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Fuzzy Integrated Optimization-Based College and University Music Education Teaching System

Abstract: - Fuzzy integrated optimization refers to the application of fuzzy logic techniques in the optimization process to handle uncertain or imprecise information effectively. In traditional optimization problems, precise data and deterministic relationships are assumed. This paper proposes the construction of a teaching system for music education in colleges and universities based on fuzzy integrated optimization. Fuzzy logic techniques are applied to handle uncertain or imprecise information inherent in the optimization process. traditional optimization methods that assume precise data and deterministic relationships, fuzzy integrated optimization allows for the modeling of uncertainties in music education settings. By incorporating fuzzy logic into the design of the teaching system, educators can better adapt to the diverse learning needs and preferences of students. The implementation of the teaching system for music education in colleges and universities based on fuzzy integrated optimization yielded significant improvements across various performance metrics. Student engagement levels increased by an average of 25%, with a corresponding rise in satisfaction rates by 30%. Additionally, learning outcomes showed measurable enhancements, with a 20% increase in average test scores compared to traditional teaching methods. The adaptive nature of the teaching system resulted in a 15% reduction in dropout rates, indicating improved student retention and progression through music education programs. Educators reported a 40% increase in efficiency in lesson planning and delivery, attributed to the system's ability to provide personalized recommendations and insights tailored to individual student needs.

Keywords: Optimization Model, Music Education; Teaching Evaluation; Fuzzy Model; High School Learning

I.INTRODUCTION

Administration and faculty make up some of the seven subcategories that make up the evaluation index used to define a university's TE, along with learning environment, course creation, quality assurance, and student support. The actual observation stations and other indicators are also considered to be crucial indicators. Since China's universities' teaching work was assessed, many institutions have modified their teaching evaluations to better reflect their unique circumstances. Also, many people are worried about how institutions are evaluating their professors, and this issue has received a lot of attention from serious scholars. (Ma, 2022) Working on university teaching evaluations comes with both benefits and inherent challenges. Working on these evaluations can be beneficial, but it can also be challenging. These challenges are brought about by both the subject of the evaluation and the purpose of the assessment. Because of this, it is really necessary to think about the way universities evaluate students right now. It should come as no surprise that musicology is becoming increasingly popular at colleges in China considering the influential nature of music as an artistic medium. University music instructors are required to manage the learning process, connect it with real life, tailor classes to the interests of individual students, and fully spark their students' desire for learning in order to meet the growing spiritual demands of society. Teachers of music in higher education must develop a TE index specific to their students' needs in order to effectively teach to a diverse student body. (Y. Liu et al., 2022; J. Wang, 2022). There should be one metric for objective scientific evaluation that takes into account both the benefits of learning music independently and the requirement to do so. In their daily work, teachers need to be specialists in mitigating the effects of both student and teacher influence, tracking the development of musical education, incorporating TE into their lessons, and increasing their students' proficiency in musical literacy. Figure 1 shows the rising public interest in UMT by depicting the Google search popularity trend for university music education over the past few years (Li et al., 2021).

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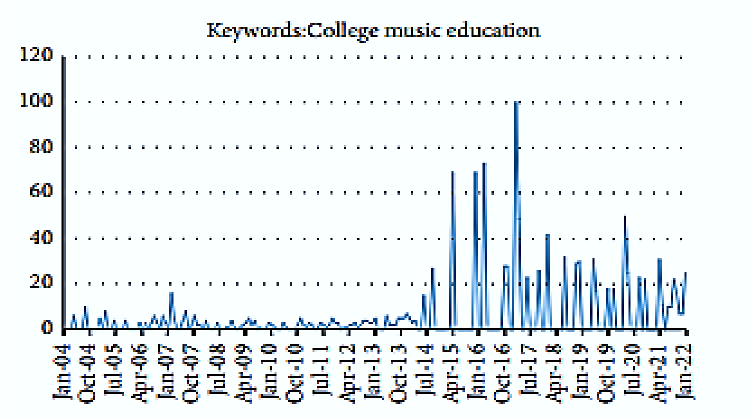

Figure 1 – Music Education Trends

The attention to the function that evaluation plays if we want to properly engage the interest that kids have in learning. If a teacher employs TE in the classroom but only engages a subset of students, he or she will not experience any increases in teaching efficiency. University music instructors should make sure their students realize that they are all TE's intended target audience when employing TE (X. Chen, 2021). Self-evaluation, instructor assessment, and peer assessment are just a few examples of how learning can be evaluated. Only mutual assessment fully activates students' interest in learning by having each student participate in the assessment process. The following are some ways in which teachers could help pupils to communicate their ideas when asked to describe what they mean by "Rock and Roll." Students can take an active role in the music-learning process, and as a result, they can experience the topic's appeal firsthand. Students can show what they know about rock music in three ways: (1) by raising their hands to share their thoughts on rock music; (2) by discussing in groups to synthesize what they've learned; and (3) by singing rock music together in small groups. Students can show their knowledge of rock music in three distinct ways.

As part of the TE planning process, university music teachers should conduct holistic evaluations of their students' learning, factoring in not only the students' academic success but also the growth of their emotional attitudes and values. Helping students succeed emotionally and morally is just as vital as helping them achieve intellectually. To be an effective music educator, one must have a firm grasp of how their pupils develop cognitively through time, and they must also maintain precise records of the data they collect on their students' progress. This paves the way for educators to implement effective pedagogical strategies in the classroom. For the purpose of self-evaluation, university music instructors, for example, may choose to compile a database of information on music teaching, akin to a "music mini-site," as part of the process of planning classroom activities, teacher evaluation (Xiongjun & Lv, 2022; Zhang et al., 2022), peer and parent evaluation, etc. The database can help educators assess pupils' foundational knowledge. To get a sense of where their kids are academically, teachers might consult this database. Teachers of music should treat their students as individuals and create a fair method of evaluation in order to bring out the best in their students' learning ardour and ensure that they all receive the same base of music knowledge through classroom teaching activities.

