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*Research Article*

# Research on Neural Network Prediction Model of Whole Process Risk Management Based on Building Information Model

**Shihong Huang**,[1] **Chengye Liang**,[2] **and Jiao Liu**[1]

[1]*Guangxi University of Finance and Economics, Nanning 530007, Guangxi, China*
[2]*Belarusian State University, Minsk 116699, Belarus*

Correspondence should be addressed to Chengye Liang; leonchengye@hotmail.com

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With the rapid development of China's construction industry and the acceleration of urbanization, large-scale public building projects are becoming increasingly important in urban development, and the risk management problems of them should be pay more attention to. Based on the integration of back propagation (BP) neural network and building information model (BIM) technology, this paper carries out the research on risk management process of the whole life cycle of large public buildings and identifies the risk factors of large public buildings from the application dimension and the management dimension. The risk management evaluation index system is constructed and identified, and assessment, early warning, prevention, and control of risk management are applied and analyzed throughout the process. The international large public sports center project is used as a case study to establish a BIM model, while the BP neural network risk management model is used for prediction and calculation. The results of this study show that, first, the maximum deviation rate of the output indicators of the BP neural network risk model is 3.57% in the design period (B2) and the minimum deviation rate is 0.00% in the commissioning period (B4), which verifies the reliability of the training results of the model. Second, the best effect of risk management in the whole life cycle of the building is in the investment period (B1) and the highest risk is in the construction period (B3). Last, this paper constructs a new risk management framework to realise the risk management of the whole cycle of construction projects from design to operation, which helps to improve the management level and risk response ability of construction projects and ensure the smooth and sustainable development of the whole life cycle of construction.

**Keywords:** BP neural network; building information modeling; prediction model; risk management

## 1. Introduction

In recent years, with the acceleration of China's urbanization process and the continuous expansion of the scale of urban construction, the development of the construction industry, as an important pillar industry of the national economy, is facing increasingly complex challenges and risks. The whole life cycle of a large-scale public building project involves multiple stages, such as design, construction, and operation, which is characterized by a variety of risk factors, such as safety hazards, long construction period, and large social effects. The relationship between different types of risks is intricate and complex causing serious impacts on the smooth progress of the project and the interests of stakeholders. At present, the risk management in China's construction industry has deficiencies such as the relative lagging of technical means and methods. While the whole life cycle of large-scale public buildings involves many subjects, and the construction environment is variable and complex. Existing risk management models and tools are often difficult to comprehensively cover a variety of risk factors, lack of relevance, and practicality [1–4].

Building information model (BIM) has played a vital role in risk management in the construction industry, which has the advantages of information integration and data support provide comprehensive and accurate risk management tools for construction projects, greatly reducing the risks of construction projects. In the design phase of large public building projects, BIM can create 3D models that include building

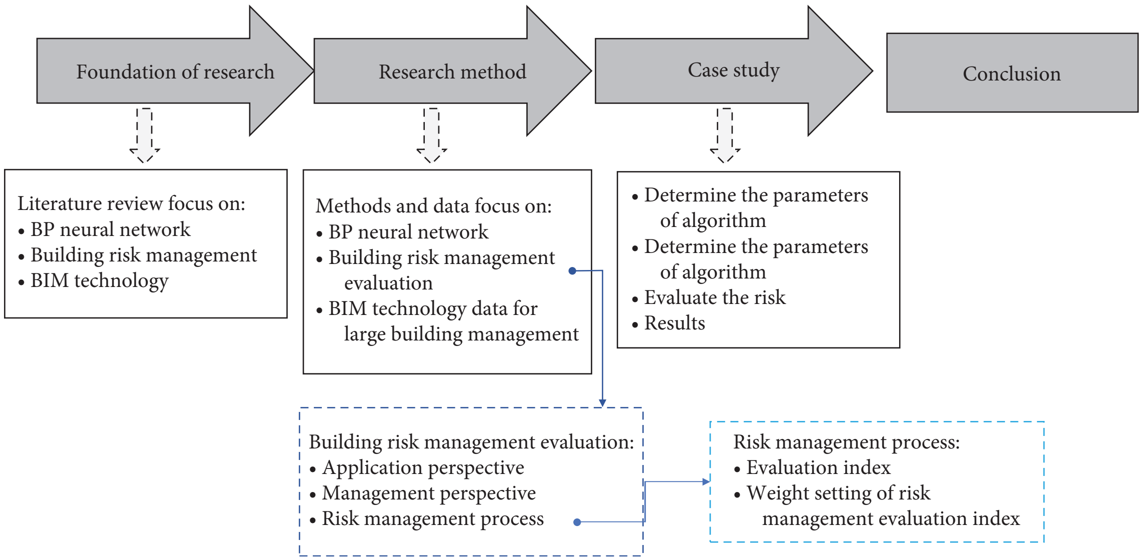



FIGURE 1: Research path.

construction, materials, and spatial information. In the construction phase, it helps supervisors better control the construction progress and reduce delays and errors. In the risk management process, BIM data can be utilized for risk identification and analysis, swiftly pinpointing potential risk points and high-risk areas and implementing targeted preventive and control measures, thereby reducing the likelihood and impact of risk occurrence.

Back propagation (BP) neural network was first proposed in the 1980s. And the construction process of neural network model is through the process of data input and output to autonomously mine the intrinsic connection and law, without setting up the function relationship in advance. Compared with traditional risk management methods, neural network technology has stronger adaptive and nonlinear modeling capabilities, which can better handle complex construction risk problems. The outstanding advantage of the neural network model is that it can mine the intrinsic connections and laws by training a large amount of input data. This data-driven approach can adapt to the variability and complexity of construction projects, which provide more accurate prediction and decision support for risk management. This paper combines the advantages of self-finding and self-adjustment of BP neural network and the characteristics of information integration of BIM technology to carry out research on the risk management problem of large public buildings.

The remainder of this paper is organized as follows: Section 2 reviews several works on the risk analysis and BIM technology in construction industry. In Section 3, the methods and data sources are introduced to determine the evaluation index system based on BIM technology. Section 4 takes the international standard swimming pool project built in China as a research case to derive the degree of influence of different factors on risk management. Conclusions and future work are discussed in Section 5. The specific research contents are illustrated in Figure 1.

This study aims to combine BIM technology and machine learning (ML) principles in the field of construction project management, which will solve the problem of quantitative risk assessment over the full life cycle of a construction project. In addition, BIM and ML models will improve the accuracy of prediction and assessment.

The main innovations of this study can be divided into two aspects. On the one hand, the innovative combination of BP neural network and risk management prediction and assessment. The idea of BP neural network in ML is mainly utilized to construct a construction engineering risk assessment model based on the risk management process. On the other hand, the depth of informatization research of construction risk assessment is expanded. Through BIM technology, building information data are incorporated into the index system of traditional risk assessment to improve the rationality.

## 2. Literature Reviews

*2.1. Risk Analysis Review.* In the 1990s, risk assessment gained attention and gradually expanded its application in the construction field. Based on the practical experience and theoretical research, various quantitative risk analysis methods have been developed, such as the index rating method and the analytic hierarchy process. For instance, Larsson and Field [5] used the index method to calculate the probability of safety accidents occurring at construction sites. Jannadi and Almishari [6] proposed a framework for assessing safety risks in construction based on the risk–cost model and combined with the analytic hierarchy process. The level of safety hazards in the construction process was quantified, while existing risk factors were simulated and analyzed using software. Aneziris, Topali, and Papazoglou [7] based on the concept of groups, used the analytic hierarchy process to determine the rank order of influencing factors in risk management. Dagdeviren and Ihsan [8] analyzed and classified construction risk factors using a combination of quantitative and qualitative approaches, and quantified evaluation indicators. Rozenfeld et al. [9] applied lean management methods to carry out risk management in construction sites, understanding task requirements to evaluate the probability and impact of various risks, and further establishing a risk management evaluation system. Benjaoran and Bhokha [10] conducted a comparative analysis of safety risks related to work plans and accident hazards in the construction process, providing insights for the safety application of risk management during construction.

