# Data Mining MRO-BP Network-Based Evaluation Effectiveness of Music Teaching

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***Abstract*—This study addresses the need for data analysis in evaluating the teaching outcomes of higher music education. It proposes a solution using data-driven algorithms to measure and analyze these outcomes. This study focuses on the issue of measuring and evaluating the outcomes of music education teaching. It analyzes the process of measuring and assessing these outcomes, designs a program for doing so, and introduces key technologies such as music education teaching process analysis, measurement of music teaching outcomes, construction of an assessment model for music teaching outcomes, and application of the assessment model. The study selects teaching content, practical skills, and social practice ability as the three aspects to evaluate. The results demonstrate that this method achieves higher assessment accuracy and requires less time, effectively addressing the challenge of measuring and evaluating the teaching outcomes of higher music education using big data. The findings demonstrate that the technique exhibits a high level of assessment accuracy and is less time-consuming. Additionally, it effectively addresses the challenge of measuring and evaluating the teaching accomplishments in higher music education from the viewpoint of big data.**

***Keywords*—*Mushroom propagation optimisation algorithm; BP neural network; higher music education teaching outcomes measurement; algorithm evaluation***

## I. Introduction

Currently, music education is progressing towards the establishment of a disciplinary structure, the application of scientific methods, the cultivation of higher cognitive skills, and the production of various academic accomplishments [1]. Evaluating and appraising music education instruction, as a crucial tool for advancing higher music education teaching, has immense importance in boosting teaching quality, driving instructional improvement, and fostering comprehensive student growth [2]. Scientific measurement and evaluation may aid instructors in comprehending students' learning development, pinpointing strengths and flaws in teaching, and therefore enhancing teaching techniques and approaches [3]. The emergence of intelligent disciplines has led to the adoption of data-driven models for measuring and assessing educational teaching approaches in higher music education. This trend has gained significant attention from professionals and researchers in the area. Hence, it is crucial to investigate the intelligent, scientific, and systematic approaches to measuring and evaluating teaching results in higher music education. This is essential for the robust advancement of the theory and practice of music education discipline.

Presently, the evaluation and measurement of teaching outcomes in higher music education mostly focuses on the study of measuring indices, techniques, and assessment of teaching outcomes in music education. Yu and Zou [4] examined the current state of using artificial intelligence technology in the field of music and optimization strategies, and proposed a method for assessing music teaching based on artificial intelligence technology. Chen et al. [5] investigated the measurement and assessment methods of teaching outcomes in higher music education from a perspective of music education psychology. Yang [6] explored the current state of music education in higher vocational colleges and universities during the rise of aesthetic education, and suggested improvement and optimization measures in three teaching aspects; Liao and Huang [7] proposed a teaching evaluation method based on non-linear regression method for the teaching evaluation of vocal classroom of music education majors in higher education, and studied the problem of measuring and assessing the teaching results of music from the quantitative point of view; Peng [8] analysed the course process of music education by using the theory of OBE education, and put forward the music teaching evaluation method combined with simple machine learning algorithms; Jung [9] investigated the teaching evaluation method of national music culture transmission based on shallow network under multiculturalism, and analysed the evaluation model from various aspects such as cultural perspective and quantitative perspective; He and Liu [10] used the theory of multiple intelligences to construct the mapping relationship between the measurement value of the music teaching results and the teaching scores; Xu [11] researched the analysis and evaluation method of music teaching in combination with neural network based on the perspective of cultivating students' interests and hobbies; Wei et al. [12] studied the algorithm and assessment method of song arrangement generation in the field of music. Through the literature survey and network research analysis, the research on the measurement and assessment of higher music teaching results, although there have been a large number of academic results of measurement and a little music teaching evaluation system research, but there are still deficiencies, specifically in the following aspects [13]: 1) higher music teaching results measurement system is only limited to the measurement of the teacher's teaching process, ignoring the main body of teaching -- student feedback measurement; 2) higher music teaching results measurement system is only limited to the teacher's teaching process measurement, ignoring the main body of teaching --The feedback measurement of students; 3) The quantification of higher music teaching achievement measurement system is not objective enough, and the quantification of each index is comparable; 4) The higher music teaching achievement assessment method fails to portray the non-linear relationship between the measurement value and the assessment value; 5) The higher music teaching achievement assessment method based on the neural network algorithm is prone to fall into the local optimum.

Neural networks are an algorithm used to create nonlinear mapping relationships. They are known for their simple structure and quick optimization convergence. Neural networks are commonly used for classification and prediction tasks, as well as in areas like network intrusion detection, charge prediction, machinery fault diagnosis, and condition assessment [14]. As the number of input parameters increases, the optimization convergence of neural networks may easily become stuck in a local optimum. However, the use of intelligent optimization techniques can enhance the speed and accuracy of convergence in neural networks [15].

