

Decision Support System for Teacher Performance Evaluation Using LODECI Weighting and CODAS Method

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Abstract

The quality of teacher performance evaluation plays an important role in improving educational outcomes, yet conventional assessment approaches often suffer from subjectivity, inconsistency, and lack of transparent weighting mechanisms. This study proposes a Decision Support System (DSS) model by integrating the LODECI method for objective criteria weighting and the CODAS method for alternative ranking to produce more accurate and data-driven evaluation results. The LODECI method determines criterion weights based on data distribution characteristics, resulting in proportional weights where Classroom Management (0.1881), Pedagogical Competence (0.1825), and Creativity and Innovation (0.1702) are identified as the most influential criteria. Furthermore, the CODAS method evaluates teacher performance using a distance-based approach to the negative ideal solution, producing preference values that enable clear differentiation among alternatives. The ranking results show that A7 – Gina achieves Rank 1 with a value of -0.2399, followed by A3 – Citra in Rank 2 with -0.2181, and A9 – Intan in Rank 3 with -0.1374, indicating their superior performance compared to other alternatives. To ensure robustness, a sensitivity analysis was conducted using 18 threshold (ϕ) scenarios ranging from 0.1 to 0.95. The results demonstrate that the top-ranked alternatives (A7, A3, and A9) consistently maintain their positions across all scenarios, indicating that the proposed model is stable and not significantly affected by parameter changes. Therefore, the integration of LODECI and CODAS within a DSS framework proves to be effective in producing objective, consistent, and reliable teacher performance evaluations that can support decision-making in educational institutions.

Keywords: DSS, LODECI Method, CODAS Method, Teacher Performance Evaluation, MCDM.

1. INTRODUCTION

The quality of education is strongly influenced by teachers' ability to manage learning effectively, making an objective and continuous performance evaluation system essential to measure how well teachers achieve learning goals in terms of subject mastery, teaching methods, and interaction with students [1], [2]. Such evaluation not only provides a clear picture of teacher performance but also serves as a foundation

for improving educational quality through policy formulation, including training needs and competency development, while fostering a professional work culture based on measurable indicators. However, conventional evaluation practices often face significant challenges, including high subjectivity, unfairness due to differences in evaluators' perceptions, inconsistency in applying assessment criteria, and the absence of a clear weighting system, resulting in evaluations that do not proportionally reflect overall performance. Additionally,

limitations in processing complex evaluation data reduce accuracy, and the lack of transparency in the evaluation process can lead to doubts about the results, especially when they are not supported by rational and clearly explainable calculation methods.

The role of decision support systems (DSS) in assisting decision-making is becoming increasingly important amid the complexity of problems involving multiple criteria and alternatives [3][4][5]. DSS functions as a tool that can process data systematically to produce information that is more structured and easier for decision-makers to understand. By utilizing various analytical methods, DSS can reduce the level of subjectivity that often arises in manual assessment processes, making the decisions produced more objective and rational. In addition, DSS also allows the integration of various data sources, both quantitative and qualitative, resulting in a more comprehensive picture of a problem. Another advantage of DSS is its ability to perform simulations and comparisons of various decision alternatives quickly and accurately [6][7][8]. This is very helpful in determining the best choice based on previously established criteria without having to go through a long and repetitive manual process.

The multi-criteria decision making (MCDM) approach has various advantages that make it very effective in handling decision-making problems involving multiple conflicting criteria [9][10][11]. One of its main strengths is its ability to accommodate various types of criteria, both quantitative and qualitative, providing high flexibility in different decision-making contexts. In addition, MCDM allows the determination of weights for each criterion according to its level of importance, making the decision results more proportional and reflecting the true priorities. This method also helps increase transparency because each calculation step can be traced and explained systematically. Another advantage lies in its ability to compare many alternatives simultaneously, making it easier to determine the best choice based on a comprehensive evaluation. The MCDM approach can also reduce subjective bias because decisions are based on a structured and consistent mathematical model [12][13][14]. In addition, various methods in MCDM can be combined to produce stronger and more stable analysis against changes in data or preferences. DSS and MCDM are two concepts that are closely related in supporting complex and structured decision-making processes. DSS functions as a computer-based system designed to assist decision-makers in processing data, organizing information, and generating alternative solutions systematically [15][16][17].

The selection of the LODECI method as an objective weighting approach is based on its ability to produce more stable and representative criterion weights according to the characteristics of the data used [18], [19]. LODECI can reduce dependence on subjective judgment because the weight determination process is carried out through mathematical analysis of the distribution and variation of data for each criterion. This allows each criterion to be assessed proportionally according to its contribution in differentiating the available alternatives. In addition, LODECI has the advantage of capturing important information often

overlooked by conventional weighting methods, especially in conditions where data is unbalanced or has a diverse spread of values. This method also provides more consistent results when data changes occur, making it suitable for use in dynamic decision-making environments. With a systematic and data-driven approach, LODECI is able to improve accuracy in determining the weight of criteria as a basis for more objective evaluations.

The selection of the CODAS method as a ranking approach is based on its ability to evaluate alternatives based on the distance to the negative ideal solution, thus providing a different perspective compared to other methods that generally focus on proximity to the positive ideal solution [20], [21]. The CODAS method utilizes Euclidean and Taxicab distance calculations to measure the level of superiority of each alternative more comprehensively, especially in distinguishing alternatives with almost similar values. The main advantage of this method lies in its sensitivity to small differences between alternatives, making the ranking results more discriminative and accurate. In addition, the CODAS method has a relatively simple calculation structure but is still able to produce stable decisions under various data conditions. This method is also effective in reducing ambiguity in the selection process because it provides clear evaluation values based on the concept of distance. With these characteristics, the CODAS method becomes the right choice for use in decision support systems that require definite and reliable ranking results.

