant basis for evaluating teaching quality (Biggs & Tang, 2011; Permendikbud RI, 2020). Furthermore, the integration of research and community service into teaching is viewed as a strategy for enhancing students' conceptual understanding and strengthening the relevance of learning to real-world contexts, while teaching innovation serves to reinforce the overall quality of the teaching–learning process (Healey, 2007; Brew, 2006). Through this assessment approach, institutions not only evaluate the administrative implementation of teaching activities but also substantively encourage lecturers to improve learning quality through the integration of research and community service, as well as the application of creative, relevant, and learning-outcome-oriented instructional methods.

b. Thesis Supervision

Thesis supervision by lecturers is evaluated based on two main aspects: 1) quantity, which refers to the percentage proportion between the number of students who successfully graduate within one academic year and the total number of active supervised students (Formula (1)); and 2) the quality aspect of thesis supervision is assessed by examining the frequency of guidance sessions, as reflected in the lecturer's level of involvement in the supervision process. This approach aligns with the view that successful thesis completion is not determined solely by graduation outcomes, but is strongly influenced by the intensity of academic interaction and the quality of guidance provided by the supervisor (Lee & Lee, 2008). Table 4 describes the scoring guidelines for thesis supervision based on the quantity aspect, meanwhile, Table 5 describes the scoring guidelines for thesis supervision based on the quality aspect.

$$\text{TSQP} = \frac{\text{NG}}{\text{NAS}} \times 100\% \quad (1)$$

TSQP = Thesis Supervision Proportion Percentage

NG = Number of students who graduated in one academic year

NAS = Total number of active students under supervision

Table 4. Scoring Guidelines for Thesis Supervision: Quantity Aspect

TSQP	Score	Category
$\text{TSQP} < 30\%$	1	Poor
$30\% \leq \text{TSQP} < 60\%$	2	Fair
$60\% \leq \text{TSQP} < 90\%$	3	Good
$\text{TSQP} \geq 90\%$	4	Excellent

Notes: TSQP = Thesis Supervision Proportion Percentage

Table 5. Scoring Guidelines for Thesis Supervision on Quality Aspect

Indicator	Score 1 (Poor)	Score 2 (Fair)	Score 3 (Good)	Score 4 (Excellent)
Frequency of Supervision	≤ 4 sessions	5 – 7 sessions	8 – 10 sessions	> 10 sessions
Quality of Academic Supervision	Not systematic; minimal guidance	Systematic but limited depth	Systematic and moderately in-depth	Highly systematic and academically in-depth guidance

The quantitative aspect, represented by the TSQP, is used to describe the lecturer's effectiveness in guiding students toward timely completion of their studies. This indicator is relevant as a performance measure because it reflects the lecturer's ability to manage supervisory workload and facilitate students' academic progress (Wisker et al., 2007). However, relying solely on quantitative indicators may lead to based assessment if the supervision process itself is not adequately considered. Therefore, the qualitative aspect is assigned a greater weight (60%) than the quantitative aspect (40%). The emphasis on quality is grounded in findings from previous studies showing that sufficient supervision frequency and constructive academic feedback contribute significantly to students' success in producing independent and high-quality scholarly (Lee & Murray, 2015). By assigning a greater weight to the qualitative dimension, the assessment system encourages lecturers not only to pursue student graduation outcomes but also to ensure that the scholarly mentoring process is conducted in a systematic, in-depth, and academically rigorous manner. The minimum score obtained from thesis supervision is 1.6, while the maximum score is 6.4.

c. Academic Advising

Academic advising is one of the core responsibilities of lecturers in guiding and supporting students' academic development. Advising performance is measured not only by the number of students advised, but also by the quality of how the advising function is carried out. Therefore, an assessment system is needed that can fairly and objectively measure both quantitative and qualitative aspects (Powers et al., 2014). The purpose of this assessment system is to: (1) evaluate lecturers' performance in carrying

out their academic advising responsibilities; (2) provide a measurable and systematic evaluation of the implementation of academic advising; and (3) encourage lecturers to improve the quality of academic advising and personal development of students.