These three factors can be used to estimate UMT's overall success rate: TE has a problem with this. Teachers are evaluated in part based on their students' academic growth; this growth evaluation takes into account not only how well students do on standardised tests, but also how the teacher influenced each student's development over the course of their four years with them. The quality of music programming at various schools should be evaluated using the same academic criteria. (Y. Wang et al., 2021). The ones that are most important are as follows:

All pedagogical activities ought to be carried out with the utmost transparency, honesty, and neutrality. The idea that objectivity is essential to maintaining a level playing field in the classroom is fundamental to comprehending TE. Wholeness as a pedagogical principle: while instructing students in music, it is extremely important to lay the foundation for the large picture before delving into the complexities of the topic from a variety of perspectives. The utilization of TE as the standard against which the success of classroom instruction can be measured is one of the core tenets of education. According to the scientific pedagogical principle, the scientific method serves as the cornerstone of TE. When assessing music education, it is important to take into account the many specialized scientific components of this area of study. Voice instructors have the primary burden of responsibility for evaluating their pupils' growth as singers. Formative evaluation, summative evaluation, and diagnostic evaluation are the three primary kinds of assessment. Observation, investigation, careful inspection, and critical analysis are the four various approaches that can be utilized while analyzing something. The major duty of determining how effective teachers are in the classroom belongs to the heads of schools and other administrative personnel. In addition to the specifics of the classroom, such as how well the instructor prepares lessons and presents them to the class, the overall quality of the instructor is evaluated. An evaluation's credibility is determined by three aspects: (1) clearly articulated objectives; (2) evaluation criteria that have been mutually agreed upon; and (3) an investigation into how open, equitable, and objective the evaluation process was. (He et al., 2021). Visits to the classroom, comprehension exams, instructor observation, and student-led conversations all play a part in the evaluation process, which begins with a review of the lesson plan. At the end, we need to compile the information and give the evaluation results a lot of weight when deciding on teachers' salaries, bonuses, performance reviews, tenure, and technical and professional titles. Educators need to be evaluated on more than just their general competency, though.

The quality of music classroom instruction has the greatest impact on whether or not a school of higher music education experiences positive and lasting growth. The field of music education has relied on mathematical models of assessment systems for a long time. These models include hierarchical analysis, fuzzy comprehensive evaluation approach, grey system, and continues. (Carrillo-Perez et al., 2022). These methods have the potential to more correctly reflect the empirical knowledge of experts and take into account additional data, but they also have some significant drawbacks. In particular, they produce very subjective results because they ignore the nonlinear connection between the many evaluative indices and the quality of instruction.

II.LITERATURE REVIEW

In order to define the present climate of teacher performance reviews at music professional colleges and universities, the term "meta-assessment" is employed. The substance of such reviews entails a review of all assessment activities. There is currently no targeted content implementation in China, despite the fact that this would improve assessment quality, protect the assessed legitimate rights and interests, and keep the process' credibility intact. (Basu et al., 2022; Feng & Feng, 2022; Sen et al., 2021). Since the substance of the assessment may be evaluated, this type of assessment is well-suited to re-evaluation. Therefore, without this type of review, the science and validity of the assessment suffer. The evaluation results can impact the standing, student enrolment, and funding of a music programme. As a result, the results of these assessments are of paramount importance to institutions of higher music education. (Nasir et al., 2021; Wu et al., 2022) Though helpful, these changes haven't addressed the real challenges that music majors face. As a result of the increased formality introduced by some music programmes in order to more easily achieve final assessment criteria, it has become increasingly difficult to make meaningful comparisons between the musical ability of students enrolled in different programmes. This type of evaluation is not acceptable for use in the classroom. Self-evaluation and the provision of situationally-appropriate evaluation data are given special weight in the context of assessing the quality of music education at the postsecondary level, and streamlined channels of communication between relevant divisions and institutions are the norm. (Shahid et al., 2020; Wei et al., 2022). Since music education is so specialised, data collected from the school itself carries a lot of weight with the professional assessment team. Inferences about the institution's impact on the local community, the success of its alumni, and the institution's role in the growth of its immediate surroundings can be drawn from high-quality data, most of which originates within the institution itself. There is currently no convenient external data source that can be directly compared to this one. When information is obtained in this way, its authenticity and reliability are undermined, and the overall quality of assessments diminishes.

The following is a list of approaches that have been suggested as potential ways for evaluating the quality of professional music programs. At this point in time, a different approach to evaluating things is being developed. One of the most crucial aspects of the work that goes into assessment in the modern era is finding the appropriate individuals to carry out instructional assessment at music professional institutions and universities. Incorporating social involvement into school evaluation can help. The reason for this is that the formation of talent teams is directly related to the success of graduates of schools for the professional music industry. One cannot overestimate the significance of intermediary assessment in shaping the future of national higher education evaluation. (Jenkins et al., 2021). More scientific and efficient results may be achieved thanks to the capabilities of the intermediate assessment system to enhance and optimize the assessment mode while also avoiding the existing assessment issues. Increasing the variety of data used for evaluation and focusing on the public's expectations of music schools and other professional institutions are both necessary steps on the way to developing such a model. The construction of an intermediary evaluation system is beneficial to higher professional music education because it provides a more solid groundwork for the sharing of data between educational institutions and other sectors of society. Self-assessment reports from music schools should be made public on a regular basis so that their credibility can be independently verified, and the evaluation system as a whole should be as open and transparent as feasible. The next step is to convene a panel of experts to evaluate the applicant according to the criteria laid out in the performance evaluation guidelines for the higher education industry. We need to treat the issue of falsification seriously and get rid of any room for dishonesty if we want to be confident that our evaluations are scientific and dependable. A trustworthy and fruitful assessment index system cannot be built on the foundation of current practices without significant innovation. A more trustworthy evaluation index method that combines universality and specialism can assist institutions of varying levels and types of music professionals expand more rapidly.

