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Study on The Optimal Setting of Architectural Reference Area and The Number of Classrooms of Middle- and Primary-School Classroom by Neural Network

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ABSTRACT

Recently, the architectural and design sector of the school has been very concerned with the rational setting of classroom area in accordance with the actual requirements of changing from traditional classroom structure to multifunctional classroom structure with intensive modern educational technology. In this paper, we consider how to construct the optimal model for the architectural reference area setting and the determination of classroom number in middle- and primary-schools using the principle of ANN and to verify the effectiveness of the proposed optimal model by means of an application example.

Keywords: classroom area, optimal, school architecture

1. Introduction

In recent years, the design and architecture of educational facilities have increasingly focused on enhancing the quality and functionality of learning spaces. With the rise of modern educational technology and evolving pedagogical methods, there has been a notable shift from traditional classroom layouts to multifunctional learning environments that emphasize adaptability, sustainability, and student well-being [1] [2] [3] [4] [5] [6]. This evolution has introduced the urgent need to redefine conventional standards in school architecture, particularly in determining the appropriate classroom reference area and the number of classrooms necessary to support effective educational delivery. The central aim of this study is to explore the optimal architectural settings for middle- and primary-school classrooms by leveraging the predictive capabilities of artificial neural networks (ANN), specifically the Back Propagation (BP) neural network model. This approach is grounded in the principle that intelligent computational tools can analyze complex, multidimensional data to generate highly accurate and practical predictions relevant to architectural planning.

The motivation behind this research stems from both environmental and pedagogical concerns. Traditional classroom design often emphasized physical capacity alone, based on basic metrics such as the number of students per room and the necessary arrangement of desks and chairs. However, contemporary classroom environments demand greater sensitivity to a range of parameters, including effective visual and auditory ranges, carbon dioxide levels, air quality, lighting, and acoustic conditions [7] [8] [9] [10]. These factors not only affect student health and comfort but also influence learning outcomes and teacher effectiveness. Furthermore, with the integration of multifunctional classroom spaces—such as laboratories, design rooms, and flexible lecture halls—the need for more nuanced and dynamic architectural planning has become increasingly evident. In this context, the study proposes the application of BP neural networks as a tool for architectural optimization. The research questions addressed include: (1) how to scientifically determine the classroom reference area per student in a way that aligns with modern environmental and educational standards, and (2) how to accurately predict the number of classrooms required based on the distribution of teaching hours, student demographics, and classroom functions.

The hypothesis guiding this work is that a neural network-based model can outperform traditional linear or heuristic methods in classroom space planning by offering a more adaptive, data-driven solution. By training the BP neural network on various environmental, physiological, and educational input parameters, the model aims to deliver precise output predictions for both classroom area and quantity. The expected benefit of this approach lies in its flexibility to accommodate different educational scenarios and its robustness in handling variable input conditions. Ultimately, the purpose of this study is not only to present a computational model for educational architectural design but also to contribute to the development of smarter, greener, and more student-friendly learning environments. Through a comprehensive application of neural network modeling, this research seeks to establish a new standard for optimizing school infrastructure that aligns with contemporary demands for educational quality and environmental sustainability.

2. Methods

This study adopted a quantitative computational approach using a Back Propagation (BP) neural network to predict the optimal classroom reference area and the number of classrooms in middle- and primary-school architectural design. The methodology involved the construction, training, and validation of predictive models through a six-stage neural network modeling process. First, the research identified and selected relevant design parameters, such as the number of students per class, effective auditory and visual ranges, carbon dioxide concentration, and visual field. These parameters were deemed crucial for accurately modeling the functional and environmental demands of contemporary school architecture.

Next, the neural network architecture was defined, consisting of an input layer with a number of neurons equal to the design parameters, one hidden layer, and a single output neuron corresponding to the predicted classroom area or classroom count. The sigmoid activation function was selected for both hidden and output layers to accommodate the range of normalized values. The hidden layer was experimentally tuned between four and eight neurons to optimize model accuracy and training efficiency.