The indicators used to evaluate lecturer performance in the academic advising component are: (1) the number of students advised; and (2) the quality of the implementation of advising duties. The indicator “number of students advised” measures the quantity of students under the academic advisor’s responsibility. The number of students refers to the total of active students who are administratively and academically advised by a lecturer during an academic year. Within the framework of academic advisor performance assessment, this indicator is used to measure task implementation based on the proportion of the actual advising load compared to the ideal advising allocation (Formula 2). The number of students advised by a lecturer is not assessed in absolute terms, but rather through a percentage realization approach, which is calculated using Formula 3. This is because variations in the number of active students and the availability of academic advisors across academic years may lead to imbalances in workload if not properly normalized. Therefore, a ratio- and realization-based percentage approach is considered more adaptive to the dynamics of higher education institutions and more representative of the actual workload borne by academic advisors (Kuh et al., 2006).

$$IR = \frac{NSA \text{ Study Program}}{NAL \text{ Study Program}} \quad (2)$$

IR = Ideal Ratio

NSA = Number of Active Students Advised

NAL = Number of Active Lecturers as Advisors

$$CAPR = \frac{NSA \text{ n year}}{NIA \text{ n year}} \times 100\% \quad (3)$$

CAPR = Cumulative Actual Percentage Realization

NSA = Number of Students Advised

NIA = Number of Ideally Assigned Advisees

This approach takes into account the variation in the number of students and academic advisors every year, thereby producing a fairer, more measurable assessment that aligns with the dynamics of higher education institutions. A realization percentage that approaches or exceeds the ideal proportion is awarded a higher score as a form of appreciation for the additional workload borne by the lecturer in continuously supporting students. Based on the percentage values, the performance of academic advisors is classified into four categories, as shown in Table 6 below.

Table 6. Guidelines for Assessing Academic Advisor Activities

CAPR	Score	Category
$CAPR < 50\%$	1	Poor
$50\% \leq CAPR < 70\%$	2	Fair
$70\% \leq CAPR < 100\%$	3	Good
$CAPR \geq 100\%$	4	Excellent

Notes: CAPR = Cumulative Actual Percentage Realization

The indicator “quality of academic advising” is used to assess the quality of lecturers’ performance in fulfilling their role as academic advisors; therefore, it is necessary to establish a set of sub-indicators that can measure the implementation of these responsibilities in a holistic and measurable manner. The quality indicators for academic advising include the intensity and quality of guidance. This classification aims to observe not only the achievement of quantitative targets but also the quality of interaction and support provided to students. In the context of lecturer performance assessment for the academic advising indicator, the minimum score assigned is 2. This is based on the assumption that every academic advisor is expected to carry out at least one advising activity, either during the Course Registration period or in the student graduation process. Although this activity is carried out at a minimal level, the role of the academic advisor still has an impact on students’ academic progress. Therefore, it cannot be considered equivalent to not performing any advising duties at all—which is typically assigned a score of 1. Although this activity is carried out at a minimal level, the role of the academic advisor still has an impact on students’ academic progress. Therefore, a score of 1 is not applicable for this indicator, because the presence and intervention of the academic advisor in a single advising cycle still indicate a measurable contribution to performance. Assigning a score of 2 as the lower limit reflects an acknowledgment of the academic advisor’s fundamental role at a minimal level yet essential in guiding and supporting students. The classification of academic advising quality indicators is presented in Table 7 as follows.

Table 7. Classification of Indicators in the Academic Advising Quality Aspect

Indicator	Description	Number of Meetings	Score	Category
Frequency	Measures how often the academic advisor engages in active interaction with students, either face-to-face, online consultation, or via other communication media.	2	1	Fair
		3 – 4	2	Good
		5 – 6	3	Excellent
		≥ 7	4	Overload
Quality	Assesses the extent to which the academic advisor provides guidance, solutions, and constructive motivation regarding students’ academic and non-academic development.	Communication only occurs for administrative purposes (e.g., course registration card), with no real support provided.	2	Fair
		Provides general advice without considering the individual student’s needs.	3	Good

Indicator	Description	Number of Meetings	Score	Category
		Provides specific guidance and mentoring tailored to each student's condition.	4	Excellent

The final assessment of a lecturer's performance in carrying out academic advising duties is determined using a combined approach between quantitative and qualitative aspects, each with its own assigned weight. This approach is intended to assess not only the number of students advised by the lecturer but also the quality of academic advising practices, thereby producing a more fair, comprehensive, and objective evaluation. Numerous studies indicate that the effectiveness of academic advising is more strongly influenced by the quality of interaction and mentoring than by the sheer number of students advised (Tinto, 2012; Drake, 2011). The assessment weight as follows: 1) 40% for the quantitative aspect, namely the number of students advised compared to the ideal lecturer-to-student ratio (1:45); and 2) 60% is allocated to the qualitative aspect, which includes indicators of the intensity and quality of academic advising provided by the academic advisor. The minimum score for the academic advising component is 1.6, while the maximum score is 6.4.