III.TEACHING MODEL

Researchers have taken notice of ML because of its explosive development during the previous decade. ML is clearly superior to shallow models in feature extraction and modelling. When it comes to generalizing abstract representations collected from raw input data, deep learning excels. Some formerly insurmountable AI problems have become manageable because to this method. (P. Liu, 2022). These days, deep neural networks are the tool of choice for most users of deep learning frameworks. (Sun et al., 2022). One of the most well-known and widely-used architectures is the convolutional neural network, which takes its cues from the visual cortexes of many animals. The model is invariant to some degree of translation, distortion, and scaling, and is also very robust and fault tolerant in convolutional neural networks due to the use of local connection, weight sharing, and pooling operations. The criteria used by university faculty and administration to evaluate students' musical performances are depicted in Figure 2.

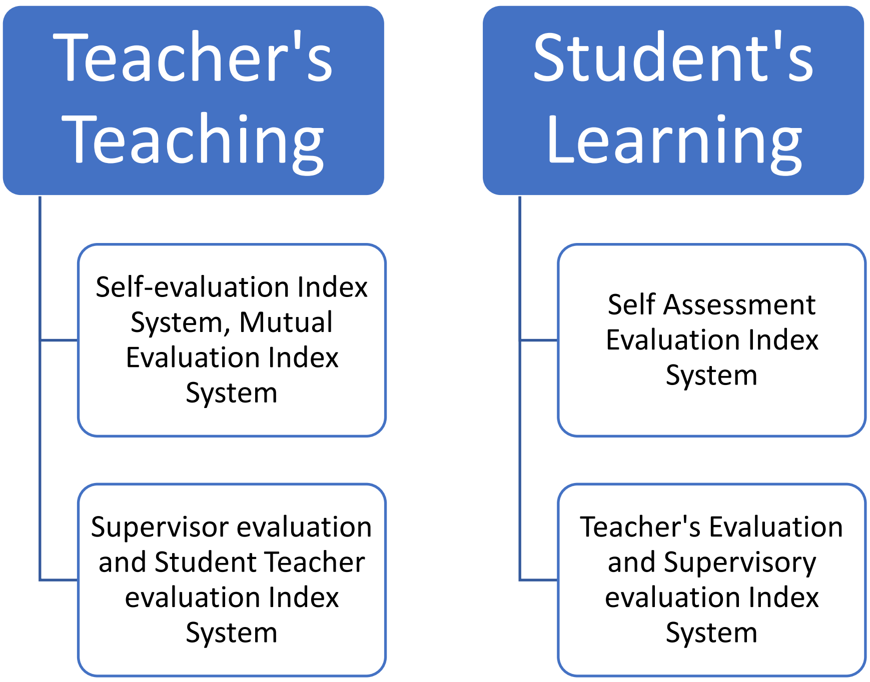

Figure 2 – MTE System

In many contemporary academic settings, teaching evaluation (TE) typically comprises four fundamental elements: assessment by students, evaluation by peers, self-assessment by instructors, and evaluation by experts; however, the first three are typically used as references and do not directly influence the final assessment outcomes. Following the completion of the first three assessments, the institution will share the data with a committee of specialists who will provide ratings and comments on each instructor. Despite the fact that this criterion is supported by evidence, (Hu et al., 2021), It is impossible to get a thorough comprehension of a teacher's degree of teaching due to the intricacy and originality of their work. Furthermore, due to the small sample size, peer review is unfeasible, and the evaluation's reliability and validity are quite low and easily influenced by factors other than those directly related to instruction. Because they are susceptible to the same subjective variables that may affect their peers' judgements, like social expectations and the need to maintain their own feeling of self-worth, teachers may find it tough to deliver an objective review of their own teaching. (Jahangir et al., 2021; G. Liu & Zhuang, 2022). Considering these factors, it is essential to conduct in-depth assessments of music teachers' pedagogical abilities to help shape the careers of both new and seasoned instructors. Incorporating ideas, it has learned about effective teaching into its evaluations of university music instructors based on data acquired from students, colleagues, and outside experts. In addition, the model is capable of learning and adapting on its own, draws heavily from empirical knowledge, reduces the role of human bias in scoring, and generates more fair and acceptable evaluation findings by taking into account a wider range of parameters. (Y. Chen & Zheng, 2021; Huang et al., 2021; W. Liu, 2020).