Training data were collected based on existing architectural planning data and environmental performance standards. For the prediction of classroom area, twelve training samples were compiled, while six were used to train the model for classroom number prediction. The datasets were normalized to a range of [0,1] to align with the characteristics of the sigmoid function, and to ensure consistent learning performance across input dimensions.

The neural network was trained using MATLAB 10.0, employing 50,000 training cycles and an inertia coefficient of 0.1 to refine the connection weights between neurons. A least-squares error minimization approach was used to adjust weights and thresholds iteratively. To avoid overfitting and ensure generalization, the dataset was split in a 2:1 ratio, with two-thirds used for training and one-third reserved for testing. The model's prediction accuracy was validated by comparing the predicted output with the known target values, resulting in a relative error of 0.09% for classroom area and 0.063% for classroom count—indicating high precision and reliability.

The final output of the model recommended an average classroom reference area of 1.8 m² per student and an optimal classroom count of 67 for the given educational parameters. These results underscore the effectiveness of neural network modeling in optimizing educational architecture design based on both spatial and environmental variables.

3. Result and Discussion

Realistic requirements of setting the architectural reference area

To fulfill its educational mission effectively, a school must be equipped with a comprehensive range of learning spaces, including classrooms, laboratories, design studios, and practice rooms, all of which support the full implementation of the educational curriculum while simultaneously enhancing the learning environment. Classrooms, in particular, play a central role in shaping the spatial planning and volume of the school building, making their appropriate sizing and layout crucial in providing a conducive educational atmosphere. According to [11], the number of students per class in general education is typically estimated between 30 and 40. The required area is calculated based on the layout of essential classroom furniture, such as desks and chairs, along with additional space allocated for student activities. However, this traditional approach proves insufficient, especially in higher education institutions where the focus is on science, engineering, and hands-on practical education. Given the global trend toward environmentally sustainable learning environments, determining classroom area solely based on student occupancy and facility dimensions is no longer adequate.

In response to evolving educational needs, school architecture has progressed toward multifunctional classroom structures that integrate modern educational technologies. These developments demand a reevaluation of classroom design, emphasizing sustainability, adaptability, and environmental quality. For instance, [12] suggests that creating a green school involves optimizing natural lighting, indoor air quality, acoustic performance, and temperature control. Moreover, there is a shift toward using environmentally friendly and recyclable materials—such as bamboo, cork, and linoleum derived from linseed oil—instead of traditional, non-renewable materials like steel and those containing volatile organic compounds (VOCs). A case study presented in [13] describes a primary school in the United States that adopted a “natural classroom” model, integrating features such as artificial turf and green flooring within a traditionally structured classroom.

Furthermore, [12] emphasizes a design philosophy rooted in "ecoculture" and "humanities culture," wherein school architecture must harmonize with the historical, social, and economic context of its location. This approach underscores the need to consider environmental factors alongside construction scale, duration, and method. Therefore, a holistic design strategy should aim to merge humanistic and ecological values. Complementing this, [14] introduces methods for designing noise barriers in classrooms, taking into account acoustic requirements, aesthetics, and structural stability. Meanwhile, [15] highlights how the Melbourne School of Design combines large lecture spaces with smaller, collaborative areas to foster multifunctional learning. A simulation study by [16] demonstrates that determining classroom area based on student numbers is critical for enhancing teaching efficiency and allocating resources effectively.

Key parameters for calculating the optimal number of students per class include effective visual and auditory ranges, visual fields, carbon dioxide concentration, and reference area per student. These findings reinforce the idea that designing classroom spaces involves more than just meeting physical space requirements—it is about cultivating a healthy, engaging, and future-ready learning environment. Consequently, classroom size should be determined by a combination of student capacity, appropriate educational equipment, age-related needs, and environmental and physical conditions that collectively uphold the quality of education.