With the continuous deepening and specialization of risk management research, mathematical theory-based safety assessment has become particularly prominent in recent years. Kim et al. [11] assessed the safety conditions of construction sites using a combination of qualitative analysis based on the analytic hierarchy process and quantitative analysis using fuzzy evaluation methods, considering the current level of construction risk assessment research. Zhaoying and Shuicheng [12] used fuzzy mathematics theory to assess fire risks in buildings. Dongping et al. [13, 14] approached the topic from psychological theory and reflected on the safety of the work environment and its impact on project risk management by considering the physiological and psychological reactions of personnel in the construction environment. Huajun [15] established safety evaluation standards specifically for steel formwork construction using the fuzzy comprehensive evaluation method. Wanqing et al. [16] introduced an imprecise measurement model into practical construction risk assessment work.

*2.2. BIM for Risk Management Review.* Construction projects generate various types of risks throughout the lifecycle, and the focus of risk management varies at different stages. Research on risk management related to schedule management, quality management, cost management, et cetera, combined with the vast amount of building information provided by BIM technology, has provided reliable technical means to enrich the research on construction project risk management. Baldwin et al. [17] proposed a dynamic BIM model of on-site material supply that recognizes the dynamic process of material usage and can be presented in an optimal way. Material management risks are reduced by generating an optimal material management plan. Lin and Su [18] proposed the integration of BIM and geographic information system (GIS) to assist in the construction of smart cities and conducted a case study using Tokyo Central. They provided an intelligent solution to enhance the management level of large-scale public building projects and reduce construction risks. Lau, Zakaria, and Aminudin [19] proposed the application of BIM technology starting from the preconstruction phase. The multifunctionality of BIM can help integrate information in geotechnical engineering and optimize construction plans, thereby addressing design and construction risks. Nadim and Goulding [20] analyzed building shadows through the integration of BIM and GIS. As data development moves towards more detailed and larger-scale directions, the information integration capability of BIM platforms provides support for rational spatial planning and avoids risks that may occur due to design errors or omissions. Chen et al. [21] pointed out that the holistic management concept of BIM helps in risk management for renovation projects and plays an important role in data support. Jaillon and Poon [22] evaluated the effectiveness of BIM in risk management through questionnaire surveys. Yongmin et al. [23] analyzed the current status of BIM adoption in China and pointed out the lack of BIM talent and unclear requirements for BIM in risk management.

*2.3. BIM Technology and ML Integration Review.* ML refers to the ability of computers to learn human learning mechanisms and behaviors based on massive data and certain algorithms, and this ability will continue to improve over time. ML is the foundation of artificial intelligence, and its theory is derived from cognitive science and statistics, and the algorithm implementation is based on computer science.

Currently, the research on ML prediction models is expanding. Chen, Guo, and Cao [24] used local neural networks to build a prediction model and verified the robustness of this method. Newton approximation method was used to determine the optimal solution of the proportion under different ambient temperatures to achieve the purpose of precise control of parameters. Wang et al. [25] established the prediction model of target data by analyzing the algorithm and basic principle of radial basis function (RBF) neural network model. Based on the support of a large amount of data, Yuan [26] built a prediction model based on a big data system, and then optimized the existing data prediction model to achieve the best control effect. Especially in the whole life cycle stage of construction projects, many literatures have also discussed the application research and typical cases of ML theory at various stages, and especially in the implementation of project management. The integration of ML and BIM and other related information technologies can provide effective modeling tools for the risk assessment of construction projects [27–30].

The BP neural network predictive modeling method is used to learn the sample data and correct the error, which has the ability of distributed processing and strong self-organization. However, there is still a large research gap on the risk prediction of construction projects by using BP neural network. With the continuous maturity and improvement of BIM technology, the massive information formed by BIM technology is utilized to train and simulate more accurately the prediction of various types of risks in construction projects. Thus, the integration of ML and BIM technology in the construction field can be improved. In summary, the research contribution of this paper is to broaden the application dimension of ML and building informatization, and improve the scientificity and feasibility of building risk management prediction.

## 3. Methods and Data

*3.1. Characteristics and Algorithm Flow of BP Neural Network*

*3.1.1. Characteristics of BP Neural Network.* Due to the long construction period and numerous risk factors associated

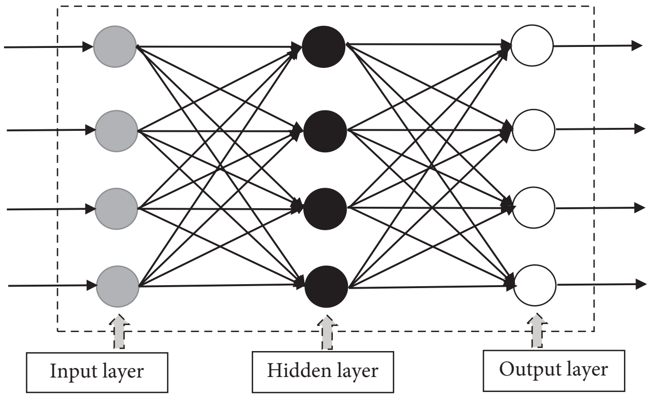



FIGURE 2: Presents the framework structure of a BP neural network.

with buildings, risk management becomes a complex system issue in project management, involving various qualitative and quantitative risk evaluation methods [24, 25]. Neural networks, especially the BP neural network, provide a reliable quantitative research technique for the purpose which overcomes the traditional bottleneck in addressing nonlinear problems and exhibits significant advantages in dealing with incomplete, contradictory, and fuzzy information [26]. BP neural networks can extract, transform, and store knowledge through self-learning [27]. After continuous training to develop its thinking capabilities, it can quickly identify principles within complex system problems and provide specific guidance, clarifying ambiguous issues [28, 29].

The BP neural network consists of an input layer, an output layer, and one or more hidden layers, forming a multilayer perceptron structure [30]. Figure 2 shows a typical BP neural network model including input, output, and one hidden layer. The depicted topology represents a BP network with only one hidden layer, without feedback connections between neurons. Nonlinear functions, with sigmoid functions being the most common, are typically used as activation functions in the hidden layer [31]. The output layer of the network can utilize both linear and nonlinear functions as activation functions, depending on the specific situation and the mapping relationship between inputs and outputs.

*3.1.2. The Algorithmic Process of the BP Neural Network.* The training process of a BP neural network consists of inputting training samples to the input layer, then transferring them to the hidden layer, followed by passing the data to the hidden layer. After understanding the difference between the actual output values and the desired output values, the weights are adjusted continuously in a backward manner, repeating the above training process until the desired level of accuracy is achieved. The main idea behind the BP neural network is to estimate the error in the previous layer based on the error in the output layer, and then use this error to estimate the error in the next layer, thus obtaining error estimates for all layers. These error estimates can be understood as partial derivatives, and we adjust the connection weights of each layer based on these derivatives. The output error is recalculated using the adjusted connection weights, and this process continues until the output error meets the specified requirements or the iteration count exceeds a predetermined value. Thus achieving the ultimate goal of performance evaluation research. This study establishes a risk management model for large public buildings based on the BP neural network, and the specific modeling and analysis process is shown in Figure 3.

In the structure diagram of the multilayer feedforward BP neural network, it can be observed that the nodes within the same layer are interconnected, and nodes between different layers can also form connections. However, the direction of connections is unidirectional, exerting influence only forward to the nodes of the next layer. Based on this principle, when using BP neural networks for analysis, the raw data is first filtered, and then the information elements are propagated forward until the results are formed and outputted [32]. After comparing the output values with the set values, if the difference exceeds the specified error range, the network begins the process of backward adjustment to identify the source of the error. Subsequently, calculations are performed until the output matches the desired accuracy. The entire process can be divided into the following four steps:

1. Calculate the input data $X_j$ for the nodes in the hidden layer, according to the following formula:

$$X_j = \sum_{i=1}^{n} \omega_{ij} - \beta_j, \ (j = 1, 2, \ldots, n). \tag{1}$$

2. In the equation, $n$ represents the number of neural nodes in the hidden layer and $\beta_j$ represents the range value for the neuron $j$ in the hidden layer.
3. Calculate the output data $Y_j$ for each node in the hidden layer.

$$Y_j = f\left(X_j\right) = \frac{1}{1 + \mathrm{e}^{-X_j}}, \ (j = 1, 2, \ldots, n). \tag{2}$$

4. Determine the model's output values in the output layer.

During the process of data simulation and training, it is necessary to have a training dataset and a test dataset. The training dataset is a set of foundational data used to discover patterns in the data, while the test dataset is a set of control data used to evaluate the predictive performance and accuracy. When using Matlab software for BP neural network model calculations, a certain number of training data should be set for simulation and training calculations. At least one set of test data is needed for comparison to assess the fitting degree or deviation rate of the data simulation.