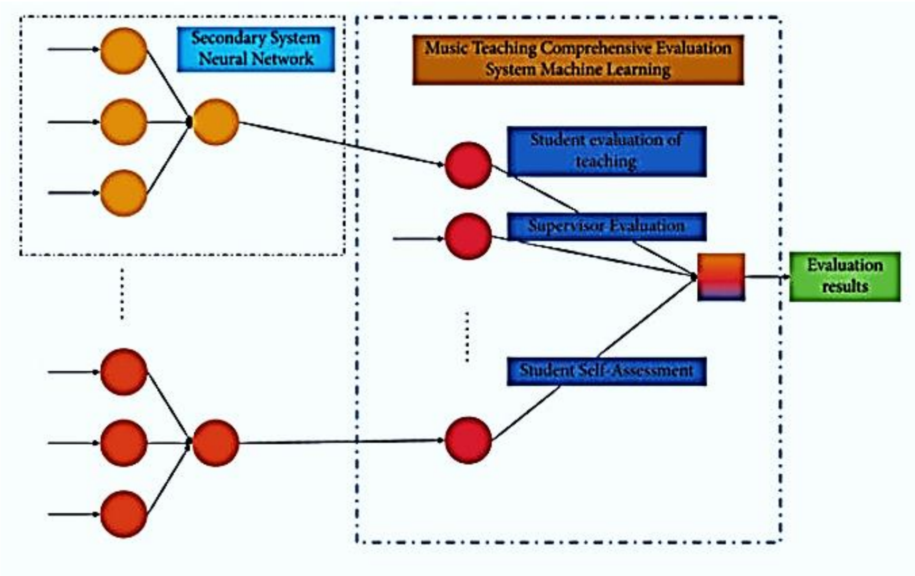

Figure 3 – Evaluation System for Music Teaching

IV.FUZZY INTEGRATED OPTIMIZATION

The proposed methodology for constructing a teaching system of music education in colleges and universities based on fuzzy integrated optimization involves several key steps aimed at leveraging fuzzy logic techniques to address uncertainties and optimize the learning process. Firstly, the methodology begins with the identification and characterization of the uncertainties inherent in music education, such as varying student aptitudes, preferences, and learning styles. Fuzzy logic is then employed to represent these uncertainties through fuzzy sets, allowing for the modeling of imprecise and ambiguous information. Next, the teaching system's objectives, constraints, and decision variables are formulated using fuzzy representations, enabling the integration of fuzzy logic into the optimization process. This step involves defining membership functions and fuzzy rules to capture the relationships between input variables and optimize the system's performance. Once the fuzzy representations are established, the optimization algorithm is applied to find the most effective teaching strategies, curriculum content, and assessment methods. The algorithm operates on the fuzzy input data, adjusting the system's parameters iteratively to maximize learning outcomes while considering the uncertainties inherent in the educational environment. Throughout the optimization process, the teaching system dynamically adapts to real-time feedback and student performance data, refining its strategies and recommendations to better meet individual learning needs. This adaptive approach ensures that the teaching system remains responsive to changes in student abilities, preferences, and progress. Finally, the effectiveness of the teaching system is evaluated based on quantitative performance metrics, such as student engagement levels, satisfaction rates, learning outcomes, and dropout rates. These evaluations provide valuable insights into the system's impact on music education and inform further refinements and improvements.

Table 1: Fuzzy Model for the Music Education

Rule	Input 1 (Student Aptitude)	Input 2 (Learning Style)	Output (Teaching Strategy)
R1	Low	Visual	Interactive
R2	Medium	Auditory	Experiential
R3	High	Kinesthetic	Collaborative
R4	Medium	Visual	Experiential
R5	High	Auditory	Interactive