Neural network selection for architectural reference area calculation of classrooms

Numerous studies have explored and analyzed various models for determining the appropriate area requirements for classroom buildings. For instance, [11] presents a model aimed at establishing the optimal spatial dimensions for key learning environments, including classrooms, laboratories, and research labs, particularly within high school buildings designed with specialized classroom configurations. To facilitate effective discussion, collaborative learning, and self-directed study among students, classroom furniture—namely desks and chairs—is arranged in multiple configurations based on group learning formats. This flexibility in arrangement allows a shift from traditional knowledge- and memory-based teaching methods toward more interactive, thinking-oriented pedagogies that nurture students' creativity. Grouping strategies are tailored according to the subject matter and educational context, with common configurations including groups of two, four, or six students. In one scenario, when the classroom was designed for 24 individual users, and each desk and chair were allocated per student, different layout plans were implemented depending on the grouping method, which in turn influenced the calculation of the classroom's total area.

S=S1+S2

S1: the desk, chair and teacher's desk occupied area in the classroom(m^2)

S2: area for learning (m^2)

The laboratory area is determined by performing a planar simulation according to the layout of the laboratory table, chair, experimental stand, and other furniture based on the analysis of the characteristics of the experiment according to the course.

E=E1+E2+E3

where

E : area of the table and chair (m^2).

E1: the storage area of fittings and the experimental apparatus (m^2)

E2: area of the teacher's desk, the cleaning table (m^2).

E3: area for the experiment (m^2).

The research laboratory (multi-functional classroom) requires the free placement of equipment and furniture, unlike the classroom or laboratory, and all the skills necessary for students' exploratory activities. Depending on the function, the research laboratory space can be categorized as space for the experiment, space for the computer work, space for the model and the demonstration, space for the teacher's guidance, etc.

That is, the area of the research laboratory consists of the sum of the areas of these functional spaces.

M=M1+M2+M3+M4

where

M: area of the research laboratory (m^2).

M1: area for experiment (m^2)

M2: area for computer work (m^2)

M3: area for model or demonstration (m^2).

M4: area under teacher's guidance (m^2)

On the other hand, the general formula for calculating the number of specialized classrooms for major subjects is as follows :

The number of specialized classrooms for major subjects (mathematics, physics, chemistry, biology, etc.) is equal to the number of all-school concurrent lessons in the subject, which depends on the number of lessons per week in the subject. Calculating the number of specialized classrooms by arithmetic method based on the course (number of lessons per week of the subject) is as follows:

A=A1/D

where

A: the number of specialized classrooms involved.

D: total number of lessons per week.

A1: average number of lessons per week in each grade of the subject in the major class.

N1: number of classes in each grade of the major class.

A2 : number of lessons per week in each grade for other classes except the major class.

N2: number of classes in each grade except for the major class.

As previously discussed, traditional school architecture design has often determined classroom area based solely on physical usage—accounting for the space occupied by desks, chairs, and student work areas. However, modern approaches to designing green classrooms require a more comprehensive perspective. Contemporary educational architecture must integrate not only physical dimensions but also environmental parameters such as effective visual and auditory ranges, noise levels, lighting quality, and visual field coverage. In response to this need, the present study proposes a method for predicting both classroom area and the number of classrooms using Back Propagation (BP) neural networks. BP neural networks, widely utilized in various fields—including economics, culture, military strategy, and information processing—are capable of recognizing, predicting, controlling, and optimizing complex systems and phenomena. The core principle of predictive modeling via BP neural networks lies in minimizing the squared error between actual and expected outcomes using a gradient-based least-squares error method. Learning in a BP neural network involves two main processes: forward propagation of the input signal and backward propagation of the resulting error. During forward propagation, input data is processed through hidden layers and transmitted to the output layer. If the output does not match the expected result, the error is propagated backward, adjusting the model iteratively. This repeated cycle constitutes the network's learning process, ultimately producing the desired output. The educational architecture prediction model developed in this study follows a six-step process: (1) identification of design parameters, (2) determination of the number of neurons in the input, hidden, and output layers, (3) selection of neuron response functions for both hidden and output layers, (4) collection of training samples, (5) training of the BP neural network, and (6) validation of the final prediction model.

First, the identification of the design parameters is a fundamental work to determine the structure of the prediction model by BP neural network. A rational design parameter system must provide completeness so that it can reflect all aspects necessary to set classroom area and number of classrooms, as simple as possible, and as clear as possible, the degree of correlation of each design parameter should be as low as possible.