Previous research that applied DSS in evaluating teacher performance has increasingly developed by utilizing various MCDM methods. Research by [22] through the article Decision Support System for Assessing Teacher Performance Using the Simple Additive Weighting (SAW) Method emphasizes that the use of the SAW method is able to transform the previously subjective assessment process into a more structured and quantitative data-based process. Meanwhile, research from [23] shows that the TOPSIS approach is effective in determining the best alternative based on closeness to the positive and negative ideal solutions, thus producing more consistent and rational rankings. On the other hand, research from [24] shows that the Weighted Product method has an advantage in considering the ratio between criteria, resulting in a more selective ranking.

Although various previous studies have shown that the implementation of DSS using the SAW, TOPSIS, and WP methods can improve the structure and objectivity of teacher performance assessments based on quantitative data, these approaches still have limitations in determining the criteria weights, which often do not fully reflect the dynamic level of importance. Therefore, the integration of the LODECI method as an approach to more objectively determine criteria weights with the CODAS method, which can evaluate alternatives based on Euclidean and Taxicab distances to the negative solution, is expected to overcome the weaknesses of the previous methods and produce teacher performance evaluations that are more accurate, robust, and representative.

This research proposes a more structured, objective, and precise approach to evaluating teacher performance by integrating the LODECI method for determining criterion

weights and the CODAS method for ranking alternatives within a Decision Support System. The approach is designed to overcome the limitations of conventional evaluation practices that often rely on subjective judgment and lack consistency, thereby supporting more transparent and evidence-based assessment results. It generally reflects the use of complementary techniques in which criterion weighting and ranking processes are combined to enhance decision-making quality. In addition, the study provides a practical framework that can be applied by educational institutions to conduct performance evaluations in a more systematic manner, while also contributing in a general sense to the advancement of MCDM-based approaches for improving the reliability of evaluation outcomes and supporting overall educational quality improvement.

II. RESEARCH METHODOLOGY

A. Research Stage

Research stages are a framework systematically arranged to ensure that the research process proceeds in a directed, logical manner and aligns with the objectives intended to be achieved. This framework functions as a guide in managing all research activities so that every process carried out has a clear basis and can be scientifically accounted for. The presence of structured research stages can minimize errors in data processing and increase consistency in the analysis conducted. Furthermore, research stages also play an important role in maintaining the flow of thinking so that it remains focused on the issues under study without deviating from the main research objectives. Clarity in arranging these stages also supports transparency and makes it easier to understand the research process by others, both for evaluation purposes and the development of future research. The research stages conducted are shown in Figure 1.

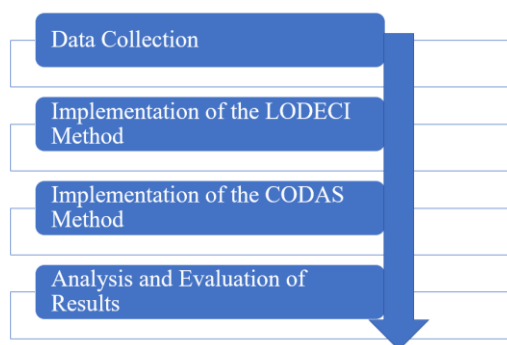


Figure 1. Research Stage

The research process begins with the data collection stage, where all relevant information related to evaluation criteria and assessed alternatives is gathered to ensure that the dataset accurately reflects real conditions. Afterward, the collected data is analyzed using the LODECI method to objectively determine the weight of each criterion based on the distribution of its values, allowing the level of importance for each criterion to be defined in a balanced manner. The resulting weights are

then applied within the CODAS method to evaluate and rank the alternatives by measuring their distance from the negative ideal solution, producing an ordered list based on the best performance outcomes. Finally, the process concludes with an analysis and evaluation phase aimed at examining the accuracy, consistency, and reliability of the applied methods in supporting effective decision-making.

B. Data Collection

Data collection is an important stage in research aimed at obtaining accurate and relevant information as a basis for the analysis process. At this stage, data is collected from various sources related to the research object, both in the form of primary and secondary data, so that it can provide a comprehensive picture of the issues being studied. The quality of the data obtained greatly determines the accuracy of the research results, so the collection process must be carried out systematically and planned. In addition, determining criteria and alternatives is also an important part of this stage so that the data collected aligns with the needs of the method used. Good data collection will minimize errors in the processing process and increase the validity of the results obtained.

The criteria used in evaluating teacher performance consist of several important aspects that reflect professional quality in the learning process. Pedagogical Competence (C1) describes the teacher's ability to design, implement, and evaluate learning effectively according to the characteristics of the students. Mastery of Material (C2) indicates the extent to which the teacher understands the substance of the subject being taught so that they can deliver the material clearly and comprehensively. Communication Skills (C3) relate to the teacher's ability to convey information effectively, both verbally and non-verbally, so that it is easily understood by students. Empathy and Care (C4) reflect a teacher's attitude in understanding the emotional conditions and needs of students, as well as their ability to create positive relationships in the learning environment. Classroom Management (C5) describes a teacher's ability to manage the classroom atmosphere so that it remains conducive, orderly, and supportive of optimal learning processes. Creativity and Innovation (C6) demonstrate a teacher's ability to develop engaging teaching methods and strategies that are adaptive to the times. All of these criteria fall into the benefit category, which means the higher the score obtained, the better the teacher's performance.

In this study, there are 9 teacher candidates who are assessed as alternatives in the performance evaluation process, where each teacher has different characteristics and levels of ability in each of the predetermined criteria. These nine candidates become the objects of assessment to determine a comprehensive comparison of performance based on aspects of pedagogical competence, mastery of material, communication skills, empathy and care, classroom management, as well as creativity and innovation. Each teacher is assessed using collected data, resulting in scores that represent their performance in the teaching and learning process. The presence of several alternatives allows the evaluation process to be conducted comparatively, enabling

the identification of teachers with the best performance as well as those who still require improvement.