*3.2. BIM Technology and Data Analysis.* BIM integrates all project-related information and combines it with the architectural 3D model to generate a BIM. This model can

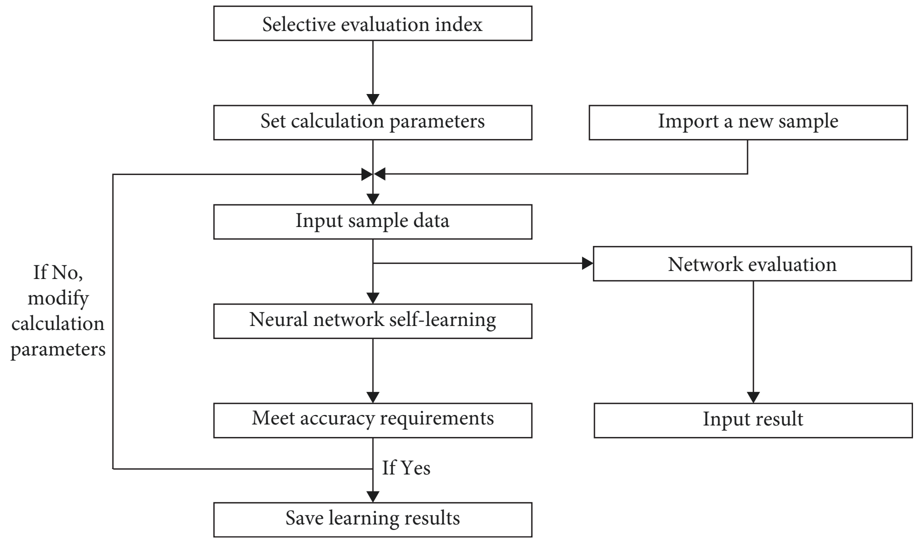



FIGURE 3: Depicts the algorithmic process of a BP neural network.

simultaneously reflect the physical characteristics and functional properties of the project, enabling simulation and analysis. BIM provides a new thinking mode for various management tasks in the construction field. It encompasses not only the physical model of the building but also behavioral information and other aspects related to the construction process. It enables multidimensional and multistakeholder collaborative management throughout the construction process, representing another transformation in the architecture/engineering/construction (A/E/C) industry [33].

During the design phase, BIM technology enables multidisciplinary clash detection, reducing the risk of design errors and omissions. In the construction phase, it facilitates construction site layout and visual communication, thereby reducing construction technology and management risks. In the project operation and maintenance phase, BIM provides a foundation for data integration. It collects multidimensional operation and maintenance information to support project management, risk assessment, and early warning. This allows maintenance personnel to develop management plans and contingency plans. Therefore, BIM technology has already begun to play an important role in risk management throughout the life-cycle of construction projects. With the continuous improvement of BIM technology and the increasing complexity of risk management systems, the application of BIM technology to support the risk management of the entire building life cycle will become a more systematic requirement.

*3.3. Analysis of Risk Factors for Large Public Buildings.* The risk management of large public construction projects is more complex than that of general buildings in terms of content and influencing factors. Therefore, when analyzing risk factors, it is necessary to consider from multiple perspectives and levels [34]. Risk management is a complex system engineering that requires comprehensive consideration from multiple dimensions [35, 36]. Therefore, the risk assessment system should be established based on factors, such as scientificity, objectivity, and data relevance, which can reflect the connotation of risk management and form a scientific management program [37, 38]. Before establishing a risk management evaluation system for large public buildings and determining management plans, it is necessary to analyze factors that may cause risk events in large public buildings. Considering the complexity of the risk management system, this paper discusses risk factors from the application dimension and management dimension as well as technical and management perspectives.

*3.3.1. Application Dimension*

*3.3.1.1. Human Factors.* Large-scale public construction projects involve multiple professional disciplines and processes. In China, the majority of construction projects still rely on labor-intensive production methods. Therefore, personnel factors play a crucial role. Throughout the entire life cycle of a construction project, different personnel such as designers, technicians, managers, and maintenance staff need to monitor and manage risks at different stages. The technical competence, management skills, qualifications, and professional ethics of these personnel determine the effectiveness of risk management efforts.

*3.3.1.2. Material Factors.* Materials form the physical foundation of large-scale public construction projects and are crucial objects of risk management. To ensure smooth construction, appropriate measures must be taken before and after the arrival of materials. During the construction phase, leveraging BIM technology can facilitate the creation of a collaborative platform. Various material-related documents such as inspection reports, quality certificates, and technical specifications can be stored and cross-referenced with design documents to ensure data consistency and reduce the risk of material errors and omissions. Simultaneously, combining BIM-6D technology can assist in rational planning of material storage areas, defining material extraction processes, and accurate tracking of material resources, which can help to form a scientifically standardized and high-quality project management method.

*3.3.1.3. Machinery Factors.* Large-scale public construction projects require the use of heavy and voluminous machinery. Due to space limitations, the machines need to be installed on-site and later removed, which requires more standardized management of large machinery. The arrival, operation, and departure of large machinery are periods of heightened construction risks. Therefore, detailed risk management plans need to be developed. Additionally, accidents involving large machinery often pose significant risks to personnel safety and result in substantial losses and social impacts. Hence, when assessing and implementing risk mitigation measures related to machinery factors, it is crucial to focus on evaluating the probability and potential losses associated with relevant risks and accordingly enhance the level of risk management measures.

*3.3.1.4. Technological Factors.* From the perspective of the entire life cycle of large-scale public construction projects, the important factors affecting the management of the more obvious include the accuracy of the preliminary exploration information, the reasonableness of the design scheme, the compliance of the construction technology, and the scientificity of the operation and maintenance management. Therefore, project safety must be ensured from the early stages of project preparation. Additionally, particular attention should be given to the technological factors in the construction phase of risk management. For example, the rationality of construction organization design, the formulation of specific construction plans, and the reasonable progress of various construction arrangements are among the management aspects that control multidimensional risks.

*3.3.1.5. Environmental Factors.* Environmental factors in the risk management of large-scale public construction projects include natural environment, social environment, economic environment, policy environment, and technological environment. The natural environment encompasses geographical and geological conditions at the project site as well as weather conditions during construction. The social environment includes the level of local support for the project, the necessity and feasibility of the project, and public perception. The economic environment encompasses the financial situation of the project owner, investment models, and project profitability. The policy environment involves relevant laws, regulations, and policy documents at both national and local levels. The technological environment refers to the level of personnel and hardware and software support required for the successful completion of the large-scale public building project.

*3.3.2. Management Dimension*

*3.3.2.1. Investment Risk.* Investment risks in large-scale public building projects include deviations in cost estimation, design budget, construction drawing budget, and construction settlement amounts, which are closely related to costs. For example, design changes due to variable geological conditions and inadequate exploration will lead to huge claims. From different stages, the increase in design cost is caused by the experience of designers and design software used. In addition, design modifications and refinements due to changes in laws, regulations, or standards are also important factors affecting cost. During the construction process, cost increases due to design complexities or changes in construction materials and technology.

*3.3.2.2. Design Risk.* Comprehensive management of the influence of design work on construction including quality, schedule, safety, and cost controlling–related risk factors to improve the rationality of architectural design projects. Specific risks may include incomplete preliminary information provided by the owner, changes in project planning conditions, unclear allocation of responsibilities between contracting parties, abnormal design stage sequence, and mistakes by consulting units leading to loss of control over investment. Insufficient management capabilities and experience of design units cause the risks associated with secondary detailed design units or equipment manufacturers' selection.