2. Fuzzification Inference System (FIS)

As previously stated, this study limits the lecturer performance assessment to the variable of "education and teaching" only. The indicators used are based on the Electronic Employee Performance Targets (e-EPT) system of the Faculty of Teacher Training and Education UTM, which will serve as the basis for determining the scores of the input variables, as shown in Table 8. Each linguistic variable is expressed on a specific normalized score scale and then classified into three linguistic categories: low, medium, and high.

Table 8. Fuzzy Set

Function	Linguistic Variable	Indicator	Linguistic Category (Value)	Universe of Discourse
Input	Teaching	Conducting a minimum of 9 SCH per semester, at least 2 SCH per semester in research/service-based and at least 2 SCH per semester in innovative teaching	High Medium Low	[1, 4]
Input	Thesis Supervision	Supervising thesis students (based on quantity: at least 5 students graduate per year; and quality: frequency and quality of supervision)	High Medium Low	[1.6, 6.4]
Input	Academic Advising	Serving as an academic advisor (based on quantity: percentage realization; and quality: intensity and guidance quality)	High Medium Low	[1.6, 6.4]
Output	Lecturer Performance Decision in Education and Teaching	Overall assessment of lecturer performance in education and teaching	Excellent Fair Poor	

a. Fuzzification

The initial stage in FIS is fuzzification, which is the process of transforming crisp input values into fuzzy values based on membership functions. Membership functions are used to determine the degree of membership (μ) of an input value in each linguistic category. In this study, the membership functions are designed using a combination of trapezoidal functions for the extreme categories (low and high) and triangular functions for the medium category (Zimmermann, 1996; Ross, 2010; Bede, 2013). Trapezoidal functions provide tolerance at extreme categories, while triangular functions for medium categories allow for more sensitive value transitions. This approach is consistent with recommendations in the development of fuzzy-based assessment systems that emphasize a balance between strictness and flexibility (Bede, 2013). This approach allows for a clearer representation of boundary values in the extreme categories while enabling more gradual transitions in the medium category.

Teaching

The linguistic variable for teaching is assessed on a score range of 1 to 4, which reflects the quality of a lecturer's teaching performance. This variable is divided into three categories: low, medium, and high. The fuzzy membership functions for each category are defined as follows.

Low:

$$\mu_{P-low}(x) = \begin{cases} 1, & x \leq 2 \\ \frac{2.6-x}{0.6}, & 2 < x \leq 2.6 \\ 0, & x > 2.6 \end{cases} \quad (4)$$

Medium:

$$\mu_{P-}(x) = \begin{cases} 0, & x \leq 1.8 \\ \frac{x-1.8}{0.8}, & 1.8 < x \leq 2.6 \\ \frac{3.4-x}{0.8}, & 2.6 < x < 3.4 \\ 0, & x \geq 3.4 \end{cases} \quad (5)$$

High:

$$\mu_{P-high}(x) = \begin{cases} 0, & x \leq 1.8 \\ \frac{x-1.8}{0.8}, & 1.8 < x \leq 2.6 \\ \frac{3.4-x}{0.8}, & 2.6 < x < 3.4 \\ 0, & x \geq 3.4 \end{cases} \quad (6)$$

Figure 2 illustrates the fuzzy membership function graph for the teaching variable.