C. LODECI Weighting Method

The LODECI weighting method is one of the objective approaches in determining criterion weights based on data characteristic analysis, particularly the level of variation and value distribution for each criterion [25]. LODECI works by utilizing the information contained in the data to measure the relative contribution of each criterion in distinguishing alternatives, so that the resulting weights do not depend on the subjective judgment of the decision-maker. The main principle of this method is that criteria with a higher level of value differences among alternatives will have a greater influence in the evaluation process. The LODECI method is capable of producing weights that are more representative of the actual conditions of the data used [26]. In addition, this method is also known to have good stability when data changes occur, making it suitable for use in various dynamic decision-making contexts.

The LODECI method begins by constructing a decision matrix that represents the performance of each alternative across multiple criteria, forming the basis for analysis (Equation 1). This matrix is then normalized to eliminate differences in measurement scales, ensuring that all criteria can be compared proportionally (Equation 2). After normalization, the deviation of each criterion is calculated to capture the level of variation and to identify differences among alternatives (Equation 3). These deviation values are then transformed using a logarithmic function to produce more stable and proportionate results in accordance with the data distribution (Equation 4). Finally, the transformed values are normalized to obtain the weights of each criterion, which reflect their relative importance within the overall decision-making framework (Equation 5).

$$X = [x_{ij}]_{m \times n} \quad (1)$$

$$d_{ij} = \begin{cases} \frac{x_{ij}}{\max_j x_{ij}}; \text{benefit criteria} \\ 1 - \frac{x_{ij}}{\max_j x_{ij}}; \text{cost criteria} \end{cases} \quad (2)$$

$$SD_{ij} = \max\{|d_{ij} - d_r|\} r \neq i \quad (3)$$

$$LSD_j = \ln \left(1 + \frac{\sum_{i=1}^m SD_{ij}}{m} \right) \quad (4)$$

$$w_j = \frac{LSD_j}{\sum_{j=1}^n LSD_j} \quad (5)$$

In the LODECI method, decision matrix symbol X indicates the number of alternatives and the number of criteria. the calculation begins with the notation x_{ij} , which represents the performance value of the i^{th} alternative with respect to the j^{th} criterion. The deviation measure, denoted as SD_{ij} , reflects the largest difference between the normalized value of a

particular alternative and those of other alternatives within the same criterion, capturing the extent of data dispersion. Furthermore, the logarithmic value LSD_j is derived as the average of these deviation values for each criterion, providing a more stable representation of variation. The resulting criterion weight, w_j expresses the relative significance of each criterion in influencing the overall decision-making process.

The LODECI method has several advantages that make it effective in the process of weighting criteria objectively. One of its advantages is its ability to directly utilize the characteristics of the data, so that the weights produced truly reflect the level of variation and contribution of each criterion to the differences among alternatives. In addition, the use of logarithmic transformation in its calculations helps produce more stable and proportional values, especially when the data has uneven distribution. Another advantage is the relatively high consistency of results even when there are changes in the data, making this method suitable for use in dynamic environments. With a systematic and data-based process, the LODECI method provides a strong weighting foundation to support more accurate and reliable decision-making outcomes.

D. CODAS Method

The CODAS method is one of the techniques in MCDM used to rank alternatives based on the concept of distance from the negative ideal solution [27]. The main principle of this method is that the best alternative is the one that is farthest from the worst solution, thus indicating a higher level of performance. The CODAS method utilizes two types of distance measurements, namely Euclidean distance for primary evaluation and Taxicab distance as an additional measure to differentiate alternatives that have nearly the same value [28]. This approach allows the ranking results to be more distinct and discriminative compared to other methods that rely on only one distance measure.

The CODAS method begins with the construction of a decision matrix that contains the performance values of each alternative across all criteria as the initial step of analysis in Equation 1. This matrix is then normalized to ensure that all criteria are measured on a comparable scale, enabling a fair evaluation process (Equation 6). Following this, a weighted normalization step is performed by multiplying the normalized values with the corresponding criterion weights to represent their relative importance (Equation 7). The next stage involves determining the negative ideal solution, which reflects the lowest performance level for each criterion and serves as a benchmark in assessing the alternatives (Equation 8). Based on the weighted matrix, both Euclidean distance and Taxicab distance are calculated for each alternative relative to the negative ideal solution, acting as primary and supporting measures in the evaluation (Equation 9) and (Equation 10). The results of these distance calculations are then used to construct a relative assessment matrix that illustrates the comparative superiority among alternatives (Equation 11). Ultimately, this process produces final preference values that form the basis for ranking the alternatives from best to worst (Equation 12).

$$n_{ij} = \begin{cases} \frac{x_{ij}}{\max_i x_{ij}}; & \text{if } j \in \text{benefit} \\ \frac{\min_i x_{ij}}{x_{ij}}; & \text{if } j \in \text{cost} \end{cases} \quad (6)$$

$$r_{ij} = w_j * n_{ij} \quad (7)$$

$$ns_j = \min_i r_{ij} \quad (8)$$

$$E_i = \sqrt{\sum_{j=1}^m (r_{ij} - ns_j)^2} \quad (9)$$

$$T_i = \sum_{j=1}^m |r_{ij} - ns_j| \quad (10)$$

$$h_{ik} = (E_i - E_k) + (\varphi(E_i - E_k)) * (T_i - T_k) \quad (11)$$

$$H_i = \sum_{k=1}^n h_{ik} \quad (12)$$

The symbol n_{ij} denotes the normalized value adjusted based on benefit or cost type. The value r_{ij} indicates the weighted normalized result, and ns_j refers to the negative ideal solution obtained from the lowest value for each criterion. The term E_i represents the Euclidean distance from the negative ideal solution, while T_i indicates the Taxicab distance based on absolute differences. The symbol h_{ik} expresses the relative comparison between alternatives using distance measures and a threshold function φ . Finally, H_i represents the overall preference value used to determine the ranking of alternatives.