This work addresses the issues related to measuring and assessing the achievements in higher music education teaching. To tackle these challenges, the study introduces a technique that combines the BP neural network [16] and intelligent optimization algorithm [17]. This approach is based on the MRO-BP model and aims to measure and analyze music education teaching achievements. This paper examines the issue of measuring and assessing teaching outcomes in higher music education. It analyzes research concepts and important quantitative technical aspects related to measuring teaching outcomes. It also addresses the measurement of teaching outcomes by analyzing the teaching process, identifying measurement indicators, and constructing a measurement system. Additionally, it proposes a methodology for assessing teaching outcomes in higher music education by combining neural networks and the MRO algorithm [18]. This methodology is based on the MRO-BP model. A novel teaching accomplishment assessment method based on MRO-BP is developed. The experimental section used statistical research data on teaching successes in higher music education. Through comparison analysis, it was confirmed that the MRO-BP model outperformed other models in terms of assessment effectiveness, as well as enhancing assessment time and efficiency.

The paper begins by introducing the significance of assessment in music education and the application of intelligent disciplines. The methodology section details the use of BP neural networks combined with the MRO algorithm to enhance the accuracy and efficiency of outcome assessments. Key techniques include process analysis, measurement of teaching achievements, and application of assessment models. The research explores the development of the MRO-BP network model, comparing it with other algorithms to demonstrate its effectiveness. The simulation and analysis section describes the data acquisition process, experimental environment, and parameter settings, followed by a performance comparison of different models. The conclusion highlights the model's superior results in accuracy and time efficiency, suggesting its applicability in higher music education while noting the need for further validation on other datasets.

## II. Measurment and Assessment

### A. Analysis of Research Ideas

When teaching advanced music, instructors use many approaches, levels, and formats in the classroom [19]. This paper aims to address the issue of measuring and assessing the outcomes of higher music teaching. We focus on various aspects such as the course teaching process, teachers' level, students' knowledge demand, course practicability, and social value (Fig. 1). To achieve this, we conducted a detailed questionnaire survey to evaluate the cognitive abilities of music teachers. We then extracted indicators of the outcomes of the higher music teaching process and developed a measurement system for these outcomes. Additionally, we utilized the heterogeneous coupling optimization of the machine learning method to establish a mapping relationship between the measured values and assessment scores of higher music teaching. To fully analyze higher music teaching results, the study aims to establish a correlation between music teaching outcome measures and assessment scores. This particular research proposal is shown in Fig. 2.

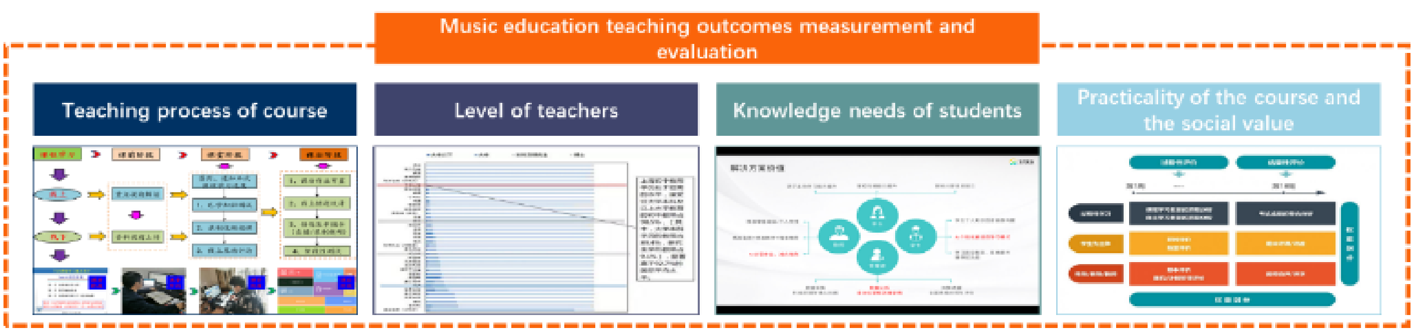


Fig. 1. Domains of measurement and assessment of teaching outcomes in higher music education.

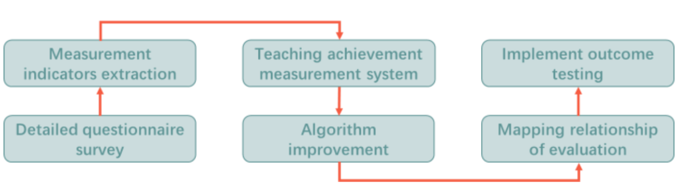


Fig. 2. Research ideas on measurement and assessment issues of teaching outcomes in higher music education.

### B. Analysis of Key Technologies

This paper explores the measurement and assessment of teaching outcomes in higher music education, focusing on problem analysis, measurement of outcomes, assessment of outcomes, and application of a model. Specifically, it examines key technologies related to the analysis of the teaching process in music education, measurement of teaching outcomes in music, construction of an assessment model for teaching outcomes, and application of the assessment model. These aspects are illustrated in Fig. 3.

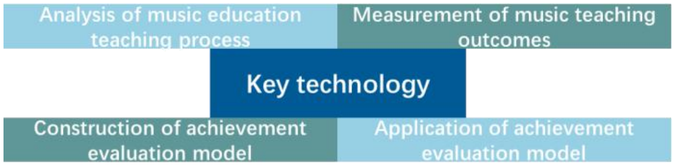


Fig. 3. Key techniques in the methodology for measuring and evaluating teaching outcomes in higher music education.