Next, for the design parameter, we define the number of neurons in the input layer, hidden layer, and output layer, and the number of neurons in input layer is determined as the number of design parameters, and the number of neurons in the output layer as the number of reaching parameters. There is no unified rule to determine the number of hidden layers, but theoretically, a single hidden layer is sufficient. Under the same training order and error constraints, the training time is relatively short and the computational speed is fast for a single hidden layer. Generally, one hidden layer is set up and BP neural network is used. The number of neurons in the hidden layer in BP neural network is one of the important parameters that determine the performance of neural network. Excessively small number of neurons reduces the network's analytic ability and convergence, whereas more neurons increase the analytic ability and convergence, but the network training becomes complicated and the training time becomes longer. The number of neurons in the hidden layer can be determined by comparing the error of the training data and the test data for the temporarily set number of neurons (e.g., 4 to 8).

In the next step, we choose the sigmoid function as a function of the response of neurons in the hidden and output layers. The sigmoid function is a function of activity that describes the activity of the output layer neuron, which includes the logarithmic sigmoid function and the tangent sigmoid function. The response function of the hidden-layer neuron necessarily uses the sigmoid function, and the response function of the output-layer neuron may use the sigmoid or linear function depending on the range of values of the output variable. The logarithmic sigmoid function is expressed as follows:

$$f(x)=\frac{1}{1+e^{-x}}$$

Next is the step of selecting the training sample set, which is the data set needed to build the BP neural network. The number of training samples should be more than the number of coupling weight coefficients and thresholds between the input and hidden neurons. The training process of the BP neural network is the modification of the coupling weight coefficient and threshold between each neuron until the total error of the neural network is satisfied with the error discrimination condition using the least error squares method (gradient principle method) with the identified training sample.

Before training the BP neural network, we must first normalize the input and output data to construct the training sample. Since the input and output data constituting the training sample are of different units and also the neurons of the hidden and output layers of the BP neural network use the sigmoid function as a response function, we have to normalize the unit by converting them to values between [0,1] or [-1,1].

The method of normalizing the training data is as follows.

For each parameter, if the maximum value taken in the training sample is $x_{i\max}$ and the minimum is $x_{i\min}$, the transformation equation that transforms the input and output data into values between [0, 1] or [-1, 1] is as follows :

$$\overline{x}_i=\frac{x_i-x_{mid}}{x_{mid}}$$

where $x_{mid}=\dfrac{x_{i\max}-x_{i\min}}{2}$

When the training sample is normalized, it is used to train the BP neural network, and the sum of the global squared error of the neural network, E, is adjusted to correct the coupling weight coefficient and threshold between each neuron in the network until the error discrimination condition is satisfied. Since it is possible to fall into local minima when training BP neural networks using the least error squares method, it is necessary to make sure that the training results converged to the global minima of the neural network by changing the parameters initial values of BP neural networks by tens or hundreds of random times. This process is programmable and, when the training of the BP neural network is successfully completed, a neural network model for the desired educational architecture design, including the determination of the classroom area and the number of classrooms, is obtained.

Finally, the verification step for the established prediction model is presented. To verify the accuracy of the established prediction model, i.e. the generalization ability, a test sample is prepared. It is important to note that the simulated samples should not be the same as the training samples.

In general, the entire data set is divided into 2:1, and 2/3 data are set as training samples and the rest as test samples.

Optimization method of educational architectural design by BP neural network

1) Optimal selection of classroom area

The training sample data set for optimally identifying classroom area is shown in Table 1.