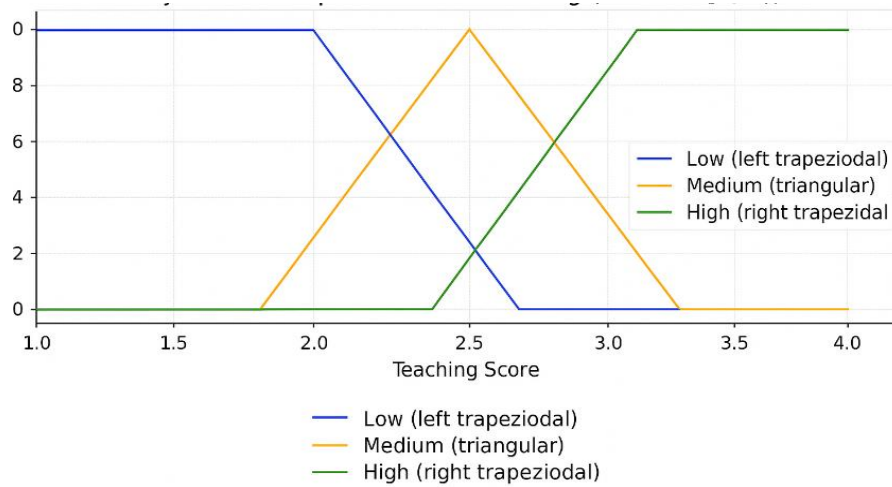


Figure 2. Fuzzy Membership Function for Teaching Variable (Domain [1, 4])

Thesis Supervision

The linguistic variable for thesis supervision is evaluated based on a score range of 1.6 to 6.4, which reflects the quality of thesis supervision carried out by the lecturer. This variable consists of three categories: low, medium, and high. The fuzzy membership functions for each category are defined as follows.

Low:

$$\mu_{PS-low}(x) = \begin{cases} 1, & x \leq 3.2 \\ \frac{4.8-x}{1.6}, & 3.2 < x \leq 4.8 \\ 0, & x > 4.8 \end{cases} \quad (7)$$

Medium:

$$\mu_{PS-medium}(x) = \begin{cases} 0, & x \leq 3.2 \\ \frac{x-3.4}{1.4}, & 3.2 < x \leq 4.8 \\ \frac{6-x}{1.2}, & 4.8 < x \leq 6 \\ 0, & x > 6 \end{cases} \quad (8)$$

High:

$$\mu_{PS-high}(x) = \begin{cases} 0, & x \leq 2.6 \\ \frac{x-2.6}{0.6}, & 2.6 < x \leq 3.2 \\ 1, & x > 3.2 \end{cases} \quad (9)$$

Figure 3 illustrates the fuzzy membership function graph for the thesis supervision variable.

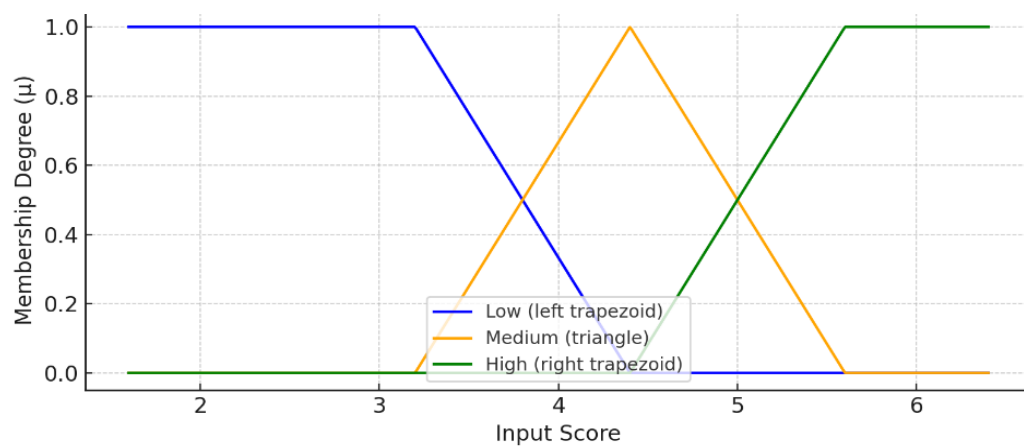


Figure 3. Fuzzy Membership Function of the Thesis Supervision Variable (Domain [1.6, 6.4])

Academic Advising

Similar to the linguistic variable of thesis supervision, the student academic advising variable is assessed based on a score range of 1.6 to 6.4, which reflects the implementation of academic advising duties. It also has 3 (three) categories: low, medium, and high. Therefore, the fuzzy membership functions for each category and the graph of the fuzzy membership function for the student academic advising variable are the same as those for the thesis supervision variable. To facilitate viewing the degree of membership for each variable, Microsoft Excel was used (Table 9).