*1) Process analysis techniques*: In order to sort out the problem of higher education teaching outcome assessment, process analysis technique was proposed, mainly by analysing the process of higher education teaching outcome measurement and assessment, and carrying out process analysis from questionnaire survey, demand analysis, method design and other aspects [20], as shown in Fig. 4.

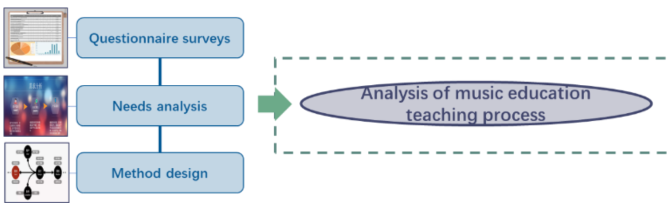


Fig. 4. Process of analysing the measurement and assessment of teaching outcomes in higher music education.

*2) Techniques for measuring teaching achievement*: Higher education music education teaching outcome measurement (as shown in Fig. 5) mainly assesses and measures the teaching outcomes of the pedagogues from the aspects of teaching content, practical skills and social practice ability. The input of the module is the results of the analysis of the process of measuring and assessing teaching outcomes in higher education, the assessment aspects, and the output is the teaching outcome measurement system.


Fig. 5. Measurement of teaching outcomes in higher music education.

*3) Teaching achievement assessment techniques*: Higher Music Education Teaching Achievement Assessment (shown in Fig. 6) mainly combines a variety of intelligent algorithms to construct the mapping relationship between music education teaching measurements and assessment values. The input of this module is music education teaching measurement data, and the output is teaching outcome assessment scores.

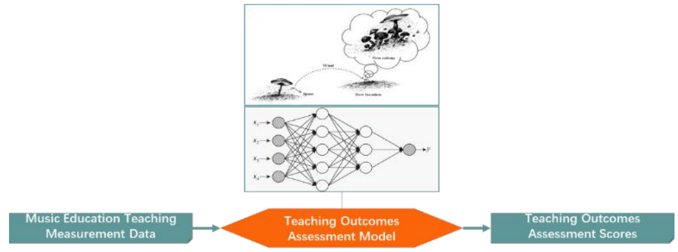


Fig. 6. Assessment of teaching outcomes in higher music education.

*4) Techniques for applying results-based assessment models*: Taking the music education teaching outcome data of higher education institutions as a case study, the trained outcome assessment model was applied to the data, and the teaching outcome measurements were collected, standardised and input into the outcome assessment model to obtain the music education teaching outcome assessment scores, as shown in Fig. 7.

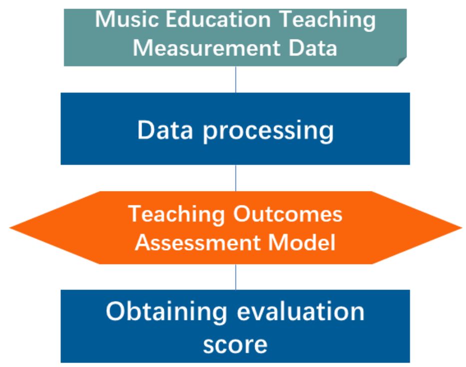


Fig. 7. Assessment of teaching outcomes in higher music education.

## III. Teaching Outcomes in Higher Music Education

According to the principles of demand-orientation, scientific, systematic and quantitative [21], this paper selects the measurement values of teaching results from three aspects, such as teaching content, practical skills and social practice ability [22], and the detailed extraction of the measurement values is shown in Fig. 8.

- Teaching content measures include measurements of regular grades, classroom practices, and final grades.
- Skills practice measurement includes academic salon activities focusing on professional skills demonstration and academic thinking exchange, and classroom practice activities focusing on teaching process design.
- Measurement of social practice ability includes internship assessment in off-campus teaching practice bases, and participation in various competitions for music education majors and teaching.

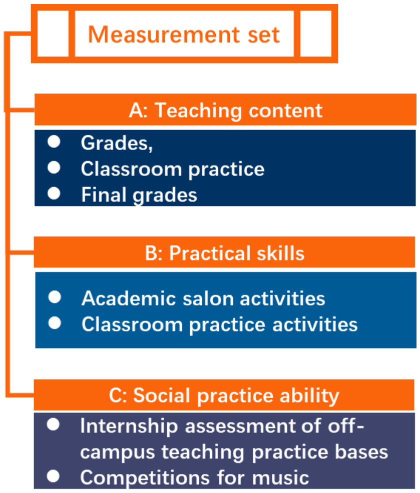


Fig. 8. Detailed extraction of the measurement values.

## IV. Research on the Algorithm for Evaluating Music Teaching Achievement Based on MRO-BP Networks

### *A. BP Neural Network*

BP neural network [23], or back-propagation neural network, is a multilayer feed-forward network that is widely used in the fields of function approximation, pattern recognition, classification, data compression, and time series prediction, as shown in Fig. 9.

The core of the BP network lies in its weight adjustment method, using the error back propagation algorithm, which adjusts the network weights to optimise the model performance by calculating the output error and back propagating it to each implicit layer, the structure of which is shown in Fig. 10 and Fig. 11.