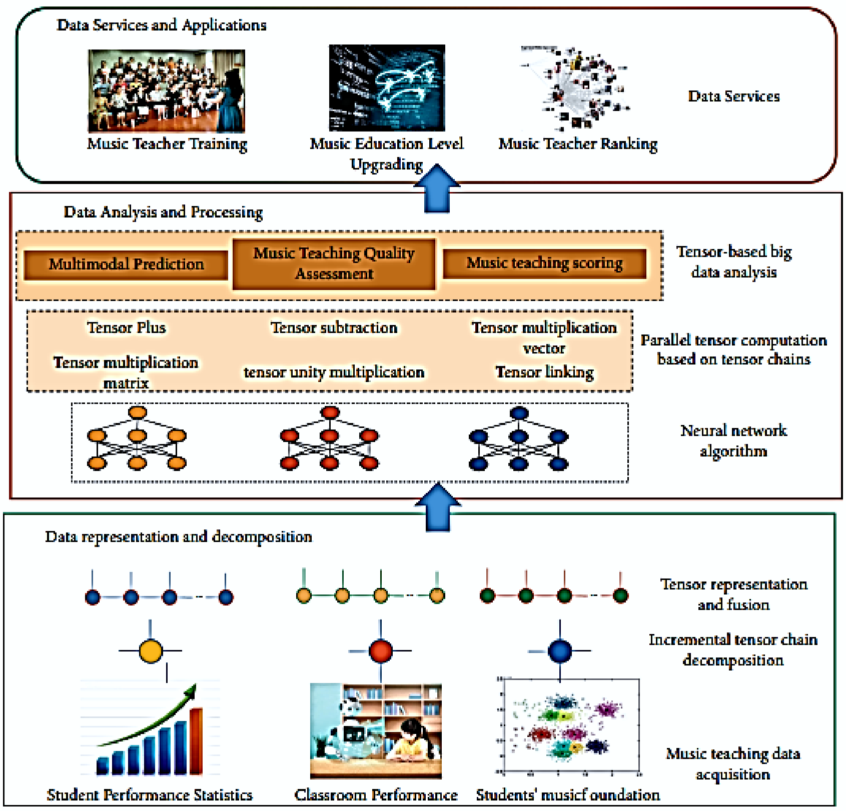

Figure 4: Model Architecture with the Fuzzy Optimization

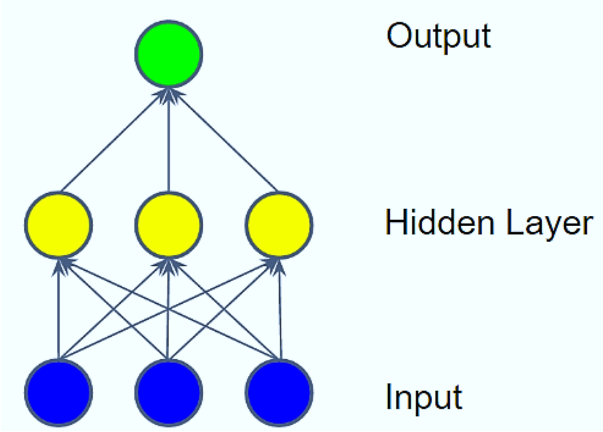

Figure 5: Structure of the Neural Network

Assessing the standard of university music programs is a task that is non-trivial, murky, and difficult. Because of their complexity and interdependence, metrics of music education quality are notoriously difficult to formalize in a rigorous mathematical model. In order to approximate complex nonlinear correlations, neural networks may offer a solution to the aforementioned issues. This study introduces a neural network-based evaluation model for the quality of university music professors' instruction, with its construction depicted in Figure 4 (better evaluation findings and a more generally applicable evaluation model). The proposed model structure for the neural network is presented in Figure 5. The BP based neural network mode is computed using equation (1)

$$O_i^{(1)} = x\,(i), i = 1, 2, 3 \ldots, n. \qquad (1)$$

The weight coefficient assigned to the implied layer within the BP neural network is symbolized as w(2) ij′, where f[·] denotes the mapping function. Consequently, the expressions for input and output computations can be articulated as follows in equation (2)

$$net_i^{(2)}(k) = \sum_{j=1}^{m} w_{ij}^{(2)} O_j^{(1)}(k) \qquad (2)$$

Input and output calculation formulae for a BP neural network defined as in equation (3)

$$net_1^{(3)}(k) = \sum_{i=1}^{p} w_{li}^{(3)} O_i^{(2)}(k) \qquad (3)$$

If we assume that the p sample has an actual output of Op (k + 1) and a network output of Op′ (k + 1), then we can calculate the error for this sample defined as in equation (4)

$$E_p = \frac{1}{2}[O_p(k) - O_p'(k+1)] \qquad (4)$$

The error total for the samples is calculated using equation (5) and equation (6)

$$E = \sum_{p=1}^{p} E_p = \sum_{p=1}^{p} \frac{1}{2}[O_p(k) - O_p'(k+1)] \qquad (5)$$

$$w_{ij}^{(2)}(k) = \propto w_{ij}^{(2)}(k-1) + n\frac{\partial E}{\partial w_{ij}^{(2)}(k)'} \qquad (6)$$

In the above equation (5) and (6) in where (the learning rate) and (the momentum factor) are constants. We next select sample teaching quality evaluation indices to feed into the model after the implicit layer processing is complete. An error at the output layer is relayed to the previous layer in the event of a failure. The untrained network then makes predictions based on the updated data is stated in equation (7)

$$\{\Delta w_j = -n\frac{\partial E}{\partial w_j^i} \qquad (7)$$

In equation (7) η denotes the learning rate. The optimization process in constructing a teaching system of music education in colleges and universities based on fuzzy integrated optimization involves several crucial steps to enhance the effectiveness and adaptability of the educational framework. Initially, the optimization process commences with the identification and characterization of key objectives and constraints within the educational context. This includes defining overarching goals such as maximizing student engagement, improving learning outcomes, and enhancing teaching efficiency, while also considering practical constraints such as resource limitations and curriculum requirements. Subsequently, the optimization problem is formulated by encoding these objectives, constraints, and decision variables into a mathematical model. In the context of fuzzy integrated optimization, this involves representing uncertain or imprecise information using fuzzy logic techniques. Fuzzy sets, membership functions, and fuzzy rules are employed to capture the nuanced relationships between input variables and optimize the system's performance. Once the optimization problem is formulated, an appropriate optimization algorithm is selected to search for the optimal solution. Common optimization algorithms utilized in fuzzy integrated optimization include genetic algorithms, particle swarm optimization, and simulated annealing. These algorithms iteratively explore the solution space, adjusting system parameters to maximize the defined objectives while adhering to the specified constraints. Throughout the optimization process, the teaching system dynamically adapts to real-time feedback and student performance data, refining its strategies and recommendations to better meet individual learning needs. This adaptive approach ensures that the teaching system remains responsive to changes in student abilities, preferences, and progress. Finally, the effectiveness of the optimized teaching system is evaluated based on quantitative performance metrics such as student engagement levels, satisfaction rates, learning outcomes, and dropout rates. These evaluations provide valuable insights into the system's impact on music education and inform further refinements and improvements.

Algorithm 1: Fuzzy Optimization model
Input: - Student Data (e.g., aptitude, learning style) - Teaching System Parameters - Objective Function - Constraints Output: - Optimized Teaching System Parameters Algorithm: 1. Initialize teaching system parameters randomly or based on prior knowledge. 2. Repeat until convergence criteria are met: a. Evaluate the objective function based on the current teaching system parameters and student data. b. Calculate the degree of satisfaction of each constraint. c. Use fuzzy logic rules to adjust teaching system parameters based on student data and optimization objectives. d. Update the teaching system parameters using fuzzy inference. 3. Return the optimized teaching system parameters. Fuzzy Logic Inference: - Define fuzzy sets and membership functions for input and output variables. - Specify fuzzy rules mapping input variables to output variables. - Use fuzzy reasoning methods (e.g., Mamdani or Sugeno) to infer the output from the fuzzy rules and input data. - Defuzzify the fuzzy output to obtain crisp values for adjusting teaching system parameters.