The CODAS method has a number of advantages that make it effective in the process of ranking alternatives in multi-criteria decision making. One of its advantages is its ability to distinguish alternatives more clearly through the use of two distance measures, namely Euclidean as the primary measure and Taxicab as the supporting measure, making evaluation results more accurate, especially when the values among alternatives are close. In addition, CODAS can reduce ambiguity in ranking determination because its approach is based on the distance to the negative ideal solution, which provides a clear perspective in assessing performance levels. This method is also relatively simple in calculation while still providing stable and consistent results against changes in data.

III. RESULT AND DISCUSSION

Decision support system for evaluating teacher performance using the LODECI method for weighting and CODAS for ranking is an approach designed to enhance objectivity and accuracy in the data-based assessment process. This system utilizes LODECI to automatically determine the weight of each criterion based on the characteristics of data distribution, so that the importance level of each aspect of teacher performance can be set more proportionally without subjective intervention. Furthermore, the CODAS method is used to rank teachers based on the calculation of distance to the negative ideal solution, thereby being able to identify performance levels more clearly and measurably. The integration of these two methods allows the evaluation process to run more systematically because all calculations are carried out mathematically and consistently. In addition, the use of a Decision Support System helps manage complex data with a large number of criteria and alternatives, making the analysis process more efficient and easier to interpret. This approach also provides results that are more transparent and accountable, thus can be used as a basis for decision-making related to improving teacher quality in the educational environment.

A. Alternative Assessment Data Collection

The collection of alternative assessment data is a very important initial stage in the multi-criteria decision-making process because it serves as the main basis for analysis. At this stage, all information related to each alternative is systematically collected based on predetermined criteria. The data obtained can come from various sources such as direct observation, expert evaluations, or summaries of previous assessments. Each alternative is then given a score for each criterion to represent the condition or performance in a more measurable and objective manner. This process also ensures that the data used is consistent and relevant to the research objectives, thus enabling accurate analysis. In addition, accuracy in data collection greatly affects the quality of the final results, because small errors at this stage can impact the subsequent calculation process. The results of the alternative assessment data collection are presented in Table 1.

Tabel 1. Alternative Assessment Data

Alternative	CG-1	CG-2	CG-3	CG-4	CG-5	CG-6
A1 – Pratama	85	88	82	80	84	83
A2 – Santoso	78	82	80	79	77	81
A3 – Citra	90	92	89	88	91	90
A4 – Anggraini	82	85	84	83	80	82
A5 – Saputra	75	78	76	74	77	75
A6 – Fajar	88	87	85	86	89	88
A7 – Gina	91	90	92	89	90	91
A8 – Wijaya	80	83	81	82	79	80
A9 – Intan	87	89	88	90	86	87

The data in Table 1 is arranged as a representation of the performance of alternatives (teachers) based on six criteria (CG-1 to CG-6) that are relevant in the evaluation process, with a relatively uniform range of values to reflect realistic and standardized assessment conditions. The variation in values among alternatives indicates a fairly clear difference in performance levels, where some alternatives such as A3 (Citra) and A7 (Gina) consistently have high scores, while other alternatives such as A5 (Saputra) tend to have lower values, making this dataset capable of illustrating the discriminative conditions needed in the ranking process. Additionally, the value distribution, which is not extreme yet still varied, allows weighting and ranking methods to operate optimally without bias toward certain values. Thus, this data is suitable to be used as a basis for analysis in DSS because it is able to represent performance comparisons objectively, consistently, and supports testing the effectiveness of methods in producing accurate decisions.

B. Implementation of the LODECI Weighting Method

The implementation of the LODECI weighting method in this study is used to produce criterion weights objectively based on the characteristics of the data. This approach is chosen because it can reduce dependence on subjective assessments, allowing each criterion's level of importance to be determined more proportionally according to the variation of values in each alternative. In the process, the collected assessment data will be processed through the stages of LODECI calculation to obtain weights that represent the contribution of each criterion to the evaluation process. The resulting weights then become an important basis in the subsequent analysis stage, particularly in the ranking method used.

The initial stage of the LODECI method is carried out by preparing a decision matrix that contains the value of each alternative against all the determined criteria. This matrix becomes the main basis in the calculation process of the LODECI method created using Equation 1 based on the

evaluation data in Table 1. The general form of the decision matrix for assessment data is as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} \end{bmatrix}$$

The decision matrix results of the assessment data are as follows.

$$X = \begin{bmatrix} 85 & 88 & 82 & 80 & 84 & 83 \\ 78 & 82 & 80 & 79 & 77 & 81 \\ 90 & 92 & 89 & 88 & 91 & 90 \\ 82 & 85 & 84 & 83 & 80 & 82 \\ 75 & 78 & 76 & 74 & 77 & 75 \\ 88 & 87 & 85 & 86 & 89 & 88 \\ 91 & 90 & 92 & 89 & 90 & 91 \\ 80 & 83 & 81 & 82 & 79 & 80 \\ 87 & 89 & 88 & 90 & 86 & 87 \end{bmatrix}$$

The next step is normalization to equalize the value scales between criteria so that they can be compared fairly. This process ensures that each value is within a uniform range without being affected by different units, which is calculated using Equation 2. The normalization results of the LODECI method are as follows.

$$d_{11} = \frac{x_{11}}{\max_1 x_{1j}} = \frac{85}{91} = 0.9341$$

Table 2 shows the results of the LODECI method normalization values for all alternatives.