*3.3.2.3. Construction Risk.* Construction processes are prone to risks related to organizational management, quality management, schedule management, safety management, and technical management. Construction management risks mainly occur during material transportation, storage, construction, and final inspection stages. The construction process is an important aspect of risk management as there are many uncertainties on the construction site such as personnel, materials, machinery, technology, and environment.

*3.3.2.4. Trial Operation Risk.* The trial operation phase is the final step in delivering and using buildings, which is critical to assessing the quality of the design, procurement, and construction processes, including the overall acceptance of the building structure and the commissioning of the electrical and mechanical equipment. Failure in trial operation directly impacts project handover and payment of project funds. Specific risk factors influencing project trial operation include water, electricity, and communication supply; approval of production plans; sewage and waste treatment; malfunctioning of equipment and systems; insufficient spare parts and materials; improper operation by trial operation personnel; hidden risks in accessories; and failure to meet local standards and regulations during trial operation.

*3.3.2.5. Operation and Maintenance Risk.* A preliminary operation and maintenance plan is developed using a BIM case library, followed by virtual simulation. The nearest neighbor method is employed to search for the most similar cases in the BIM database, identifying risk factors during the operation and maintenance processes. Expert scoring is conducted to evaluate these factors, and BP neural networks are utilized for risk assessment. Based on the assessment report obtained, the operation and maintenance plans are optimized. During the operation and maintenance process, accurately capturing equipment information and building usage status, monitoring energy consumption, and promptly inputting

Table 1: Risk measurement area.

| *P*/loss | Small loss | Large loss |
|---|---|---|
| Low probability | D-risk area | B-risk area |
| High probability | C-risk area | A-risk area |

maintenance information into the BIM model for future inspections and repairs.

### *3.4. Risk Management Process for Buildings*

*3.4.1. Risk Identification.* Risk identification, as the primary step in risk management, involves qualitatively and quantitatively determining risk factors detrimental to large-scale public building projects, forming the basis for subsequent risk management processes. Risk identification serves as the basis for the remaining steps in risk management, ultimately completing the risk management process. It is a crucial step as successful identification of key risk factors enables proactive warning and control measures. Risk identification is typically achieved by referring to relevant risk management theories, reviewing risk-related literature, drawing from past experiences, and accumulated subjective knowledge in risk management of similar projects, which enables the assessment and identification of risk factors specific to large-scale public construction projects. Common methods used for risk identification include process flow charts, Delphi method, brainstorming, model perception, SWOT analysis, and system decomposition. The selection of a specific method depends on the number and complexity of the risk factors involved.

*3.4.2. Risk Measurement and Assessment.* Risk measurement and assessment refers to the estimation of specific risk factors using a variety of methods that involve both subjective and objective judgments. Subjective estimation relies on the expertise and authoritative opinions of relevant experts when information is insufficient or research is not deeply conducted. Objective estimation is based on a large amount of data and information. The probability and severity of a risk event is obtained by mathematical modeling.

Risk measurement focuses on quantitative analysis and research, which explores two aspects of relevant data, namely, the probability of risk events occurring and the magnitude of the resulting losses. Based on these two aspects, four risk zones can be defined, as shown in Table 1.

Risk assessment is the process of using certain methods or models to evaluate the overall or partial risks of urban commercial complex projects, which is to determine the level and impact of risks. Risk estimation focuses on individual risk factors, while risk assessment is comprehensive. Based on the estimation, risks are evaluated holistically to determine the overall risk level of the project and the capacity of the stakeholders to bear it.

Risk estimation and evaluation is based on scientific, technical, and theoretical research and qualitative and quantitative analysis of risk factors. The magnitude of the hazard of the risk is determined, while the source of the risk and its possible impact are further identified. Currently, representative methods for risk estimation and assessment include expert scoring, stochastic simulation (or statistical experimentation), decision tree analysis, the analytical hierarchy process (AHP), and fuzzy evaluation.

*3.4.3. Risk Warning.* To facilitate risk management, corresponding early warning initiation plans and accompanying emergency plans are developed during the warning phase, and color-coded indicators are used to provide comprehensive monitoring and alerts for risk points. The meaning of color-coded indicators is shown in Table 2.

*3.4.4. Risk Prevention and Control.* Risk prevention and control is an indispensable part of risk management. It involves analyzing risks based on the results of risk assessment and implementing targeted measures to prevent or minimize the occurrence of risk events and their potential losses. The primary task of risk control is to develop a risk response and management plan. Specific methods of risk control include risk avoidance, risk prevention, risk retention, and risk transfer [39].

Based on the aforementioned risk management process and the integration of BIM technology and BP neural network algorithm, this study presents the application of BIM technology in the risk management process of large-scale public building projects, as illustrated in Figure 4.

### *3.5. Establishment of Risk Management and Evaluation Index System for Large-Scale Public Building Based on BIM Technology*

*3.5.1. Establishment of the Evaluation Index System.* Based on the multidimensional analysis of risk factors in large-scale public building projects discussed earlier, the dimensions applied include personnel factors, material factors, machinery factors, technology factors, and environmental factors. These are defined as input indicators. The management dimensions include investment risk, design risk, construction risk, trial operation risk, and operation risk, which are defined as output indicators. Taking into account the five processes of risk identification, measurement, evaluation, early warning, and risk control in large-scale public building risk management and referring to relevant literature on building safety assessment and risk evaluation [40–43], a risk management and evaluation index dimension system for buildings based on BIM technology is constructed, as shown in Table 3.

Based on this, we obtain Table 4 indicator system.

*3.5.2. Weights Setting of Evaluation Indicators.* The weighting of evaluation indicators for risk management in large-scale public building projects based on BIM technology is determined through extensive research using the forced-ranking method [44]. The forced-ranking method employs a 0–4 scoring system to assign weights based on the relative importance of pairwise indicators. The scoring principles for assigning weights are outlined in Table 5.

There are 10 experts that have been invited to score the evaluation indicators mentioned above and consolidate the results to obtain weight assignment in Table 6.

Table 2: Risk warning color identifier.

| Risk level | I | II | III | IV | V |
|---|---|---|---|---|---|
| Risk assessment | Very high risk | Moderate risk | High risk | Medium risk | Safety range |
| Evaluation score | <50 | 51–60 | 61–70 | 71–80 | 81–100 |
| Alert colors | ● (red) | ● (orange) | ● (yellow) | ● (blue) | ● (green) |