Table 1. Training sample data set for optimally identifying classroom area

№	Number of students per class/person	Effective auditory range/m	Visual field /°	CO_2/%	Effective visual range/m	Reference area/m^2 •$person^{-1}$
1	26	9.3	165	0.07	10.1	1.82
2	23	8.7	162	0.06	9.7	1.85
3	30	7.5	161	0.09	8.5	1.83
4	29	6.7	158	0.08	8.9	1.80
5	20	8.5	156	0.05	8.5	1.93
6	41	7.3	145	0.12	7.3	1.79
7	50	9.2	163	0.17	10.5	1.76
8	44	8.3	147	0.15	9.3	1.78
9	53	8.1	155	0.19	8.7	1.72
10	55	7.9	161	0.2	7.6	1.70
11	58	6.8	158	0.21	6.9	1.66
12	52	6.6	154	0.16	6.4	1.74

As shown in Table 1, the number of training samples was set at 12. The number of neurons in the input layer was set to 5, the number of neurons in the output layer to 1, the number of neurons in the intermediate layer to 4, the number of training to 50,000, and the inertial coefficient to 0.1. It was shown that the relative error was 0.09% with a very high accuracy. After training the BP neural network, the data of the test samples were set up.

The number of test samples was set to be one and the data of the test samples were used as standard parameters specified in the "Construction Code" now set in our country. According to it, the number of students in one classroom was 24, 28, 42 and 54 in a specialized subject classroom, a research laboratory, a joint lecture room 1 and 2 respectively, effective vision range 9 m, effective auditory range 10 m and visual field 160°in the setting of the standard parameters of the classroom.

The main reason for the high carbon dioxide content in the classroom is the metabolic activity of the students. Thus, it can be seen that there is a correlation between student numbers and classroom area and the carbon dioxide content in the classroom.

The content of carbon dioxide was set by international standards.

International standards were used for classrooms with clean air at carbon dioxide concentrations below 0.07%, for 0.07-0.1% with normal air and for 0.1-0.5% with threshold values [17]. Thus, the carbon dioxide content in the classroom was set to 0.1%.

Table 2. Test sample data set for optimally identifying classroom area

№	Number of students per class/person	Effective auditory range/m	Visual field /°	CO_2/%	Effective visual range/m
1	24	9.0	160	0.1	10.0
2	28	9.0	160	0.1	10.0
3	42	9.0	160	0.1	10.0
4	54	9.0	160	0.1	10.0

Table 2 presents the test sample data used to validate the BP neural network model in predicting the optimal classroom reference area per student. The table includes four different test samples, each representing a specific classroom scenario with a varying number of students: 24, 28, 42, and 54. Despite the differences in student numbers, the environmental parameters were standardized across all samples to ensure controlled evaluation.

Each test entry includes five key variables: the number of students per class (person), the effective auditory range (measured in meters), the visual field (in degrees), the concentration of carbon dioxide (CO_2, expressed as a percentage), and the effective visual range (in meters). These parameters are critical as they reflect both physiological and environmental factors influencing learning conditions in a classroom.

For all test samples, the effective auditory range was set to 9.0 meters, the visual field to 160 degrees, the CO_2 level to 0.1%—in line with international standards for indoor air quality—and the effective visual range to 10.0 meters. By keeping these variables constant while varying the number of students, the test set enables a precise analysis of how student density affects the recommended classroom area when environmental quality is maintained at optimal levels.

Using this dataset in the trained BP neural network model, the predicted reference area per student was found to be approximately 1.7903 m^2, supporting the conclusion that a classroom area of 1.8 m^2 per student is appropriate under these controlled conditions. This validation affirms the accuracy of the neural network model and its applicability to real-world classroom design aligned with green and ergonomic educational standards.

To predict the reference area per student in a classroom using BP neural network, a neural network simulation program was written in MATLAB (10.0), input test sample data, and then press the result view button, the result was represented as 1.7903 m^2. Thus, it was concluded that it is reasonable to set the area of classrooms of different types to 1.8 m^2 to meet the national standards based on the current scientific analysis of school classrooms.

Since the scientific accuracy of the results is ensured by the accuracy of the basic data, it is of paramount importance to accurately measure the carbon dioxide content of different students with modern measuring instruments in order to scientifically determine the classroom area using BP neural network. This should also be done considering the development of students of different school types.

2) Optimal selection of the number of classrooms

In [11], a computational model was proposed that accounts for the number of specialized classrooms for major subjects, the number of specialized classrooms for general subjects, the number of laboratories and the number of research laboratories.

The number of specialized classrooms can be obtained by

$$A_s = \frac{\sum (a_s \times n_s + a_s \times n_s)}{D_s}$$

Where

A_s : The number of specialized classrooms involved.