Table 2. Normalization Results of the LODECI Method

Alternative	CG-1	CG-2	CG-3	CG-4	CG-5	CG-6
A1 – Pratama	0.9341	0.9565	0.8913	0.8889	0.9231	0.9121
A2 – Santoso	0.8571	0.8913	0.8696	0.8778	0.8462	0.8901
A3 – Citra	0.9890	1.0000	0.9674	0.9778	1.0000	0.9890
A4 – Anggraini	0.9011	0.9239	0.9130	0.9222	0.8791	0.9011
A5 – Saputra	0.8242	0.8478	0.8261	0.8222	0.8462	0.8242
A6 – Fajar	0.9670	0.9457	0.9239	0.9556	0.9780	0.9670
A7 – Gina	1.0000	0.9783	1.0000	0.9889	0.9890	1.0000
A8 – Wijaya	0.8791	0.9022	0.8804	0.9111	0.8681	0.8791
A9 – Intan	0.9560	0.9674	0.9565	1.0000	0.9451	0.9560

The next step is to calculate the deviation values to measure the level of variation in each criterion. These deviation results indicate how large the differences in values are between alternatives within a criterion, calculated using (3). The deviation values of the LODECI method are as follows.

$$SD_{11} = \max\{|d_{11} - d_1|\} = \max\{|0.9341 - 0.9231|\}$$

$$SD_{11} = 0.0110$$

Table 3 shows the calculation results of the LODECI method's deviation values for all criteria.

Tabel 3. Deviation Values Results of the LODECI Method

Alternative	CG-1	CG-2	CG-3	CG-4	CG-5	CG-6
A1 – Pratama	0.0110	0.0217	0.0229	0.0383	0.0037	0.0122
A2 – Santoso	0.0659	0.0435	0.0447	0.0494	0.0733	0.0342
A3 – Citra	0.0659	0.0652	0.0531	0.0506	0.0806	0.0647
A4 – Anggraini	0.0220	0.0109	0.0012	0.0049	0.0403	0.0232
A5 – Saputra	0.0989	0.0870	0.0882	0.1049	0.0733	0.1001
A6 – Fajar	0.0440	0.0109	0.0097	0.0284	0.0586	0.0427
A7 – Gina	0.0769	0.0435	0.0857	0.0617	0.0696	0.0757
A8 – Wijaya	0.0440	0.0326	0.0338	0.0160	0.0513	0.0452
A9 – Intan	0.0330	0.0326	0.0423	0.0728	0.0256	0.0317

The next stage calculates the logarithmic values obtained, which are then transformed through a logarithmic transformation to produce more stable values. This stage helps reduce the influence of extreme values in the data calculated using Equation 4. The results of the logarithmic values of the LODECI method are as follows.

$$LSD_1 = \ln \left(1 + \frac{\sum_{i=1}^9 SD_{ij}}{9} \right) = \ln \left(1 + \frac{0.4615}{9} \right) = 0.0500$$

Table 4 shows the results of the logarithmic value calculations of the LODECI method for all criteria.

Tabel 4. Logarithmic Values Results of the LODECI Method

CG-1	CG-2	CG-3	CG-4	CG-5	CG-6
0.0500	0.0379	0.0415	0.0464	0.0516	0.0466

The next step is to calculate the normalization value of the logarithmic transformation results to obtain the final weight of each criterion. These weights reflect the relative importance level of each criterion in the evaluation process calculated using Equation 5, with the logarithmic values of the LODECI method as follows.

$$w_1 = \frac{LSD_1}{\sum_{j=1}^5 LSD_j} = \frac{0.0500}{0.2740} = 0.1825$$

Table 5 shows the calculation results of the LODECI method weight values for all criteria.

Tabel 5. Weight Values Results of the LODECI Method

CG-1	CG-2	CG-3	CG-4	CG-5	CG-6
0.1825	0.1384	0.1515	0.1692	0.1881	0.1702

The weighting results using the LODECI method show that each criterion has a different level of importance in performance assessment. The Classroom Management (CG-5) criterion obtained the highest weight of 0.1881, indicating that the ability to manage the classroom has the most dominant contribution in the assessment. This is followed by Pedagogical Competence (CG-1) with a weight of 0.1825 and Creativity and Innovation (CG-6) at 0.1702, which also play an important role in the evaluation process. Empathy and Care (CG-4) is in the next position with a weight of 0.1692,

showing that the aspect of caring for students remains a significant factor. Communication Skills (CG-3) received a weight of 0.1515, indicating a moderate level of influence in the assessment. Meanwhile, Mastery of Material (CG-2) has the lowest weight of 0.1384, although it still contributes to the overall performance evaluation process. In general, this weight distribution reflects that classroom management aspects and pedagogical competence are more dominant compared to mastery of the material in the context of the assessment used.

C. Implementation of the CODAS Method

The implementation of the CODAS method in this study is used as an approach to produce alternative rankings objectively based on performance relative to the worst conditions. This method relies on the concept of distance measurement to evaluate the advantage of each alternative, thus being able to provide clearer results in distinguishing performance, especially when the values between alternatives have small differences. By utilizing a combination of different distance measures, CODAS can improve accuracy in the evaluation process and reduce ambiguity in determining the final results. In addition, this method has good capability in producing stable and consistent decisions even in the presence of data variations. The use of CODAS also supports transparency because each obtained result can be explained based on structured and rational calculations.

Initial stage of alternative assessment using the CODAS method involves preparing a decision matrix that contains the values of each alternative against all the criteria used. This becomes the main basis in the analysis process using the CODAS method created using Equation 1, and the resulting CODAS decision matrix is similar to LODECI decision matrix.

The initial stage of alternative assessment using the CODAS method involves calculating normalization to equalize the scale among criteria. This process aims to allow each value to be compared fairly without being affected by differences in units, calculated using Equation 6. The results of the CODAS normalization calculation are as follows.