Table 9. Excel Formulas for Membership Degrees

Linguistic Variable	Category	Excel Formula
Teaching	High	=IF(J6<=2,6;0;IF(J6<=3,2;(J6-2,6)/0,6;IF(J6>3,2;1)))
	Medium	=IF(J6<=1,8;0;IF(J6<=2,6;(J6-1,8)/0,8;IF(J6<3,4;(3,4-J6)/0,8;IF(J6>=3,4;0))))
	Low	=IF(J6<2;1;IF(J6<=2,6;(2,6-J6)/0,6;0))
Thesis Supervision	High	=IF(S6<=4,8;0;IF(S6<=6;(S6-4,8)/1,2;IF(S6>6;1)))
	Medium	=IF(S6<=3,2;0;IF(S6<=4,8;(S6-3,4)/1,4;IF(S6<=6;(6-S6)/1,2;IF(S6>=6;0))))
	Low	=IF(S6<=3,2;1;IF(S6<=4,8;(4,8-S6)/1,6;IF(S6>4,8;0)))
Student Advising	High	=IF(S6<=4,8;0;IF(S6<=6;(S6-4,8)/1,2;IF(S6>6;1)))
	Medium	=IF(S6<=3,2;0;IF(S6<=4,8;(S6-3,4)/1,4;IF(S6<=6;(6-S6)/1,2;IF(S6>=6;0))))
	Low	=IF(S6<=3,2;1;IF(S6<=4,8;(4,8-S6)/1,6;IF(S6>4,8;0)))

b. Rule Base

Based on the three input variables, each of which has three linguistic categories (low, medium, high), a total of 27 fuzzy inference rules (rule base) are formed. These rules are used to determine the output in the form of lecturer performance categories in the field

of education and teaching, namely: poor, fair, good, and excellent. The developed rule base reflects the principle that lecturer performance is multidimensional; therefore, the final decision is not determined by a single aspect alone. For example, a lecturer with high performance in one aspect but low performance in another does not automatically receive the highest overall performance category. This approach is consistent with recent studies showing that fuzzy-based evaluation systems are better able to represent complex relationships among indicators compared to traditional methods (Tavana & Hajipour, 2020; Rizvi et al., 2020). The logical references for determining the output for each input combination are presented in Table 10, while the complete set of rules derived from the lecturer performance assessment problem in the field of education and teaching is shown in Table 11.

Table 10. Rule Base Guideline

Input Combination	Performance Output	Explanation
All inputs Low	Poor	All aspects are poor → very low performance
2 Low, 1 Medium	Poor	Majority are low → still poor
2 Low, 1 High	Fair	Inconsistent performance → some potential
1 Low, 2 Medium	Fair	Mostly medium → fair performance
All inputs Medium	Fair	Stable but not outstanding
1 High, 2 Medium	Good	Performance begins to improve
2 High, 1 Medium (not T & TS)	Good	Strength in two areas, but not in the core
High (T & TS), Medium (A)	Excellent	Special rule: Core indicators are strong, advising moderate
All inputs High	Excellent	All aspects are excellent
1 High, 1 Medium, 1 Low	Fair	Imbalance in contribution
1 High, 2 Low	Fair	Still insufficient overall performance
2 Medium, 1 Low	Fair	Majority medium, but one lacking aspect
2 High, 1 Low (T & TS high)	Good	Core indicators strong, advising weak
2 High, 1 Low (not T & TS)	Fair	Non-core indicators dominate → fair
1 Medium, 2 High (not T & S)	Good	Strength in some areas, not yet core
1 Low, 2 High (T & TS high)	Good	Core performance strong, advising lacking

Note: T = Teaching; TS = Thesis Supervision; and A = Academic Advising

Table 11. Rule Base

RB	Teaching	Thesis Supervision	Student Advising	Output
1	Low	Low	Low	Poor
2	Low	Low	Medium	Poor
3	Low	Low	High	Fair
4	Low	Medium	Low	Poor
5	Low	Medium	Medium	Fair
6	Low	Medium	High	Fair
7	Low	High	Low	Fair
8	Low	High	Medium	Fair
9	Low	High	High	Fair
10	Medium	Low	Low	Poor