D_s : Total number of lessons per week.

a_s : average number of lessons per week in each grade of the subject in the major class.

n_s : number of classes in each grade of the major class.

a_s : number of lessons per week in each grade for other classes except the major class.

n_s : number of classes in each grade except for the major class.

The number of laboratories and the number of multi-functional classrooms were calculated as follows :

$$A_e = \frac{\sum (a_e \times n_e + a_e \times n_e)}{D_e}$$

Where

A_e : number of relevant laboratories.

D_e : total number of lessons per week.

a_e :number of experiments per week in each grade of the major class.

n_e : number of classes in the each grade of the major class.

a_e : number of experiments per week in each grade in other classes except for the major class.

n_e : number of classes in each grade except for the major class.

The number of multi-functional classrooms can be calculated as follows when used as a class unit as a classroom for major and elective subject.

$$A_m = \frac{\sum (a_m \times n_m)}{D_m}$$

where

A_m :The number of multifunction classrooms.

D_m : Total number of lessons per week.

a_m : number of exploratory teaching hours per week for each grade of the major class.

n_m : The number of classes in the major class.

In [11], the number of specialized classrooms, labs and research labs in high school was determined for 17 separate classrooms using the above formula, and the total number of classrooms in the school was determined by summing them. Based on the results, the training sample data for the number of classrooms are as follows :

Table 3. Training sample data set for determining the number of classrooms

№	Number of classes	Number of classes in each grade of the major class	Number of experiments in each grade	Number of research laboratories	Average number of lessons per week	Number of total classroom s
1	41	4	60	5	28	60
2	44	5	60	6	28	62
3	47	5	60	7	30	64
4	50	6	60	7	30	67
5	53	6	60	8	30	72

6	56	7	60	8	30	74

As shown in Table 3, the number of training samples was set to six. The number of neurons in the input layer was set to 6, the number of neurons in the output layer to 1, the number of neurons in intermediate layer to 4, the number of training to 50,000, and inertial coefficient to 0.1. The relative error was 0.063%, which showed very high accuracy. After training the BP neural network, the data of the test samples were set up.

Table 4. Test sample data set for determining the number of classrooms

№	Number of classes	Number of classes in each grade of the major class	Number of experiments in each grade	Number of research laboratories	Average number of lessons per week
1	43	4	60	5	30
2	45	4	60	5	30
3	48	5	60	6	30
4	50	6	60	7	30

Table 4 provides the test sample data used to evaluate the BP neural network model's ability to predict the optimal number of classrooms required in a school setting. This dataset represents four distinct test cases, each defined by five variables that are critical to classroom allocation and architectural planning.

The first column, Number of classes, refers to the total number of classes across the school. The second column, Number of classes in each grade of the major class, reflects how the classes are distributed by grade level within the specialized subject areas. The third column, Number of experiments in each grade, captures the frequency of experimental sessions per grade, set consistently at 60 for all samples. This emphasizes the hands-on, practical component of the curriculum, particularly important for science and technology education.

The fourth variable, Number of research laboratories, represents the quantity of dedicated lab spaces required to support experimental learning activities. These range from 5 to 7 across the test samples, increasing in proportion to the number of classes and grade levels. Lastly, the Average number of lessons per week remains constant at 30 for all scenarios, serving as a control variable to assess the influence of other parameters on the predicted outcome.

This standardized setup allows the BP neural network model to assess the relationship between class distribution, laboratory needs, and teaching hours in determining the ideal number of classrooms. Upon processing these inputs through the trained model, the output consistently identified 67 as the optimal number of classrooms, demonstrating the model's ability to generalize across varying yet realistic educational structures.

When running the program, the number of optimal classrooms is calculated as follows :

```
t1 =
 66.6254
 66.6254
 66.6254
 66.6254
```

As a result, it can be seen that the most optimal total number of classrooms is 67 when the number of experiments in each grade is 60 hours and the average number of lessons per week is 30 hours.

Calculating the expected and the resulting errors, it can be seen that the predictive simulation of the number of classrooms by the training sample was implemented very closely, as shown in the figure.