The next stage in evaluating alternatives uses the CODAS method by calculating normalization to equalize the scale between criteria. This process aims to ensure that each value can be compared fairly without being affected by differences in units, calculated using Equation 6. The normalization

values obtained by the CODAS method are the same as the normalization values from the LODECI method.

The next stage is the evaluation of alternatives using the CODAS method by calculating the product of weights using Equation 7, the results of the CODAS weight multiplication calculation are as follows.

$$r_{11} = w_1 * n_{11} = 0.1825 * 0.9341 = 0.1705$$

Table 6 shows the results of the CODAS method multiplication values calculation for all alternatives.

Tabel 6. Multiplication Result of the CODAS Method

Alternative	CG-1	CG-2	CG-3	CG-4	CG-5	CG-6
A1 – Pratama	0.1705	0.1324	0.1351	0.1504	0.1737	0.1553
A2 – Santoso	0.1564	0.1233	0.1318	0.1485	0.1592	0.1515
A3 – Citra	0.1805	0.1384	0.1466	0.1655	0.1881	0.1684
A4 – Anggraini	0.1644	0.1278	0.1384	0.1561	0.1654	0.1534
A5 – Saputra	0.1504	0.1173	0.1252	0.1391	0.1592	0.1403
A6 – Fajar	0.1765	0.1309	0.1400	0.1617	0.1840	0.1646
A7 – Gina	0.1825	0.1354	0.1515	0.1673	0.1861	0.1702
A8 – Wijaya	0.1604	0.1248	0.1334	0.1542	0.1633	0.1497
A9 – Intan	0.1745	0.1339	0.1450	0.1692	0.1778	0.1627

The next stage in the evaluation of alternatives uses the CODAS method by determining the negative ideal solution, which represents the worst value of each criterion using Equation 8. The results of the CODAS method negative ideal solution are as follows.

$$ns_1 = \min_i r_{ij}$$

$$ns_1 = \min(r_{11}, r_{21}, r_{31}, r_{41}, r_{51}, r_{61}, r_{71}, r_{81}, r_{91})$$

$$ns_1 = \min(0.1705; 0.1564; 0.1805; 0.1644; 0.1504; 0.1765; 0.1825; 0.1604; 0.1745)$$

$$ns_1 = 0.1504$$

Table 7 shows the calculation results of the negative ideal solution of the CODAS method for all alternatives.

Tabel 7. Negative Ideal Solution Results of the CODAS Method

CG-1	CG-2	CG-3	CG-4	CG-5	CG-6
0.1504	0.1173	0.1252	0.1391	0.1592	0.1403

The next stage of alternative assessment using the CODAS method involves calculating the distance to the negative ideal solution using the Euclidean distance and the Taxicab distance using Equation 9 and Equation 10, the results of the Euclidean distance and Taxicab distance calculations using the CODAS method are as follows.

$$E_1 = \sqrt{\sum_{j=1}^6 (r_{1j} - ns_j)^2}$$

$$E_1 = \sqrt{(r_{11} - ns_1)^2 + (r_{12} - ns_2)^2 + (r_{13} - ns_3)^2 + (r_{14} - ns_4)^2 + (r_{15} - ns_5)^2 + (r_{16} - ns_6)^2}$$

$$E_1 = \sqrt{0.0012867} = 0.0359$$

$$T_1 = \sum_{j=1}^6 |r_{1j} - ns_j|$$

$$T_1 = |r_{11} - ns_1| + |r_{12} - ns_2| + |r_{13} - ns_3| + |r_{14} - ns_4| + |r_{15} - ns_5| + |r_{16} - ns_6|$$

$$T_1 = 0.0857$$

Table 8 shows the results of Euclidean distance and Taxicab distance calculations using the CODAS method for all alternatives.

Tabel 8. Euclidean and Taxicab Distance Result of the CODAS Method

Alternative	Euclidean Distance	Taxicab Distance
A1 – Pratama	0.0359	0.0857
A2 – Santoso	0.0182	0.0392
A3 – Citra	0.0642	0.1559
A4 – Anggraini	0.0313	0.0740
A5 – Saputra	0.0000	0.0000
A6 – Fajar	0.0529	0.1261
A7 – Gina	0.0668	0.1615
A8 – Wijaya	0.0236	0.0543
A9 – Intan	0.0548	0.1315

The next stage is the evaluation of alternatives using the CODAS method, with the distance calculations obtained subsequently utilized to form a relative evaluation matrix that reflects the level of comparative advantage among

alternatives (Equation 11). The results of the comparative distance calculations among alternatives using the CODAS method are as follows.

$$h_{12} = (E_{11} - E_{12}) + (0.5(E_{11} - E_{12})) * (T_{11} - T_{12})$$

$$h_{12} = (0.0359 - 0.0182) + (0.5(0.0359 - 0.0182)) * (0.0857 - 0.0392)$$

$$h_{12} = 0.0181$$

Table 9 shows the results of the calculation of comparative distances between alternative CODAS method options for all alternatives.

Tabel 9. Comparative Distance Result of the CODAS Method

	A1 – Pratama	A2 – Santoso	A3 – Citra	A4 – Anggraini	A5 – Saputra	A6 – Fajar	A7 – Gina	A8 – Wijaya	A9 – Intan
A1 – Pratama	-	-0.0173	0.0293	-0.0046	-0.0343	0.0174	0.0321	-0.0121	0.0193
A2 – Santoso	0.0181	-	0.0487	0.0133	-0.0178	0.0362	0.0516	0.0054	0.0383
A3 – Citra	-0.0274	-0.0434	-	-0.0316	-0.0592	-0.0112	0.0026	-0.0386	-0.0093
A4 – Anggraini	0.0046	-0.0129	0.0343	-	-0.0301	0.0222	0.0371	-0.0076	0.0242
A5 – Saputra	0.0374	0.0185	0.0692	0.0324	-	0.0562	0.0722	0.0242	0.0584
A6 – Fajar	-0.0167	-0.0332	0.0115	-0.0211	-0.0496	-	0.0142	-0.0283	0.0019
A7 – Gina	-0.0298	-0.0457	-0.0026	-0.0340	-0.0614	-0.0137	-	-0.0409	-0.0119
A8 – Wijaya	0.0125	-0.0054	0.0427	0.0078	-0.0229	0.0304	0.0456	-	0.0324
A9 – Intan	-0.0185	-0.0349	0.0096	-0.0228	-0.0512	-0.0019	0.0122	-0.0300	-