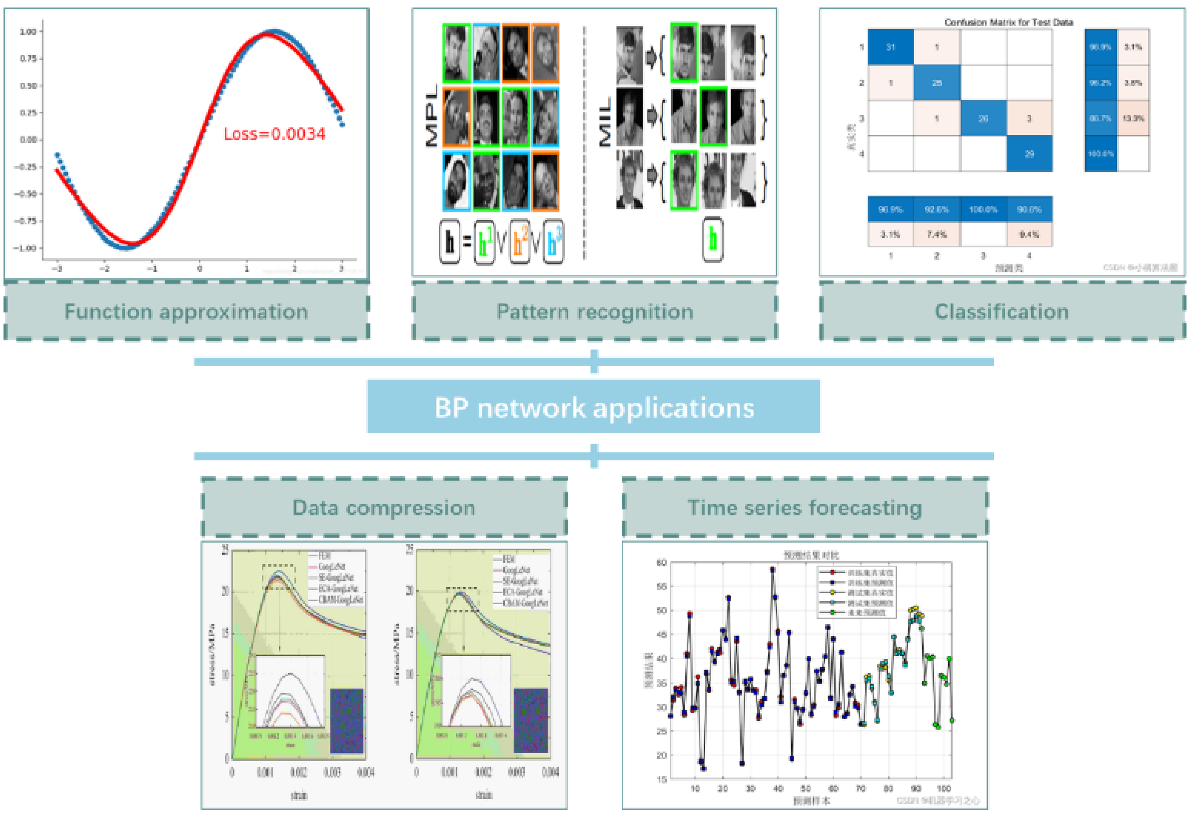


Fig. 9. BP neural network application.

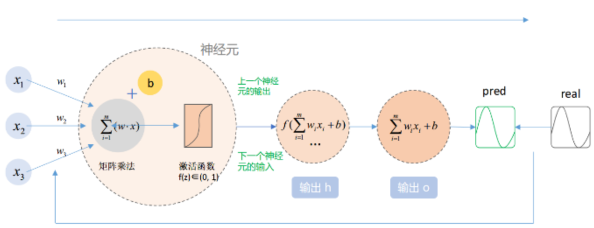


Fig. 10. Structure of BP neural network.

The basic structure of BP network includes input, hidden and output layers, with full connection between layers and no connection between the same layers. The learning process of BP network includes two phases of forward propagation of signals and back propagation of errors. 1) In forward propagation, the input signals are transmitted through the network and generate predicted values in the output layer. 2) In back propagation, according to the error between predicted values and the actual target values, the error is reduced by calculating the error gradient to adjust the weights and thresholds of the network to reduce the error.

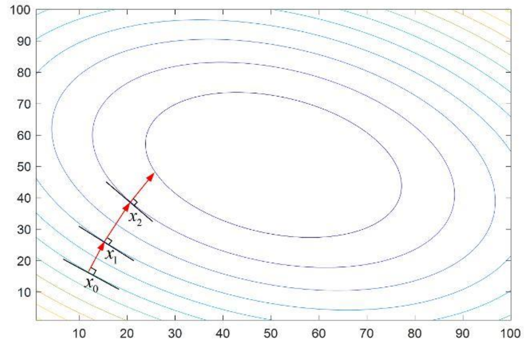


Fig. 11. Gradient descent method.

## B. *MRO-BP Network Model*

*1) MRO algorithm*: Mushroom Reproduction Optimization (MRO) [24] is a population intelligence optimisation algorithm inspired by the mechanisms of mushroom growth and reproduction in nature. The algorithm mimics mushrooms exploring the reproduction region through spore propagation and finding a more optimal reproduction region by refining the search space (Fig. 12).The MRO algorithm decides whether to perform a local search or a global search by calculating the average fitness value of each colony as well as the average fitness value of all the colonies to improve the efficiency of the search and to avoid precocious convergence to the local optimal solution.