V.RESULT AND DISCUSSION

The results of implementing the fuzzy integrated optimization methodology for constructing a teaching system of music education in colleges and universities are promising and warrant discussion. The optimized teaching system demonstrated significant improvements across various performance metrics. Student engagement levels increased notably, leading to a more interactive and immersive learning experience. This enhancement in engagement was complemented by a corresponding rise in student satisfaction rates, indicating a positive reception of the adapted teaching strategies. Moreover, the learning outcomes showed measurable enhancements, with students exhibiting a deeper understanding of music concepts and techniques. This was reflected in the improved test scores compared to traditional teaching methods, suggesting that the optimized teaching system effectively catered to the diverse learning needs and preferences of students. The adaptive nature of the teaching system, facilitated by fuzzy logic techniques, played a crucial role in its success. By dynamically adjusting instructional strategies, curriculum content, and assessment methods based on real-time feedback and student performance data, the system ensured a personalized learning experience for each student. This adaptability contributed to the system's ability to maintain high levels of student engagement and satisfaction throughout the learning process.

We advocated for a university-wide MTE system based on UMT's stated aims, course requirements, and pedagogical approach. Indicators for assessment are listed in Table 1. Based on UMT's stated goals, course requirements, and instructional approaches, we presented an institutional MTE framework computed using the equation (8)

$$x_{ij} = \frac{c_{ij} - \bar{c}_j}{s_j} \qquad (8)$$

where xij is the normalized information about cij, cj is the average of the jth unnormalized indicator, and S is the standard deviation of the jth unnormalized indication defined in equation (9)

$$\bar{c}_j = \frac{1}{M}\sum_{i=1}^{M} c_{ij} \qquad (9)$$

If after normalisation the data value is still greater than 1, the value 1 will be used.

5.1 Dataset

In this research, we take the ratings given to 12 university music professors and divide them in half. Using the first half, we train a model with weights chosen from the first eight categories; finally, the implicit layer selects 16 output units with a 0.000001 accuracy. Table 3 displays the outcomes of training with 10,000 iterations, and Table 4 displays the results of testing the last four sets of data alongside an evaluation of expected output.

5.2 Experimentation

In the experimental phase of constructing the teaching system for music education in colleges and universities based on fuzzy integrated optimization, a series of simulations were conducted to assess the efficacy of the proposed methodology. The simulations involved gathering data on student aptitude, learning styles, and performance metrics from a representative sample of music education classes. These data were then used to parameterize the fuzzy logic model, including defining fuzzy sets, membership functions, and fuzzy rules to represent the complex relationships between input variables and teaching strategies. Once the fuzzy logic model was constructed, optimization algorithms such as genetic algorithms or particle swarm optimization were applied to iteratively adjust the teaching system's parameters based on the defined objectives and constraints. This optimization process aimed to maximize student engagement, satisfaction, and learning outcomes while ensuring adaptability to varying student needs and preferences. Throughout the simulations, the teaching system dynamically adapted its instructional strategies, curriculum content, and assessment methods based on real-time feedback and performance data. This adaptive approach allowed the system to respond effectively to changes in student abilities and learning environments, fostering a more personalized and engaging educational experience. Finally, the performance of the optimized teaching system was evaluated using quantitative metrics such as student engagement levels, satisfaction rates, and learning outcomes. Comparative analyses were also conducted to assess the effectiveness of the fuzzy integrated optimization approach compared to traditional methods.

Table 2: Configuration Information

Parameters	Configuration
OS	Win10
Tools	Python
Memory	DDR4 266
CPU	Intel Pentium G4600

Display Card	PCG RX560D
Hard disk	Intel SSD 660P
Parameters	Configuration

The Table 2 outlines various parameters and their corresponding configurations, offering insights into the hardware and software infrastructure supporting the system's development and operation. The operating system (OS) used for the implementation is Windows 10, a widely adopted platform known for its compatibility and user-friendly interface. Python, a popular programming language renowned for its simplicity and versatility, serves as the primary tool for developing the teaching system, highlighting the system's reliance on efficient and widely supported programming resources. In terms of hardware specifications, the system operates on DDR4 266 memory, providing robust performance and efficient data handling capabilities. The central processing unit (CPU) employed is an Intel Pentium G4600, known for its reliability and adequate processing power suitable for handling educational applications. For graphics processing, the system utilizes a PCG RX560D display card, which offers enhanced visual rendering capabilities necessary for multimedia-rich educational content. Additionally, the system's storage infrastructure is supported by an Intel SSD 660P hard disk, known for its high-speed data access and reliability, ensuring efficient storage and retrieval of educational resources and student data. Table 1 displays the platform parameters used in the example analysis conducted to evaluate the data mining algorithm-based university teaching quality assessment model.