The final stage of evaluating alternatives using the CODAS method involves accumulation calculations to produce the final preference values that represent the performance level of each alternative using Equation 12, the results of the accumulation calculation of CODAS alternative values are as follows.

$$H_1 = \sum_{k=1}^9 h_{1k}$$

$$H_1 = h_{12} + h_{13} + h_{14} + h_{15} + h_{16} + h_{17} + h_{18} + h_{19}$$

$$H_1 = (-0.0173) + 0.0293 + (-0.0046) + (-0.0343) + 0.0174 + 0.0321 + (-0.0121) + 0.0193$$

$$H_1 = 0.0299$$

Table 10 shows the calculation results of the accumulated values of the CODAS method alternatives for all alternatives.

Tabel 10. Accumulated Result of the CODAS Method

Alternative	Accumulated Value
A1 – Pratama	0.0299
A2 – Santoso	0.1939
A3 – Citra	-0.2181
A4 – Anggraini	0.0718
A5 – Saputra	0.3686
A6 – Fajar	-0.1213
A7 – Gina	-0.2399
A8 – Wijaya	0.1430
A9 – Intan	-0.1374

The accumulated results from the CODAS method show different preference values for each alternative, reflecting variations in performance levels based on the calculation of distances to the negative ideal solution. The values produced represent the relative contribution of each alternative in the overall evaluation process, where there are both positive and negative values indicating differences in levels of excellence. This variation in values indicates that each alternative has unique performance characteristics when analyzed using a distance-based approach. In addition, the accumulated results also demonstrate the CODAS method's ability to capture small differences between alternatives more sensitively. This information serves as an important basis for understanding the distribution of alternative performance before further interpretation is conducted.

D. Analysis and Evaluation of Results

Analysis and evaluation of results are conducted to assess the quality and consistency of the outputs generated from the application of the LODECI and CODAS methods in the decision-making process. At this stage, the calculation results are thoroughly analyzed to see whether the resulting criteria weights accurately reflect proportional levels of importance and whether the obtained preference values can clearly represent differences in performance among alternatives. The evaluation also includes observations on the stability of the results when there are data variations, so it can be determined to what extent the methods used are capable of producing reliable decisions. In addition, the emerging value patterns are interpreted to understand the characteristics of each alternative based on the criteria used. This process also aims to ensure that the applied approach can reduce subjectivity and increase transparency in decision-making. Through comprehensive analysis, the obtained results can serve as a

strong foundation in supporting more accurate and rational decisions.

Alternative ranking is carried out by integrating the criterion weights generated from the LODECI method with the preference values obtained from the CODAS method, thereby producing a more objective and structured performance order. This process reflects how each alternative is comprehensively evaluated based on the contribution of each criterion as well as its closeness to the negative ideal solution. The ranking results show differences in performance levels among the alternatives, influenced by variations in the values of each criterion, thus providing a clear picture of the relative positions of each alternative. In addition, this approach is capable of producing consistent rankings because it is supported by systematic and data-based mathematical calculations. This ranking information becomes an important basis in the decision-making process because it can identify the best-performing alternatives more accurately, as shown in Table 11.

Tabel 11. Alternative Ranking

Alternative	Value	Rank
A7 – Gina	-0.2399	1
A3 – Citra	-0.2181	2
A9 – Intan	-0.1374	3
A6 – Fajar	-0.1213	4
A1 – Pratama	0.0299	5
A4 – Anggraini	0.0718	6
A8 – Wijaya	0.1430	7
A2 – Santoso	0.1939	8
A5 – Saputra	0.3686	9

The ranking results of the alternatives are based on the preference values obtained, where A7 – Gina occupies the first rank with the best score, followed by A3 – Citra in second position and A9 – Intan in third position. Next, A6 – Fajar is in fourth place, while A1 – Pratama occupies the fifth position as part of the middle group. In the following order, A4 – Anggraini and A8 – Wijaya are in sixth and seventh place respectively with relatively higher scores. Meanwhile, A2 – Santoso occupies the eighth rank, and A5 – Saputra is in the last position in this evaluation result. The distribution of scores in the table shows variations in performance among the alternatives, which serves as the basis for establishing the ranking order.

Validation of the results in this study was carried out by testing the sensitivity of the parameter ϕ in the CODAS method through 18 different scenarios to observe its effect on the stability of the evaluation results. Each scenario used a different variation of the ϕ value to observe whether there was a significant change in the resulting preference values. This testing aimed to ensure that the model used remains consistent and not overly sensitive to parameter changes, so that the obtained results can be considered robust and reliable. In addition, the analysis of these various scenarios also provides an overview of the level of flexibility of the CODAS method

in handling variations in calculation conditions. The results of the sensitivity testing of the ϕ parameter are presented in detail in Table 12.