Fig. 12. Iterative process of mushroom propagation.

The flow pseudo-code of the MRO algorithm is shown in Table I:

TABLE I. PSEUDO-CODE OF THE MRO ALGORITHM

| Algorithm 1: Mushroom Reproduction Optimisation Algorithm |
| --- |
| M parent mushroom populations were randomly generated;<br>Calculate the initialised mushroom population fitness value, with the average fitness value, and update the optimal mushroom individuals;<br>While the iteration condition is satisfied<br>    For i=1:M<br>        If Ave+Tave/c<Tave<br>            An artificial wind is used to disperse the population, select the optimal solution, and update the optimal solution;<br>        End if<br>        Randomly mutate the population, compute Ave, select the optimal solution, and update the optimal solution;<br>    End for<br>    Calculate Tave<br>End while |

The specific implementation steps of the MRO algorithm (Fig. 13) are as follows:

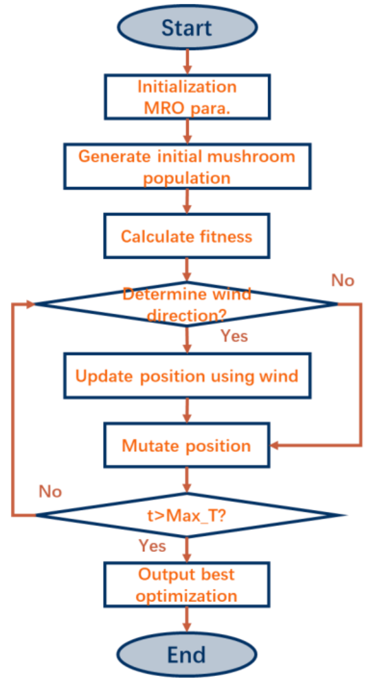


Fig. 13. Flowchart of MRO algorithm.

1) .Initialise the parameters of the MRO algorithm with the population. Initialise the maximum number of iterations $T_{\max}$, the population size $npop$, and the population individual search range. Initialise the population position:

$$X_{ij} = rand() \times (ub - lb) + lb \tag{1}$$

where $ub$ and $lb$ are the upper and lower boundaries of the mushroom search space, respectively.

2) Artificial wind determination of conditions. Artificial wind was operated on mushroom individuals that met the conditions, otherwise mushroom individuals were randomly searched within the breeding area.

$$Avg(i) + \frac{T_{Avg}}{c} > T_{Avg} \tag{2}$$

Where, $Avg(i)$ is the average fitness value of the $i^{th}$ mushroom individual, $T_{Avg}$ denotes the global average fitness value, and $c$ is the coefficient of determination.

3) Artificial wind mechanism. The simulated artificial wind operation on individual mushrooms makes the algorithm with global optimisation seeking capability.

$$Mov_j^{wind} = \left(X_i^* - X_k^*\right) \times \left(\frac{Avg(i)}{Tavg}\right)^{-m} \times Rand(-\delta,\delta) \times rs + Rand(-r,r) \tag{3}$$

Where, $Mov_j^{wind}$ denotes the distance moved by the $j^{th}$ individual, $X_i^*$ is the mushroom individual with the best fitness value in the $i^{th}$ colony, and $X_k^*$ denotes the path with the best fitness value in the $k^{th}$ colony. $Avg(i)$ is the average fitness value value of the $i^{th}$ colony, $Tavg$ is the average fitness value of all colonies. $m$ is the customisation coefficient. $\delta$ is the direction coefficient. $r$ is the step length control coefficient.

4) Breeding area search. Individual mushrooms search for better adapted locations within nearby breeding areas.

$$X_{ij} = X_i^{parent} + \overrightarrow{Rand(-r, r)} \tag{4}$$

Where $X_{ij}$ is the location of the mushroom individual, $i$ is the number of this individual in the population, and $j$ is the mushroom dimension. $r$ is the random search radius. $X_i^{parent}$ denotes the parent mushroom.

5) Finding the optimal fitness value individual and updating the mushroom location.

$$[bestmushroom] = \min\left(f\left(X_i\right)\right) \tag{5}$$

6) Determine whether the maximum number of iterations is reached, if the maximum number of iterations is reached, end the loop and output the result, otherwise carry out the next iteration.

The MRO method has superior capabilities in both global search and local refinement, making it well-suited for addressing intricate optimization issues. It may preserve population variety while searching, enabling it to escape local optimum solutions and discover the global optimal solution or a superior solution, as seen in Fig. 14. The MRO method has been used to address challenges in several domains, such as engineering design optimization and data mining [25].

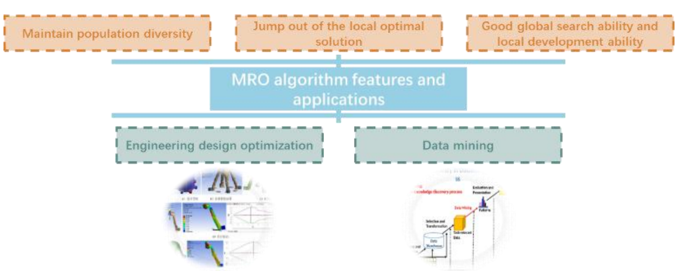


Fig. 14. MRO algorithm characteristics and applications.