RB	Teaching	Thesis Supervision	Student Advising	Output
11	Medium	Low	Medium	Fair
12	Medium	Low	High	Fair
13	Medium	Medium	Low	Fair
14	Medium	Medium	Medium	Fair
15	Medium	Medium	High	Fair
16	Medium	High	Low	Fair
17	Medium	High	Medium	Good
18	Medium	High	High	Good
19	High	Low	Low	Fair
20	High	Low	Medium	Fair
21	High	Low	High	Good
22	High	Medium	Low	Fair
23	High	Medium	Medium	Good
24	High	Medium	High	Good
25	High	High	Low	Good
26	High	High	Medium	Excellent
27	High	High	High	Excellent

Notes: RB = Rule Based

c. Inference

The next stage is fuzzy inference using the Mamdani method. This inference process applies if-then rules to map the relationship between fuzzy inputs and fuzzy outputs based on the degree of membership of each input. The Mamdani method operates by combining fuzzy input values based on IF-THEN rules, and calculating the truth degree or rule strength (α -predicate) using the AND operator, which is mathematically represented by the minimum (min) function (Bede, 2013; Zimmermann, 1996). The α -predicate indicates the degree to which the rule is considered to be “active.”

Rule: IF A AND B AND C THEN D

$$\alpha\text{-predicate} = \min(\mu_A, \mu_B, \mu_C) \quad (10)$$

The 27 rule bases can be grouped according to the type of intervention provided, as follows:

The output “Poor” appears in RB1, RB2, RB4, RB10, and RB19.

The output “Fair” appears in RB3, RB5, RB7, RB11, RB13, RB14, and RB16.

The output “Good” appears in RB6, RB8, RB12, RB15, RB17, RB20, RB22, and RB23.

The output “Excellent” appears in RB9, RB18, RB21, RB24, RB25, RB26, and RB27.

Each rule has a different α -predicate value, depending on the membership values of the input variables. For example, although RB6 and RB23 both produce the output “Good”, their α -predicate values may differ — for instance, 0.6 and 0.8, respectively. The highest membership value among all rules producing the “Good” output will be taken as the final representation of the “Good” category.

d. Defuzzification

After obtaining the aggregated fuzzy output, the final stage in FIS is defuzzification. This process aims to convert the fuzzy result into a crisp value, which can then be used as a basis for decision-making. In this study, defuzzification is performed using the Centroid Method (Center of Gravity), which involves calculating the center point (d^*) of the area under the fuzzy output curve. The centroid defuzzification method was selected due to its ability to generate stable and representative crisp values based on the overall area of the fuzzy output. This method is widely recommended in fuzzy-based decision-making systems because of its intuitive nature and ease of interpretation for policymakers (Zadeh, 1975; Rizvi et al., 2020). Theoretically, the centroid method is formulated as an integral expression (Zadeh, 1975) as follows:

$$d^* = \frac{\int_a^b x \cdot \mu(x) dx}{\int_a^b \mu(x) dx} \quad (11)$$

d^* = crisp value resulting from defuzzification
 x = output variable
 $\mu(x)$ = membership function of the aggregated fuzzy output
 a, b = lower and upper bounds of the fuzzy output domain

However, since the membership functions of the fuzzy output in this system are based on linguistic categories using triangular and trapezoidal shapes, the integral calculation is simplified into a discrete form using the midpoint approximation for each fuzzy output category. Thus, the defuzzification formula can be written (Rizvi et al., 2020) as follows:

$$x^* = \frac{\sum (x_i \cdot \mu(x_i))}{\sum \mu(x_i)} \quad (12)$$

x_i = the midpoint of each fuzzy output category (e.g., Poor, Fair, Good, Excellent)
 $\mu(x_i)$ = the degree of membership resulting from fuzzy aggregation for each respective category

In the context of this study, the result of the centroid defuzzification method will determine the final decision regarding the lecturer's performance in the field of education and teaching. A lecturer may be assigned a performance level of Poor, Fair, Good, or Excellent, based on the defuzzified output value.