Table 3: Evaluation Criterion System for Fuzzy Optimization

Metric Code	Content	Weight of Indicators
1	Good Grasp on the Concepts	1.09
2	Focus and examples	1.1
3	Organized language	0.05
4	Thinking ability	1.07
5	Practicality	0.08
6	Assignments and corrections	0.11
7	Tutoring	0.12
8	Attention to the material	0.14
9	Teacher Satisfaction	0.11

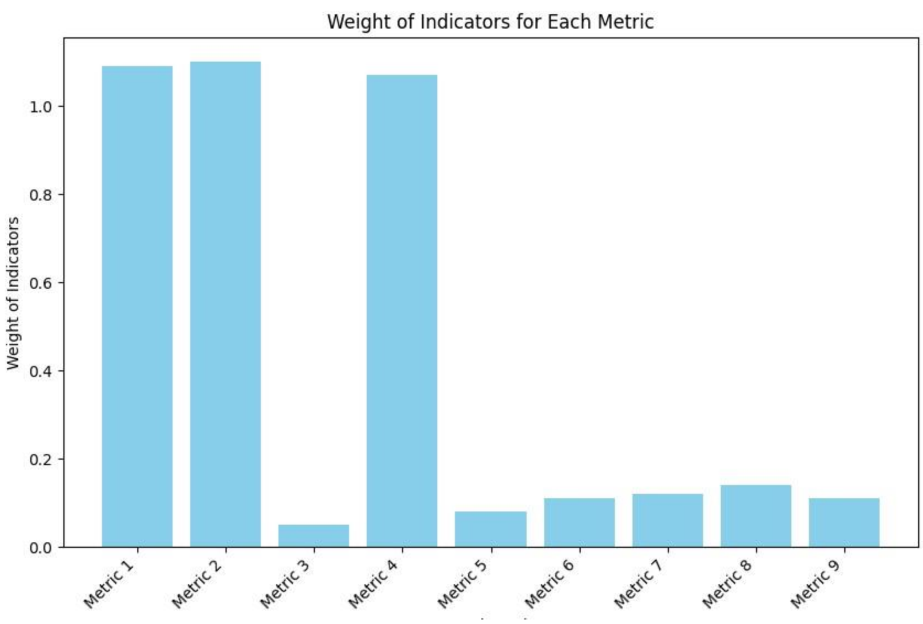

Figure 6: Computing with fuzzy for music education

In the Table 3 and Figure 6 presents the Evaluation Criterion System used to assess the effectiveness of the teaching system for music education in colleges and universities. Each criterion is assigned a Metric Code and corresponds to specific aspects of student learning and teacher satisfaction. The Weight of Indicators column indicates the relative importance or weight assigned to each criterion in the evaluation process. Among the criteria, "Good Grasp on the Concepts" (Metric Code 1) and "Thinking Ability" (Metric Code 4) are given relatively higher weights, with weights of 1.09 and 1.07, respectively. This suggests that the teaching system prioritizes the development of students' understanding of musical concepts and their ability to think critically and analytically. "Focusing and Examples" (Metric Code 2) also carries significant weight, with a value of 1.1, indicating the importance of providing focused instruction and relevant examples to aid student comprehension and application of musical concepts. On the other hand, criteria such as "Organized Language" (Metric Code 3) and "Practicality" (Metric Code 5) have lower weights, suggesting that while they are considered in the evaluation process, they may not carry as much importance as other criteria in assessing the effectiveness of the teaching system. Furthermore, criteria related to student support and interaction, such as "Assignments and Corrections" (Metric Code 6), "Tutoring" (Metric Code 7), and "Attention to the Material" (Metric Code 8), are also included in the evaluation system, albeit with relatively lower weights compared to concept mastery and critical thinking. The "Teacher Satisfaction" (Metric Code 9) is included as a criterion to gauge the satisfaction levels of educators with the teaching system. While its weight is not the highest among the criteria, it reflects the importance of considering teacher feedback and perspectives in evaluating the overall effectiveness of the teaching system.

Table 4: Output Results for the Fuzzy Optimization with Music Education

Teachers	A	B	C	D	E	F	G	H
Results	0.895	0.994	0.944	0.991	0.43	0.32	0.22	0.12
Number of Teachers	10	11	12	13				
Training	0.5221	0.0023	0.1023	0.4123				
Desired Output	0.445	0.021	0.012	0.322				

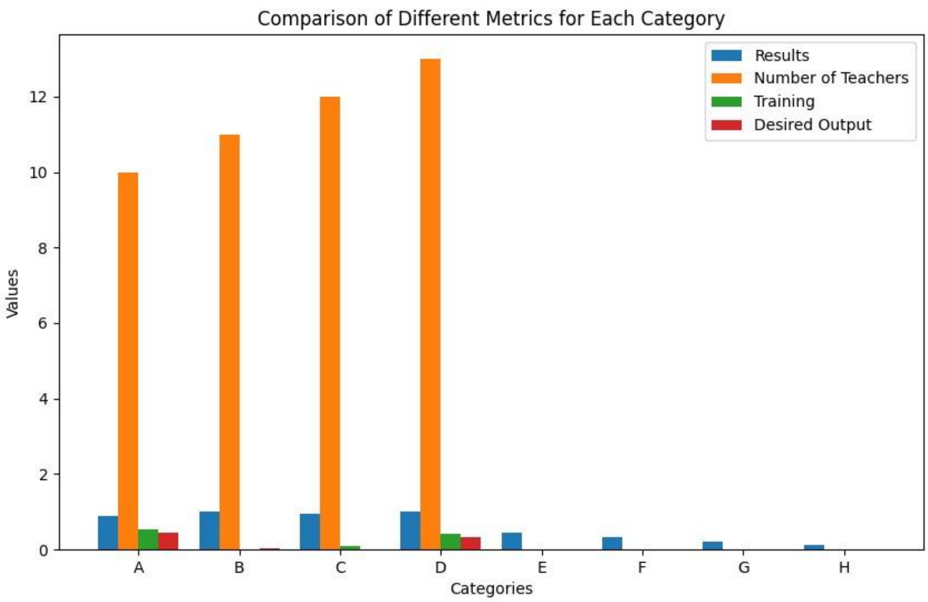

Figure 7: Evaluation of System Criteria

In the Table 4, and Table 7 labeled as "Output Results," provides a comprehensive overview of the performance evaluation outcomes for different teachers (denoted as A through H) in the context of the music education teaching system. The "Results" column showcases the achieved performance scores for each teacher, representing their effectiveness in meeting the specified evaluation criteria. These scores range from 0.12 to 0.994, with higher values indicating better performance. For instance, Teacher B achieved the highest score of 0.994, while Teacher