*2) MRO-BP network*: In this paper, the BP network structure parameter weights and biases are used as decision variables, and the mean square error between the evaluated value and the true value is used as the fitness value of the MRO-BP model, the specific structure is shown in Fig. 15, and its pseudo-code is shown in Table II.

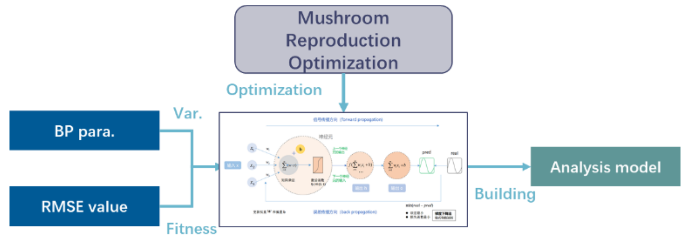


Fig. 15. MRO-BP network structure.

TABLE II. PSEUDO-CODE OF MRO-BP NETWORK ALGORITHM

| **Algorithm 2: MRO-BP network pseudo-code** |
|---|
| The MRO algorithm parameters are set, the MRO optimisation decision variables are identified, and the BP weights and biases are encoded in real numbers; |
| The RMSE is calculated as the fitness value to update the optimal mushroom individual, i.e., the current optimal BP network parameters; |
| Whether the While iteration condition is satisfied |
| Calculation of simulated artificial wind operations on individual mushrooms based on artificial wind determination conditions; |
| Mutational manipulation of individual mushrooms using breeding area search; |
| Update the network parameter individual information as well as the optimal network parameter individual; |
| End while |
| Output optimal network parameters; |
| Constructing the MRO-BP network. |

## C. Improved Network Modelling Applications

From Fig. 16, the MRO algorithm is employed in this paper to enhance the accuracy of the BP network model in the assessment of teaching achievement in higher music education. Additionally, the measurement system of teaching achievement in higher music education is investigated. The precise sequence of actions in the procedure is as follows:

- Through the examination of the challenges associated with measuring and evaluating the outcomes of higher music education, we develop a framework for analyzing the teaching outcomes of higher music education based on three key dimensions: teaching content, practical skills, and social practice ability.
- Acquire the measurement data for evaluating the outcomes of higher music education. Utilize the distinctive indicators of the measurement system to input the data into the MRO-BP model. Train and optimize the model to get an assessment model for evaluating the outcomes of higher music education.
- Choose validation data to get improved measures of music education teaching outcomes, input them into the MRO-BP network-based model, and generate better scores for assessing music education teaching outcomes.

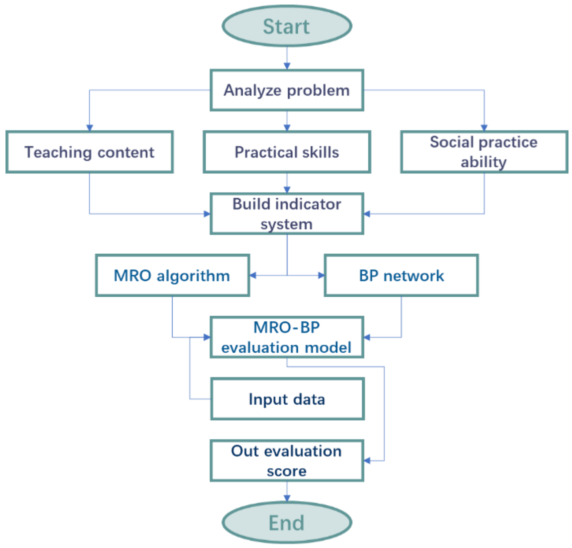


Fig. 16. MRO-BP network model application.

## V. Simulation and Analysis

### A. Experimental Data Acquisition

The cognitive assessment of music learners was conducted by a comprehensive questionnaire, which took into consideration several factors such as the teaching method, the proficiency of instructors, the knowledge requirements of students, and the practicality and social significance of the course. The survey findings were used to extract the higher music education teaching outcome measurement data. This data was then split into three sets: the MRO-BP model training set, validation set, and test set. The particular division ratio, number, and purpose of each set are provided in Table III.

### B. Experimental Environmental Setup

The specific settings of hardware environment, software environment and other experimental environments used for algorithm verification in this paper are shown in Table IV.

TABLE III. Experimental Data Settings

| Serial number | Data set | Proportions | Quantities | Goal |
|---|---|---|---|---|
| 1 | test set | 15% | 552 | Testing the evaluation performance of the MRO-BP model |
| 2 | validation set | 15% | 553 | Calculating the fitness value of the MRO algorithm for optimising BP networks |
| 3 | training set | 70 per cent | 2580 | Training the optimal BP network model, i.e. MRO-BP model |

TABLE IV. Experimental Environmental Settings

| Name of the environment | Parameterisation |
|---|---|
| software | AMD Ryzen 9 5900HX with Radeon Graphics 3.30 GHz |
| operating system | Windows 10 |
| programming software | Python 3.8 |
| visualisation software | Matlab2021a |

### C. Contrast Algorithm Parameter Settings

Methods for measuring and assessing teaching outcomes in higher music education employing comparison algorithms such as BP, TLBO-BP, GWO-BP, MPA-BP, AVOA-BP, and MRO-BP. The BP model utilizes the gradient descent method to calculate error feedback. The number of nodes in the hidden layer is determined based on the analysis in section 5.4. The TLBO [24], GWO [25], MPA [26], AVOA [27], and MRO algorithms have a maximum iteration limit of 1000, and the number of populations is determined based on the experiments in Section V (D). The specific parameter settings for the comparison algorithms can be found in Table V.