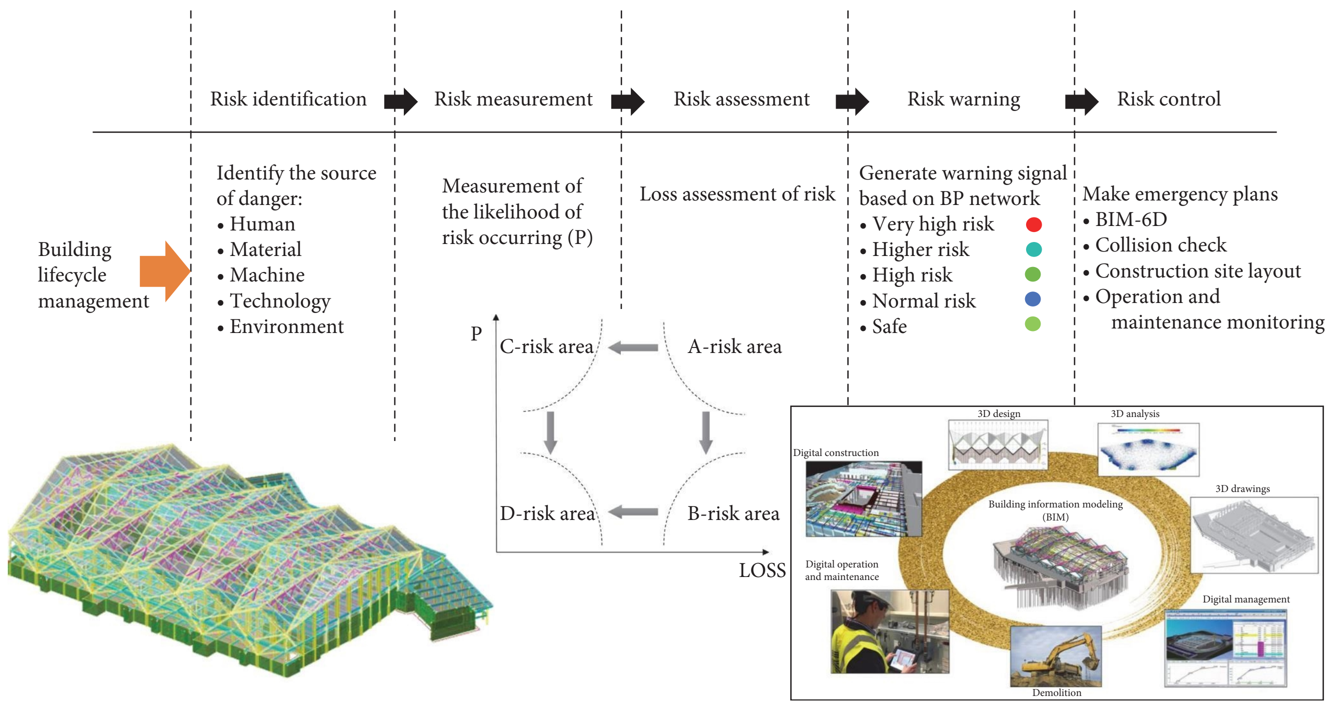



Figure 4: Risk management process of large-scale public building projects based on the integration of BP neural network and BIM technology.

## 4. Case Study

Take a large public building project as an example to explore the feasibility and scientificity of risk management assessment by combining BP neural network algorithm and BIM technology. The specific process follows the flowchart shown in Figure 5.

*4.1. Determine the Parameters of Algorithm.* Each of the five input and output indicators have been categorized into five grades: excellent, good, intermediate, normal and poor, as shown in Table 7.

*4.2. Collect Samples and Train the Neural Network.* In Section 3.5 of this paper, the weights of the indicator layer were determined. In order to proceed with the next step of neural network training, a certain amount of sample data needs to be collected for training. The Delphi evaluation method was used for training, and the collected samples were scored based on the five indicators using a two-stage expert rating process. The raw data is shown in Table 2. After combining the indicator weights, the indicator scores were calculated and used as input parameters for training.

Although in the process of training neural networks, the larger the number of samples, the more accurate and scientific the trained network will be. On the one hand, it is restricted by the actual situation that the number of samples cannot reach an unlimited limit. On the other hand, the training time of neural networks should also be considered. Many practices have shown that the accuracy and stability of the result prediction can be ensured on the premise of a reasonable sample size. For example, the American social survey corporation conducted the survey prediction of the US election by using thousands of sample sizes to measure the results of millions of votes, and the positive and negative error of the prediction results did not exceed 1%, which has reached the requirement of scientific accuracy. Based on considering the time and space dimensions of this study, the sample size selected is sufficient to meet the accuracy and stability of the results. Therefore, with reference to the relevant literature [45, 46], the number of training samples and verification samples in this study have met the calculation requirements.

A total of 11 relevant data on risk management assessment for similar projects were collected for this study. After

Table 3: Evaluation system of coupling coordination between urbanization and ecology.

| Dimension | Personnel | Materials | Machinery | Technology | Environment |
|---|---|---|---|---|---|
| Investment | Professionalism of investment personnel (certification and familiarity with the professional field) | Compliance with relevant policy documents and materials | Fixed asset investment | Completeness of technical standards | Assessment of the investment and financing environment |
| Design | Professionalism of design personnel (certification and familiarity with the professional field) | Scientific and regulatory compliance of design basis | Scientific and cost-effectiveness of equipment selection | Feasibility of the design proposal | Detailed design, design option comparison, and optimization |
| Construction | Professionalism of construction personnel (certification and familiarity with the professional field) and training system | Norms of material procurement, quality inspection standards, completeness of documentation, and authenticity | Selection of construction equipment and allocation of construction machinery personnel | Construction organization design, specific construction plans (if any), construction processes, and quality acceptance standards | Safe and civilized construction |
| Trial run | Training of trial run personnel | Testing standards | Operation status of supporting facilities for testing | User manuals and operating procedures for various types of equipment and facilities | Stability of the external environment |
| Operations and maintenance (O&M) | Training of maintenance personnel, certification of professional personnel | Operation and maintenance regulations, usage standards, etc. | Operation status of supporting facilities | Safety operation manual, emergency response plan, etc. | Sustainability of the external environment |

Table 4: Risk management evaluation indicator system for buildings based on BIM technology.

| Primary indicators | Secondary indicators | Indicator code |
|---|---|---|
| Personnel factors (A1) | Certification of professional personnel at each stage (including BIM engineers) | A11 |
| | Familiarity with the professional field at each stage (including BIM engineers) | A12 |
| | Training system for professional personnel at each stage (including BIM engineers) | A13 |
| Material factors (A2) | Support from relevant policy documents | A21 |
| | Compliance of professional materials with scientific regulations (including BIM data) | A22 |
| | Norms for material procurement | A23 |
| | Standards for material quality inspection | A24 |
| | Completeness and authenticity of documentation | A25 |
| | Testing standards | A26 |
| | BIM operation, maintenance regulations, and usage standards | A27 |
| Mechanical factors (A3) | Procurement of fixed assets | A31 |
| | Scientific and cost-effectiveness of BIM analysis equipment selection | A32 |
| | Allocation of construction machinery personnel | A33 |
| | Operation status of supporting facilities | A34 |
| Technical factors (A4) | Completeness of technical standards | A41 |
| | Feasibility of BIM-validated design proposals | A42 |
| | Construction organization design (BIM delivery) | A43 |
| | Specific construction plans (BIM delivery) | A44 |
| | Construction processes (BIM delivery) | A45 |
| | Quality acceptance standards | A46 |
| | Completeness of user manuals and operating procedures for various types of equipment | A47 |
| | Emergency response plans for various scenarios | A48 |
| Environmental factors (A5) | Evaluation of the investment and financing environment | A51 |
| | BIM-driven detailed design | A52 |
| | BIM design option comparison and optimization | A53 |
| | BIM-based safe and civilized construction | A54 |
| | Stability of the external environment | A55 |
| | Sustainability of the external environment | A56 |

Table 5: Scoring principles for assigning weights to evaluate indicators in risk management for large-scale public building projects based on BIM technology.

| No. | Evaluation | Grade |
|---|---|---|
| 1 | A is very important for B | A (4 score)/B (0 score) |
| 2 | A is relatively important for B | A (3 score)/B (1 score) |
| 3 | A and B are equally important | A (2 score)/B (2 score) |

describing the project conditions and creating detailed materials and reports, 10 experts were invited to score the projects. The scoring principle was based on higher scores indicating higher risks, and the scoring rule involved removing the highest and lowest scores and taking the arithmetic average. The 11th project was used as a reference project for comparison with the training results, while the first 10 projects were used for neural network training. The raw data is shown in Table 8.