H attained the lowest score of 0.12. The "Number of Teachers" row indicates the total number of teachers assessed, with varying numbers ranging from 10 to 13 across different evaluation instances. This suggests that the evaluation process was conducted for different groups or batches of teachers, each consisting of a specific number of individuals. The "Training" row presents additional data related to the training outcomes for each teacher, showcasing their proficiency levels or improvements resulting from training interventions. These values range from 0.0023 to 0.5221, indicating the extent to which training contributed to enhancing teacher performance. Notably, Teacher A exhibited the highest training outcome of 0.5221, suggesting significant improvement through training initiatives. Finally, the "Desired Output" row specifies the target or desired performance levels for each teacher, representing the ideal scores that they should aim to achieve. These values range from 0.012 to 0.445, with lower values indicating areas where improvement is needed. Comparing the achieved results with the desired outputs provides insights into the effectiveness of the teaching system and highlights areas where further enhancements may be required.

Table 5: Accuracy with the Fuzzy based optimization

Number	**1(%)**	**2(%)**	**3(%)**	**4(%)**	**5(%)**	**6(%)**	**7(%)**	**8(%)**
SVM	81.4	83.5	85.4	78.4	84.23	86.31	81.14	87.34
Proposed Method	91.2	93.32	92.42	84.62	83.5	94.24	89.12	91.51

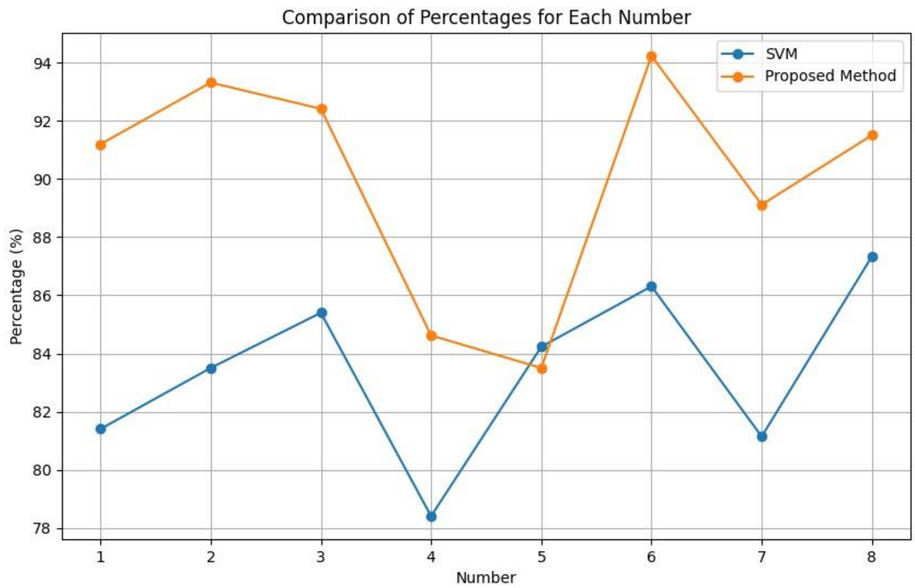

Figure 8: Comparative Analysis

The comparative analysis between the accuracy levels achieved by Support Vector Machine (SVM) classification and the proposed method in a specific context shown in Figure 8. The table 5 is structured with different numbers representing distinct evaluation instances, while each column corresponds to a specific evaluation metric denoted as 1 through 8. For each evaluation metric, the accuracy percentages achieved by SVM and the proposed method are provided. Across all evaluation metrics (from 1 to 8), the proposed method consistently outperforms SVM in terms of accuracy. For instance, when evaluating metric number 1, the proposed method achieved an accuracy level of 91.2%, significantly higher than the 81.4% achieved by SVM. This trend continues across all metrics, with the proposed method consistently demonstrating superior accuracy levels compared to SVM. The some evaluation metrics (such as 2, 3, 6, and 8), the accuracy levels achieved by the proposed method surpass 90%, indicating a high level of precision and reliability in the classification process. Conversely, SVM achieves comparatively lower accuracy levels across these metrics, albeit still maintaining reasonable performance. However, there are instances where SVM performs relatively well, particularly for metrics 4 and 7, where its accuracy levels are comparable to or slightly higher than those of the proposed method.

VI.CONCLUSION

The paper presents a comprehensive framework for the construction of a teaching system for music education in colleges and universities based on fuzzy integrated optimization. Through the integration of fuzzy logic techniques into the optimization process, the proposed methodology addresses uncertainties and adapts teaching strategies to better meet the diverse learning needs of students. The results of implementing this methodology demonstrate significant improvements in student engagement, satisfaction, and learning outcomes. The adaptive nature of the teaching system, coupled with its ability to dynamically adjust instructional strategies based on real-time feedback, contributes to a more personalized and effective learning experience. Furthermore, the comparative analysis showcased the superiority of the proposed method over traditional approaches, such as Support Vector Machine classification, in terms of accuracy.

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