3. Case Study and Comparison of Assessment Results

To illustrate the application of the proposed Mamdani method, a case study involving the performance evaluation of Lecturer A in the area of education and teaching was conducted. Lecturer A carried a teaching workload of 12 credit units, comprising 4 credit units of research-based teaching and 6 credit units employing innovative teaching methods. In thesis supervision, Lecturer A supervised 20 undergraduate students, of whom 19 successfully completed their theses. Throughout one semester, thesis supervision was conducted through eight systematic

and in-depth meetings. Regarding academic advising, Lecturer A had 20 existing advisees and was assigned 20 new first-year students, resulting in a total of 40 academic advisees. The study program where Lecturer A serves consists of 28 lecturers and 250 first-year students, who are distributed among lecturers for academic advising. In carrying out academic advising duties, Lecturer A met with students only during the course registration process. The case study data were subsequently evaluated using two different approaches: the conventional performance assessment method based on the e-SKP system and the proposed Mamdani method.

Conventional Performance Assessment

The conventional performance assessment followed the e-SKP performance evaluation mechanism, which consists of two main components: work performance and work behavior. Work performance is evaluated based on the achievement of predefined performance indicators supported by the required evidence, whereas work behavior is assessed using the seven core values of the Indonesian Civil Service (ASN BerAKHLAK): service-oriented, accountable, competent, harmonious, loyal, adaptive, and collaborative. The results of these two components are then integrated to determine the employee's overall performance rating. For the purpose of comparison, the work performance assessment was limited to the same indicators used as input variables in the proposed FIS model, namely teaching, thesis supervision, and academic advising. This restriction was applied to ensure an apple-to-apple comparison between the conventional assessment method and the proposed FIS model.

For the teaching component, Lecturer A fulfilled a teaching workload of 12 credit units, including 4 credit units of research-based teaching and 6 credit units employing innovative teaching methods. Therefore, this component was assessed as Meeting Expectations. For thesis supervision, Lecturer A successfully guided 19 out of 20 undergraduate students to complete their theses. Thesis supervision was conducted through eight systematic and in-depth meetings during one semester. Based on these achievements, the thesis supervision component was also classified as Meeting Expectations. For academic advising, Lecturer A provided advising services to 40 students, although academic interactions were limited to the course registration approval process. According to the e-EPT assessment mechanism, this component still satisfied the required performance indicators and was therefore classified as Meeting Expectations. Consequently, Lecturer A's overall work performance was categorized as Meeting Expectations.

In addition to work performance, the conventional assessment also considers work behavior. According to the e-EPT evaluation mechanism, work behavior is assessed based on the seven dimensions of the ASN BerAKHLAK core values. In this case study, it was assumed that Lecturer A met the expected standards for all seven behavioral dimensions in accordance with the e-EPT evaluation criteria. Therefore, the work behavior component was also categorized as Meeting Expectations. Based on the combined results of work performance and work behavior, the overall performance rating produced by the conventional assessment method was Good.

Assessment Using the Fuzzy Inference System (FIS) with Mamdani Method

Unlike the conventional assessment method, which directly evaluates the achievement of performance indicators against predefined targets, the proposed Mamdani method processes each indicator as a fuzzy variable, enabling performance achievement to be represented in a more gradual manner. Three input variables were used in this study, namely Teaching (T), Thesis Supervision (TS), and Student Advising (SA). These variables were derived from the same case study data used in the conventional assessment, ensuring that both approaches employed identical data sources. Before the inference process, the case study data were converted into crisp scores based on the proposed scoring guidelines. The resulting scores were 4 for Teaching, 5.8 for Thesis Supervision, and 2.8 for Student Advising. These crisp values were subsequently transformed into fuzzy values through the fuzzification process to determine their degrees of membership in the three fuzzy sets: low, medium, and high.

The next stage involved the Mamdani inference process, in which all 27 fuzzy rules (rule base) were evaluated. Each rule generated an α -predicate value using the minimum operator, after which the outputs were aggregated into four linguistic categories: poor, fair, good, and excellent. The aggregation results indicated that the poor and fair categories did not contribute to the final decision, whereas the maximum α -predicate values for the good and excellent categories were 0.2 and 1.0, respectively. These results indicate that the strong performance in Teaching and Thesis Supervision had a dominant influence on the final decision, despite the relatively lower score obtained for Student Advising.

Finally, the centroid defuzzification method was applied to obtain a single crisp output representing the system's final decision. The defuzzification process produced a centroid value of 81.6, which falls within the Excellent performance category. Unlike the conventional assessment method, which produces only a final performance category, the proposed FIS with Mamdani method provides additional quantitative information, including the centroid value, the degree of membership of each input variable, and the contribution of each inference rule to the final decision.