*4.3. Evaluate the Risk.* Considering the small dimension of the evaluation vector and the sample size of 10, a simple single-hidden-layer neural network structure is used when determining the number of hidden layers. Despite having only one hidden layer, it can still perform the required mapping, satisfying the evaluation needs of this study [47]. Next, an activation function needs to be selected for the input layer, hidden layer, and output layer, respectively. The mathematical expression of the purelin function is the simplest, and its derivative is a constant. For the evaluation of large-scale public building risk management, its characteristics also follow the law of diminishing marginal returns. Therefore, one of the activation functions in tansig and logsig functions is chosen for the input layer and hidden layer of the neural network model in this article (Formula 3), and the purelin function is chosen for the output layer (Formula 4) [48]. Since the purelin function has a fast convergence speed, stable slope, and a value range of all real numbers, it can provide accurate evaluation results with fewer training iterations. Therefore, it is selected as the output layer function in this research.

$$\mathrm{logsig}: f(x) = \frac{1}{1+\mathrm{e}^{-x}} \, (0<f(x)<1). \tag{3}$$

$$\mathrm{purelin}: f(x) = x. \tag{4}$$

When training a neural network using MATLAB, if the data values in the samples are relatively large, it can lead to

Table 6: Weight allocation of evaluation indicators for risk management in large-scale public building projects based on BIM technology.

| Primary indicators | Secondary indicators | Indicator code | Weight |
|---|---|---|---|
| Personnel factors (A1) | Certification of professional personnel at each stage (including BIM engineers) | A11 | 0.04 |
| | Familiarity with the professional field at each stage (including BIM engineers) | A12 | 0.04 |
| | Training system for professional personnel at each stage (including BIM engineers) | A13 | 0.04 |
| Material factors (A2) | Support from relevant policy documents | A21 | 0.03 |
| | Compliance of professional materials with scientific regulations (including BIM data) | A22 | 0.03 |
| | Norms for material procurement | A23 | 0.04 |
| | Standards for material quality inspection | A24 | 0.04 |
| | Completeness and authenticity of documentation | A25 | 0.04 |
| | Testing standards | A26 | 0.04 |
| | BIM operation, maintenance regulations, and usage standards | A27 | 0.03 |
| Mechanical factors (A3) | Procurement of fixed assets | A31 | 0.04 |
| | Scientific and cost-effectiveness of BIM analysis equipment selection | A32 | 0.04 |
| | Allocation of construction machinery personnel | A33 | 0.04 |
| | Operation status of supporting facilities | A34 | 0.03 |
| Technical factors (A4) | Completeness of technical standards | A41 | 0.03 |
| | Feasibility of BIM-validated design proposals | A42 | 0.04 |
| | Construction organization design (BIM delivery) | A43 | 0.04 |
| | Specific construction plans (BIM delivery) | A44 | 0.03 |
| | Construction processes (BIM delivery) | A45 | 0.04 |
| | Quality acceptance standards | A46 | 0.03 |
| | Completeness of user manuals and operating procedures for various types of equipment | A47 | 0.03 |
| | Emergency response plans for various scenarios | A48 | 0.03 |
| Environmental factors (A5) | Evaluation of the investment and financing environment | A51 | 0.03 |
| | BIM-driven detailed design | A52 | 0.04 |
| | BIM design option comparison and optimization | A53 | 0.03 |
| | BIM-based safe and civilized construction | A54 | 0.03 |
| | Stability of the external environment | A55 | 0.04 |
| | Sustainability of the external environment | A56 | 0.03 |

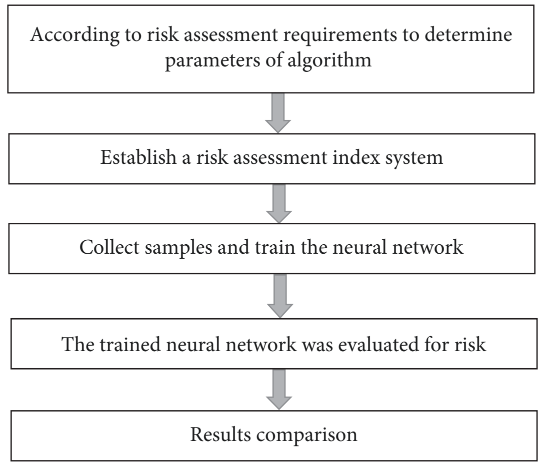



FIGURE 5: BP neural network process for risk assessment in large-scale public building projects.

TABLE 7: Input indicators and evaluation criteria.

| Type | Code | Poor | Normal | Intermediate | Good | Excellent |
|---|---|---|---|---|---|---|
| Input index | Human (A1) | <60 | 60–70 | 70–80 | 80–90 | 90–100 |
| | Materials (A2) | | | | | |
| | Machines (A3) | | | | | |
| | Technology (A4) | | | | | |
| | Environment (A5) | | | | | |
| Output index | Investment (B1) | | | | | |
| | Design (B2) | | | | | |
| | Construction (B3) | | | | | |
| | Trial operation (B4) | | | | | |
| | Operation and maintenance (B5) | | | | | |

TABLE 8: Scores of input indicators.

| Case | A1 | A2 | A3 | A4 | A5 | B1 | B2 | B3 | B4 | B5 |
|---|---|---|---|---|---|---|---|---|---|---|
| Case 1 | 59 | 52 | 86 | 72 | 65 | 90 | 56 | 94 | 94 | 57 |
| Case 2 | 75 | 82 | 56 | 97 | 72 | 73 | 95 | 66 | 54 | 85 |
| Case 3 | 71 | 79 | 73 | 53 | 53 | 97 | 71 | 92 | 78 | 76 |
| Case 4 | 85 | 96 | 56 | 64 | 55 | 82 | 92 | 54 | 88 | 65 |
| Case 5 | 81 | 78 | 88 | 53 | 87 | 60 | 88 | 71 | 93 | 70 |
| Case 6 | 57 | 81 | 62 | 86 | 58 | 82 | 76 | 96 | 91 | 50 |
| Case 7 | 54 | 94 | 81 | 69 | 87 | 71 | 60 | 96 | 78 | 61 |
| Case 8 | 56 | 89 | 88 | 71 | 67 | 65 | 98 | 95 | 82 | 85 |
| Case 9 | 61 | 84 | 58 | 91 | 71 | 96 | 56 | 53 | 76 | 64 |
| Case 10 | 76 | 54 | 78 | 80 | 84 | 82 | 71 | 84 | 98 | 51 |
| Case 11 | 77 | 55 | 79 | 81 | 85 | 83 | 81 | 85 | 84 | 82 |

excessively long training times and insufficient convergence speed. It has been proven that input data values within the range of (0, 1) are most suitable for neural network training. Therefore, the aforementioned raw data is normalized to the range of (0, 1) to facilitate training calculations. The normalized data is shown in Table 9.

Matlab software was used to train the neural network. Figure 6 shows the mean square error results of the neural network training, which reached convergence after 18,575 training sessions. Figure 7 shows that the model is robust, updating parameters during training is effective, and the model has good generalization ability.

Table 9: Normalized input indicator scores.

| Case | A1 | A2 | A3 | A4 | A5 | B1 | B2 | B3 | B4 | B5 |
|---|---|---|---|---|---|---|---|---|---|---|
| Case 1 | 0.16 | 0.00 | 0.94 | 0.43 | 0.35 | 0.81 | 0.00 | 0.95 | 0.91 | 0.20 |
| Case 2 | 0.68 | 0.68 | 0.00 | 1.00 | 0.56 | 0.35 | 0.93 | 0.30 | 0.00 | 1.00 |
| Case 3 | 0.55 | 0.61 | 0.53 | 0.00 | 0.00 | 1.00 | 0.36 | 0.91 | 0.55 | 0.74 |
| Case 4 | 1.00 | 1.00 | 0.00 | 0.25 | 0.06 | 0.59 | 0.86 | 0.02 | 0.77 | 0.43 |
| Case 5 | 0.87 | 0.59 | 1.00 | 0.00 | 1.00 | 0.00 | 0.76 | 0.42 | 0.89 | 0.57 |
| Case 6 | 0.10 | 0.66 | 0.19 | 0.75 | 0.15 | 0.59 | 0.48 | 1.00 | 0.84 | 0.00 |
| Case 7 | 0.00 | 0.95 | 0.78 | 0.36 | 1.00 | 0.30 | 0.10 | 1.00 | 0.55 | 0.31 |
| Case 8 | 0.06 | 0.84 | 1.00 | 0.41 | 0.41 | 0.14 | 1.00 | 0.98 | 0.64 | 1.00 |
| Case 9 | 0.23 | 0.73 | 0.06 | 0.86 | 0.53 | 0.97 | 0.00 | 0.00 | 0.50 | 0.40 |
| Case 10 | 0.71 | 0.05 | 0.69 | 0.61 | 0.91 | 0.59 | 0.36 | 0.72 | 1.00 | 0.03 |