TABLE V. Comparison of Algorithm Parameter Settings

| Serial number | Arithmetic | Parameterisation |
|---|---|---|
| 1 | BP | The activation function is a radial basis function |
| 2 | TLBO-BP | TF=round[(1+rand)] |
| 3 | GWO-BP | a decreases linearly from 2 to 0 |
| 4 | MPA-BP | P = 0.5, R is a uniformly distributed random vector, FADs = 0.2, U = 0 or 1 |
| 5 | AVOA-BP | L1 = 0.8, L2 = 0.2, w = 2.5, P1 = 0.6, P2 = 0.4, P3 = 0.3 |
| 6 | MRO-BP | Fmin=0.07, Fmax=0.75, τ=4.125, a0=6.25, a1=100, a2=0.0005 |

### D. Analysis of Results

*1) Parameter setting analysis*: To ensure that the parameters are in accordance with the BP and optimization algorithms, this paper evaluates the accuracy and time consumption of the assessment models of teaching outcomes in higher music education using varying numbers of hidden layer nodes and populations. The results are illustrated in Fig. 17, Fig. 18, Fig. 19 and Fig. 20. According to the Fig. 17. From the data, it is evident that as the number of hidden layer nodes in the BP algorithm increases, the accuracy of the measurement and assessment of music education teaching outcomes in each model initially decreases and then stabilizes. Additionally, the time required for the assessment model also increases. As the population size increases, the precision of the algorithm used to measure and assess the outcomes of higher music education teaching improves. However, after reaching a population size of 75, the accuracy remains stable and does not decrease. Additionally, the time required for each model to process the data increases as the population size increases. The paper's detailed study reveals that the number of hidden layer nodes in the BP algorithm is 90, and each optimization technique has a population size of 75.

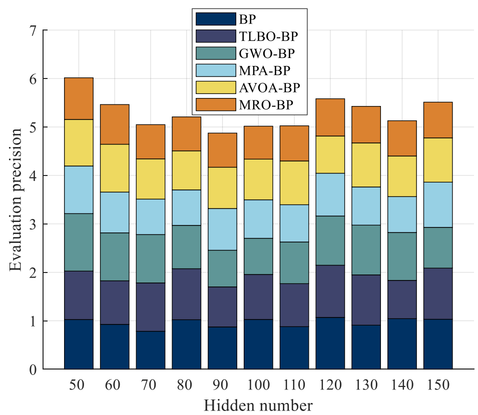


Fig. 17. Accuracy analysis of the evaluation model based on different number of hidden layer nodes.

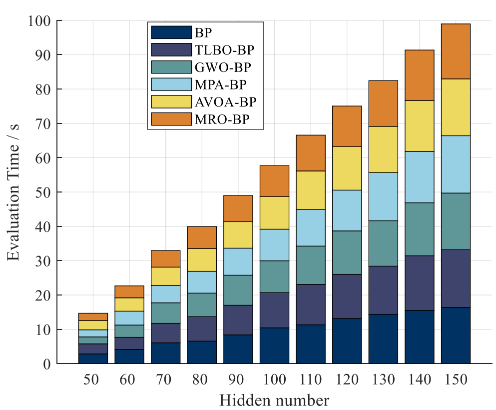


Fig. 18. Time-consuming analysis of the evaluation model based on different number of hidden layer nodes.

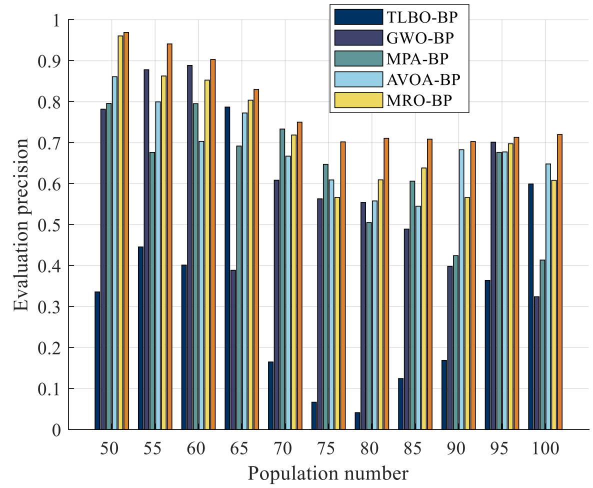


Fig. 19. Accuracy analysis of the assessment model based on different population sizes.