Prediction of the educational architecture by BP neural network can be applied to predict the total number of classrooms in schools with parameter values affecting the determination of the number of classrooms in the design process. It is also applicable to predicting how much the number of classrooms will increase under the influence of certain conditions, based on the analysis of various factors on the number of classrooms.

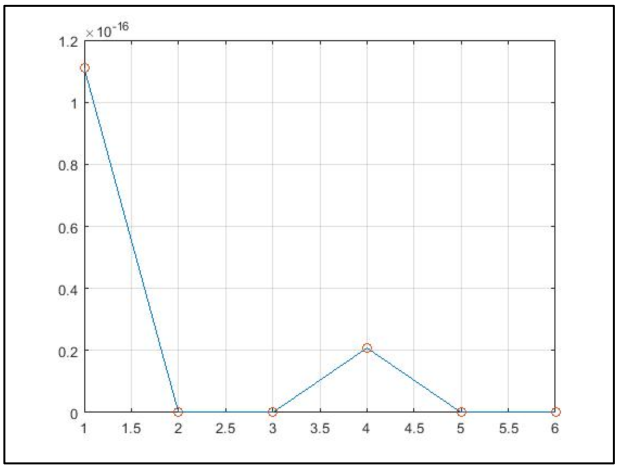

Figure 1 Error Convergence of BP Neural Network Model for Classroom Prediction

Figure 1 illustrates the convergence behavior of the Back Propagation (BP) neural network model used in predicting classroom-related outputs, such as classroom area or the number of classrooms. The x-axis represents the test sample indices (from 1 to 6), while the y-axis shows the magnitude of prediction error, likely indicating the residuals or the differences between predicted and actual values. As shown in Figure 1, the prediction error across all test samples is exceptionally low—approximately on the order of 10−1610^{-16}, which is nearly negligible. This minimal error indicates the model's excellent performance and high precision. The first sample displays a slightly higher error, but it quickly drops close to zero for the remaining samples, showing only minor fluctuations. The near-zero error values confirm that the BP neural network has effectively learned the input-output relationships and can generalize well to new data. This suggests that the model is robust and reliable for application in educational architecture design, particularly in determining optimal classroom parameters with high accuracy.

Prediction of educational architectural design by BP neural network is widely applicable to the prediction of the overall architectural scale of school, i.e. the architectural site and the architectural area of school buildings, in relation to the classroom area and the number of classrooms.

However, in the prediction of the educational architecture by BP neural network, the inherent characteristics of BP neural network should be well considered and applied to the prediction.

The BP neural network-based educational architecture prediction is only applicable to target design prediction. When predicting the general classroom area or the number of classrooms, BP neural networks should not be beyond the range of the parameters set in the training sample, as the predictions cannot be deviated from the threshold of the underlying data.

4. Conclusion

This study successfully demonstrates the application of Back Propagation (BP) neural networks to optimize the architectural reference area and the number of classrooms in middle- and primary-school buildings. By integrating a range of critical parameters—such as student number, auditory and visual range, carbon dioxide levels, and spatial requirements—the research offers a data-driven framework that supports more accurate and environmentally responsive school design.

The results indicate that the classroom area per student should ideally be set at approximately 1.8 m^2, aligning with national standards and ensuring a balance between space efficiency and environmental quality. Moreover, the predictive model for determining the number of classrooms, grounded in actual lesson and usage patterns, provides a reliable estimate that can support educational facility planning.

This study reaffirms the potential of artificial neural networks as powerful tools in architectural design, especially where complex and nonlinear variables are involved. From a broader perspective, the integration of AI in educational architecture paves the way for more intelligent, adaptable, and sustainable design solutions that meet evolving pedagogical needs.

Going forward, it is recommended that future research incorporates larger datasets and explores real-time environmental monitoring to further refine model accuracy. Additionally, collaboration between architects, educators, and environmental scientists could enhance the interdisciplinary robustness of such predictive tools.

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6. Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper. The research was conducted independently, without any financial or personal relationships that could inappropriately influence or bias the findings and interpretations.

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