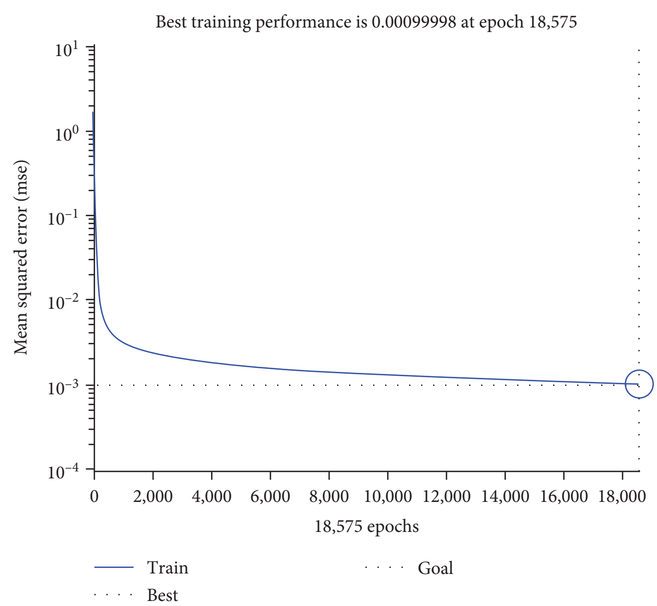



Figure 6: The mean square error curve of BP neural network training.

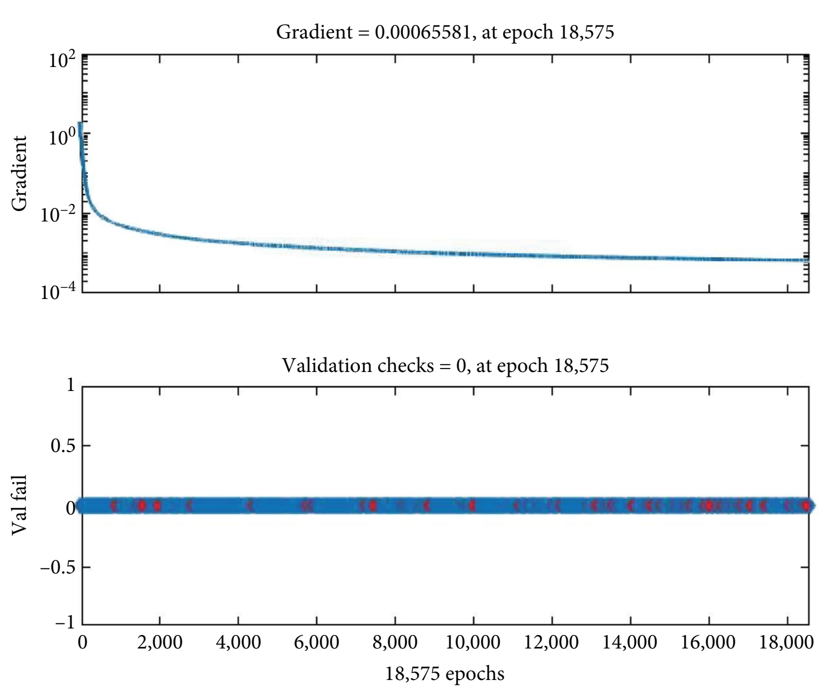



Figure 7: The gradient change curve of BP neural network training.

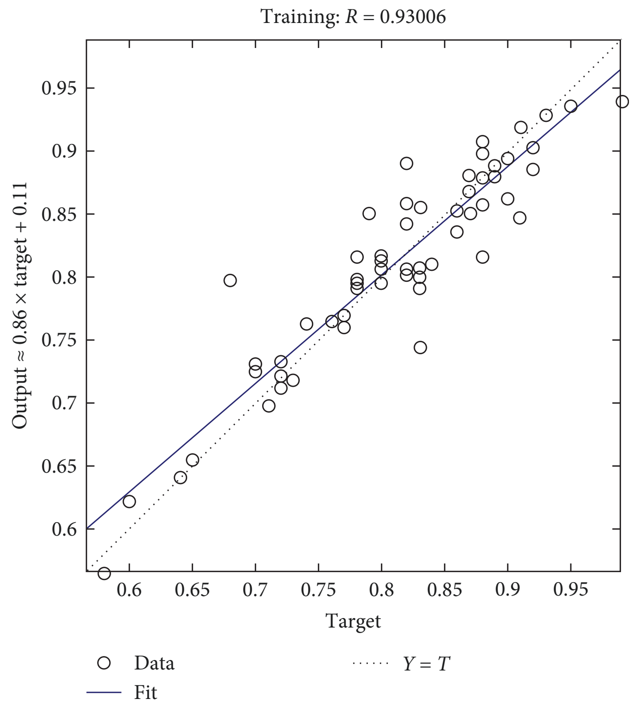
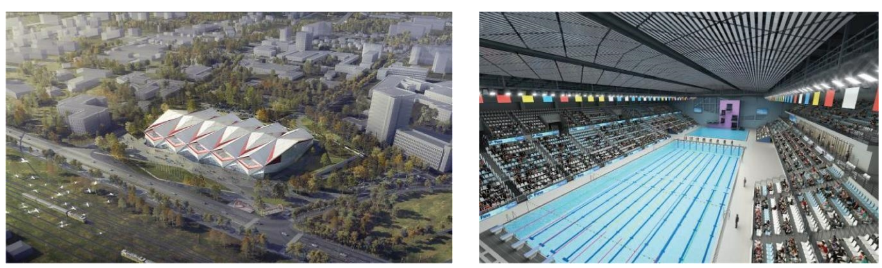



Figure 8: The regression of BP neural network training.



(a) (b)

Figure 9: Project renderings. (a) External rendering of the project. (b) Internal rendering of the project.

Figure 8 shows the results of the regression effect of BP neural network training, the output values are distributed on the ideal diagonal line, which indicates that the model predicted values are in line with the actual values, and the model has an accurate prediction degree.

*4.4. Results and Discussion.* The project is a Chinese-built international standard swimming pool project located in country B, which will be mainly used for various training and competitions of aquatic sports after completion (Figure 9). The scope of work for the Chinese contractors includes the project's foundation and base, main structures, architectural decoration, roofing, plumbing, drainage and heating systems, ventilation and air conditioning, electrical systems, intelligent building features, energy-saving measures, elevators, and outdoor engineering. The total duration of the project is 1,094 calendar days.

The BIM model established in this project is shown in Figure 10, which clearly shows the external structural layout and design features of the swimming pool, providing a comprehensive reference for the planning, design, and construction of the project. Figure 11 shows the operation page of using the BIM-6D platform to realize the information management of the whole process of the project building.

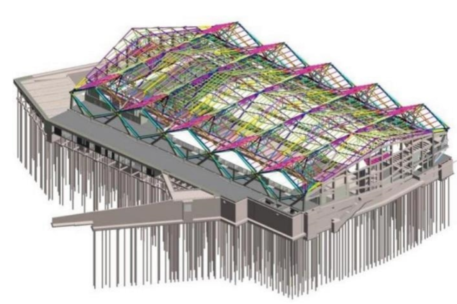


Figure 10: Project BIM.