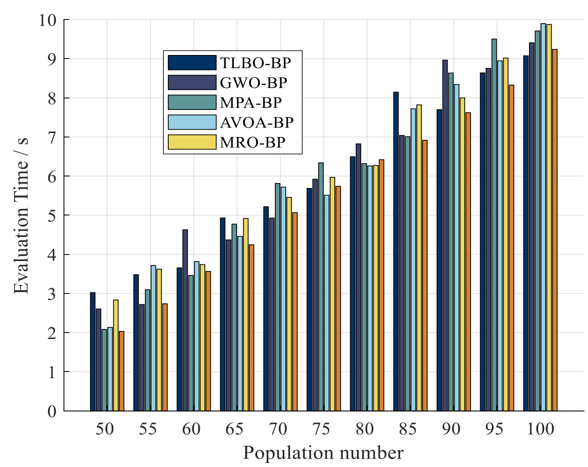


Fig. 20. Time-consuming analysis of assessment models based on different population sizes.

*2) Evaluation performance analysis*: To analyze and compare the effectiveness of the measurement and evaluation methods for teaching outcomes in higher music education proposed in this paper, we utilized several techniques: BP, TLBO-BP, GWO-BP, MPA-BP, AVOA-BP, and MRO-BP. The comparative analysis results are presented in Fig. 21 and Table VI.

According to the figure. Based on the data, it is evident that the MRO-BP network has the highest convergence accuracy for measuring and assessing teaching outcomes in higher music education. It is followed by AVOA-BP, MPA-BP, GWO-BP, and TLBO-BP. Additionally, the speed of convergence for each optimization network in measuring and assessing teaching outcomes in higher music education is approximately equal.

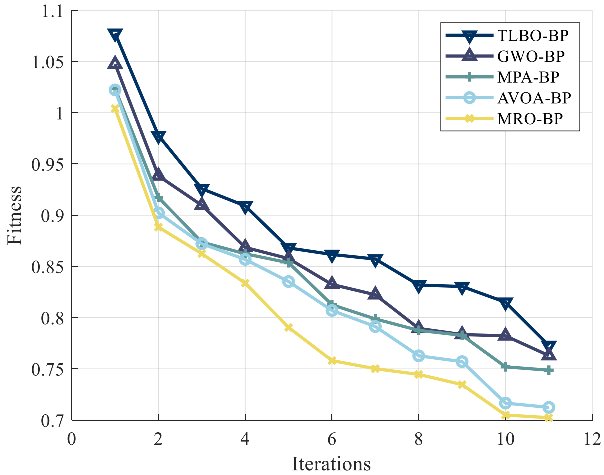


Fig. 21. Optimisation convergence curves of different optimisation algorithms.

Table VI shows that the MRO-BP network-based measurement and assessment of teaching outcomes in higher music education has the smallest RMSE value, followed by GWO-BP, MPA-BP, AVOA-BP, TLBO-BP, and BP. In terms of MAPE, the MRO-BP network-based measurement and assessment of teaching outcomes in higher music education has the smallest MAPE value of 0.7314, followed by AVOA-BP, MPA-BP, GWO-BP, TLBO-BP, and BP. The MRO-BP model also has the smallest MAE value of 0.49, followed by AVOA-BP, GWO-BP, MPA-BP, BP, and TLBO-BP. In terms of time-consuming, the MRO-BP model takes 7.744, followed by AVOA-BP, MPA-BP, GWO-BP, TLBO-BP, and BP. In summary, the MRO-BP model is the most accurate and requires the least amount of time.

TABLE VI. RESULTS OF PERFORMANCE COMPARISON OF DIFFERENT ASSESSMENT MODELS

| arithmetic | RMSE | MAPE | MAE | Time/s |
|---|---|---|---|---|
| BP | 0.892 | 0.9342 | 0.78 | 8.822 |
| TLBO-BP | 0.829 | 0.8561 | 0.91 | 8.729 |
| GWO-BP | 0.728 | 0.8373 | 0.63 | 8.397 |
| MPA-BP | 0.731 | 0.7783 | 0.71 | 7.758 |
| AVOA-BP | 0.737 | 0.7761 | 0.61 | 7.647 |
| MRO-BP | 0.701 | 0.7314 | 0.49 | 7.744 |

## VI. CONCLUSION

As music education teaching data continues to grow, the analysis of music behavior data and the assessment of music teaching outcomes have emerged as key areas of focus in the field of data-driven music research. This study addresses the issue of measuring and evaluating the teaching outcomes of data-driven algorithmic applications. It provides a technique for measuring and evaluating the teaching outcomes of higher music education using a combination of the MRO algorithm and BP network, known as the MRO-BP network model. This paper examines the issue of measuring and evaluating the teaching outcomes of music education. It focuses on designing the main technology and identifying the measurement indicators for teaching outcomes from three perspectives: teaching content, practical skills, and social practice ability. The paper constructs a measurement system for music teaching outcomes by combining the MRO algorithm and BP network. Additionally, it proposes an algorithm for assessing the teaching outcomes of music based on the MRO-BP network. The method proposed in this paper demonstrates superior results in terms of RMSE, MAPE, MAE, and time consumption when analyzing teaching outcome data in higher education. It effectively addresses the challenge of measuring and assessing teaching outcomes. The MRO-BP network model outperforms other models and is applicable to analyzing teaching outcomes in higher education, specifically in music education. However, its generalization and stability should be further validated using other datasets. Subsequently, it is necessary to use the MRO-BP network model for addressing further difficulties and enhancing the overall performance of the MRO-BP network.

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