Comparison of Assessment Results

The assessment results obtained using the conventional method and the proposed FIS with Mamdani method are presented in Table 12.

Table 12. Comparison Between Conventional Method and FIS with Mamdani Method

Aspect	Conventional Method (e-SKP)	Mamdani FIS
Data source	Case study data of Lecturer A	Case study data of Lecturer A
Assessment variables	Teaching, Thesis Supervision, Academic Advising, and Work Behavior	Teaching (T), Thesis Supervision (TS), and Student Advising (SA)
Assessment mechanism	Evaluation of indicator achievement against predefined performance expectations	Fuzzification, evaluation of 27 fuzzy rules, aggregation, and defuzzification
Work performance	Meeting Expectations	Input scores: T = 4.0, TS = 5.8, SA = 2.8
Work behavior	Meeting Expectations	Not included as an input variable
Final output	Overall Performance Rating = Good	Centroid = 81.6 (Excellent)

Based on Table 12, both methods employed the same case study data but adopted different assessment mechanisms. The conventional method generated an overall performance rating of Good by evaluating the extent to which work performance and work behavior met the predefined performance expectations established in the e-EPT system. In contrast, the proposed FIS with Mamdani method produced a centroid value of 81.6, corresponding to the Excellent performance category, through a sequence of fuzzification, fuzzy inference, aggregation, and centroid defuzzification.

The comparison demonstrates that the two methods differ not only in their computational procedures but also in the type of information they provide. The conventional method primarily determines whether performance indicators meet predefined expectations and produces a qualitative performance rating. In contrast, the proposed FIS with Mamdani method captures the gradual nature of performance achievement by representing each assessment indicator as a fuzzy variable and integrating their contributions through a rule-based inference mechanism. Consequently, the final decision reflects the combined influence of all assessment variables rather than a simple evaluation of whether expectations have been met.

In this case study, although the Student Advising component received a relatively lower score than Teaching and Thesis Supervision, the strong performance in the latter two components exerted a dominant influence on the inference process, resulting in a final centroid value of 81.6, which falls within the Excellent category. This finding illustrates the ability of the proposed FIS model to represent varying levels of achievement across multiple performance indicators while preserving the relative contribution of each component to the final assessment.

Compared with the conventional assessment method, the proposed FIS with Mamdani method provides a more informative evaluation by generating not only a final performance category but also quantitative outputs, including crisp scores, membership degrees, rule activation strengths (α -predicate values), and the centroid value. These additional outputs offer greater transparency in the decision-making process and enable a more comprehensive interpretation of lecturer performance.

D. CONCLUSION AND SUGGESTIONS

This study successfully developed a lecturer performance evaluation system based on Fuzzy Inference System (FIS) with the Mamdani method for the education and teaching domain. The proposed model adopts a Multi-Input Single-Output (MISO) framework with three assessment variables: Teaching, Thesis Supervision, and Student Advising. Each variable is represented as a linguistic variable using fuzzy membership functions and is subsequently processed through fuzzification, Mamdani inference with 27 fuzzy rules, aggregation, and centroid defuzzification to produce the final performance score.

The application of the proposed model to the case study demonstrated that the FIS with Mamdani method provides a more informative evaluation than the conventional method. Using the same performance data for Lecturer A, the conventional method produced an overall performance rating of Good, whereas the proposed FIS generated a centroid value of 81.6, corresponding to the Excellent category. In addition to producing a final performance category, the proposed FIS with Mamdani method provides information on the membership degrees of each assessment variable, rule activation strengths, and the contribution of each indicator to

the final decision. The proposed model not only produces more objective, proportional, and flexible evaluation results but also enhances the transparency of the decision-making process while representing lecturer performance in a more gradual and comprehensive manner than the conventional method.

The recommendations of this study are as follows: (1) the system development can be enhanced by incorporating real data from higher education institutions to empirically test its validity and reliability; (2) refinement of the fuzzy rules (rule base) can be carried out by involving academic experts to ensure that each rule reflects fair and representative judgment; (3) integration of the system into a digital platform or campus information system is highly recommended to enable practical use by university leaders or quality assurance units in decision-making; and (4) future research may consider adopting alternative fuzzy approaches or different defuzzification methods to improve the system's sensitivity to uncertainty and ambiguity in performance assessment.

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