Tabel 12. Scenario of Threshold Parameter Change

Testing Scenario	Parameter Threshold
Scenario 1	0.1
Scenario 2	0.15
Scenario 3	0.2
Scenario 4	0.25
Scenario 5	0.3
Scenario 6	0.35
Scenario 7	0.4
Scenario 8	0.45
Scenario 9	0.5
Scenario 10	0.55
Scenario 11	0.6
Scenario 12	0.65
Scenario 13	0.7
Scenario 14	0.75
Scenario 15	0.8
Scenario 16	0.85
Scenario 17	0.9
Scenario 18	0.95

A comparison of rankings from various testing scenarios of the threshold value (ϕ) was conducted to observe the pattern of changes in the positions of alternatives due to variations in the parameters used in the CODAS method calculations. Each scenario provides ranking results that can be compared to see shifts in positions among alternatives as well as similarities in the order that appear. This analysis focuses on how the value of ϕ affects the process of forming preference values without directly drawing conclusions about the quality of the results. By comparing the results from each scenario, an overview of the relationship between parameter changes and the dynamics of alternative rankings can be obtained. The comparison of ranking results from all the testing scenarios is shown in Figure 2.

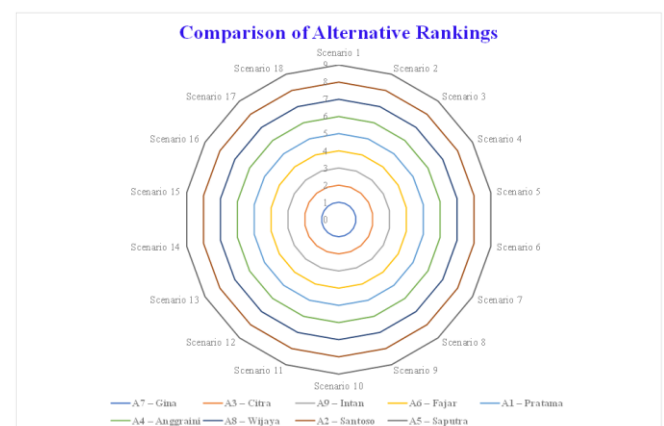


Figure 2. Comparison of Alternative Rankings Based on Threshold Value Changes

The analysis results indicate that the comparison of alternative rankings across various scenarios of threshold value changes provides an insight into the dynamics of each alternative's position in the evaluation process. The observed pattern shows how each alternative repeatedly occupies certain positions across different scenarios, making it easier to identify the tendencies of each relative position. Alternatives such as A7 – Gina, A3 – Citra, and A9 – Intan consistently occupy the top group, while A2 – Santoso and A5 – Saputra tend to be in the lower positions across all tested scenarios. Meanwhile, the other alternatives occupy middle positions with relatively limited movement between scenarios. This analysis shows a ranking distribution pattern that can be clearly observed through the presented visualization.

E. Discussion

The results of the LODECI weighting process demonstrate that the distribution of criterion weights is not uniform, indicating that each criterion contributes differently to the overall evaluation. This variation reflects the inherent characteristics of the data, where criteria with higher variability among alternatives tend to receive greater weights, such as Classroom Management (CG-5) and Pedagogical Competence (CG-1). From an analytical perspective, this suggests that performance differentiation among teachers is more strongly influenced by their ability to manage the classroom and apply pedagogical strategies rather than solely by mastery of subject matter. The use of logarithmic transformation in LODECI further enhances the robustness of the weighting process by reducing the dominance of extreme deviations, ensuring that the resulting weights remain balanced and representative. This indicates that LODECI is capable of capturing meaningful variations in performance data while maintaining stability, making it suitable for objective weighting in complex evaluation scenarios.

The implementation of the CODAS method provides deeper insight into how performance differences among alternatives are translated into measurable preference values. By utilizing both Euclidean and Taxicab distances from the negative ideal solution, CODAS is able to capture not only the magnitude of deviation but also the distribution of differences across all criteria. This dual-distance approach enhances sensitivity, particularly when alternatives have closely similar performance values, as seen in several mid-ranked candidates. The presence of both positive and negative accumulated values indicates a clear separation between higher-performing and lower-performing alternatives, allowing for more discriminative ranking outcomes. Furthermore, the method's reliance on distance from the worst-case scenario offers a practical perspective in evaluation, emphasizing how far each alternative is from the least desirable condition rather than only comparing relative closeness to the best option.

From a broader evaluation standpoint, the integration of LODECI and CODAS demonstrates a complementary relationship between objective weighting and distance-based ranking, resulting in a more comprehensive decision-making framework. The ranking results reveal consistent patterns where top-performing alternatives such as A7 (Gina), A3

(Citra), and A9 (Intan) maintain their positions across different scenarios, indicating strong performance stability. This consistency is further supported by the sensitivity analysis of the threshold parameter (ϕ), where minimal ranking shifts suggest that the model is robust against parameter variations. Such stability is crucial in decision support systems, as it ensures that the final recommendations are reliable and not easily influenced by minor changes in computational settings. Overall, the findings highlight that combining data-driven weighting with a discriminative ranking mechanism can significantly enhance the accuracy, transparency, and reliability of teacher performance evaluation.

IV. CONCLUSION

The implementation of DSS with the integration of the LODECI method as weighting and CODAS as ranking is capable of providing a more systematic, objective, and data-based approach to evaluating teacher performance. The LODECI method successfully determines the criterion weights proportionally based on the characteristics of data distribution, so that each assessment aspect has an appropriate contribution without relying on subjectivity. Furthermore, the CODAS method is able to evaluate alternatives more measurably through a distance-based approach to the negative ideal solution, thus producing preference values that can clearly illustrate performance differences. The combination of these two methods also supports a more transparent and consistent analysis process because all stages are carried out mathematically and structurally.

Sensitivity testing of the threshold parameter through various scenarios provides an overview of the impact of parameter changes on the dynamics of evaluation results. Comparison of the results from each scenario shows the pattern of movement of alternative positions that can be observed to understand the relationship between parameters and the process of forming preference values. This indicates that the approach used is not only capable of producing evaluation results but can also be further analysis in terms of its stability and flexibility. The developed model has the potential to be used as an effective decision-making tool in evaluating teacher performance more comprehensively.

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