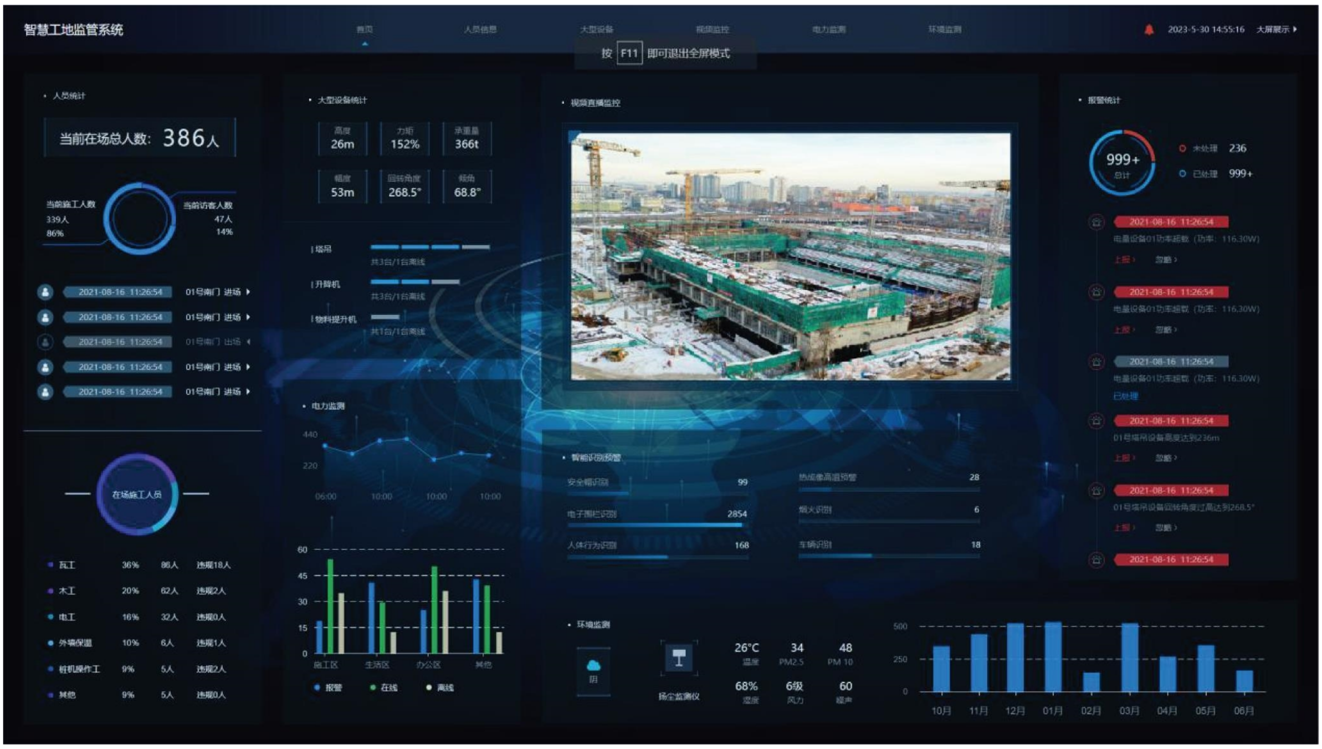



FIGURE 11: BIM-6D operation interface.

TABLE 10: Presents the comparison between the converted output results of the BP neural network and the original sample data.

| Comparison item | B1 | B2 | B3 | B4 | B5 |
|---|---|---|---|---|---|
| Test | 85 | 87 | 81 | 83 | 86 |
| Warning light | ● | ● | ● | ● | ● |
| Initial | 87 | 84 | 82 | 83 | 85 |
| Warning light | ● | ● | ● | ● | ● |
| Deviation rate | 2.30% | 3.57% | 1.22% | 0.00% | 1.18% |

The use of the information management system not only improves the efficiency and quality of the project, but also provides a strong support for sustainable building practice.

By utilizing the trained BP neural network integrated with BIM technology, as discussed earlier, the evaluation model for risk management of buildings was applied. The calculations were performed with Matlab, and the resulting output data were transformed according to the set percentage-based rules. Table 10 shows the results of comparing the converted output data with the original data.

## 5. Results

Based on the data above the table, the following conclusions can be drawn:

1. The maximum deviation rate among the five output indicators is 3.57% (B2) and the minimum deviation rate is 0.00% (B4), which satisfies the requirement of deviation accuracy and indicates that the BP neural network shows good evaluation performance in the training of the first 10 samples.
2. According to the meaning of the output variables, the risk assessment for each output indicator is green. The lowest-risk period is B1 (with the highest score), and the highest-risk phase is B3 (with the lowest score). The overall risk management throughout the process is good, indicating that the risk is manageable. This suggests that the investment (B1) phase has relatively lower risk and better risk management effectiveness, while the construction (B3) phase experiences higher risk and greater challenges in risk management.

## 6. Main Findings of the Present Study

This study shows that BP neural network can combine the five dimensions of risk factors in construction risk management including human, materials, machines, technology, and environment with sample training to conduct quantitative risk analysis at each stage of the whole life cycle, and the accuracy is high, with a high accuracy rate to meet the error requirements. It shows that BP neural network can realize the scientific calculation of risk model prediction and evaluation through the conversion of input and output layer indexes. Secondly, through the quantitative evaluation of the output layer, the standards corresponding to different scores are set, which is conducive to project managers to carry out targeted risk control based on the evaluation scores.

## 7. Implication and Explanation of Findings

By constructing human, materials, machines, technology, and environment as input layer indicators; investment, design, construction, trial operation, operation, and maintenance are the indicators of the output layer; and the black box effect formed by BP neural network is applied. Through the training of the samples, the risk situation of each stage of the construction life cycle under the existing conditions of the project can be calculated. At the same time, BIM technology provides more dimensions and more massive data information for risk management, can improve the accuracy of risk assessment, and can form information interconnection in the whole life cycle. After the risk prediction model is trained for risk assessment, the risk situation of the whole process of the project can be reflected in a quantitative form, so as to facilitate the project manager to take relevant measures. For example, through this case demonstration, we can not only verify the scientificity and accuracy of the model, but also conduct quantitative assessment of risk values at different stages and find key nodes of risk management and control.

## 8. Strengths Compared to Other Studies

Compared with the other existing sudies [49–55], the advantage of this paper is that it solves the problem of incorporating building information provided by BIM technology into the quantitative risk assessment of the whole life cycle of construction projects, which improves the accuracy of prediction and assessment. On the one hand, this study has broadened the application breadth of BIM technology in project management, demonstrates its advantages not only in technical application, but also enhances its advantages of data support. On the other hand, using the idea of ML to build a model through the data learning of existing samples can effectively improve the efficiency and accuracy of risk assessment at all stages of the life cycle of large-scale public building projects in the future.

## 9. Conclusion

This study conducted research on the life cycle risk management of buildings by integrating BIM technology with BP neural networks. The main findings include the below listed statements.

The whole life cycle risk of large public buildings includes application dimension and management dimension. The application dimension includes five elements: human, materials, machines, technology, and environment, among which the technology element has the highest weight (0.27). Materials (0.25) followed by environment (0.2). The weights of human and machines were 0.12 and 0.15, respectively, indicating that in the input layer, technical factors have the greatest impact on neural network training, followed by materials. Therefore, in the formulation of risk control measures, attention should be paid to the input and application of technology and materials.

Through the whole life cycle risk assessment system formed in this study and the sample training combined with BP neural network, the risk management of large public buildings can be accurately identified. The deviation rate of five factors in the output layer, including investment, design, construction, trial operation, operation and maintenance, is within 5%. On the one hand, it shows that the five factors of the input layer and the five factors of the output layer can form a prediction model through BP neural network. On the other hand, the model can not only predict the comprehensive risk of the whole life cycle of large-scale public projects, but also predict the risk situation of each stage, so that project managers can timely do risk management work in different stages.

In conclusion, the BP neural network model was validated using the BIM model of an international large-scale public sports center project. The validation results showed that the accuracy of the BP neural network model met the requirements, and the training results were reliable. The output evaluation results met the practical needs and could effectively guide the risk management of buildings, enabling the timely identification of weak links in risk management and assisting management personnel in eliminating safety hazards in a timely manner.

## 10. Recommendation

Large-scale public construction projects have the characteristics of large scale, long cycle, complex technology, and many influencing factors, and the loss of control of the whole process risk management of such projects is easy to cause huge losses and greater negative impact. Based on the whole-life cycle risk assessment model constructed in this paper, not only defined the relationshipp among Human (A1), Materials (A2), Machines (A3), Technology (A4), Environment (A5) in Investmen (B1), Design (B2), Construction (B3), operation (B4), Operation and maintenance (B5), but also use the trained model to evaluate the risk value of various large-scale public building projects at different stages. It is useful to take targeted risk prevention measures in time, such as risk retention, risk avoidance, risk transfer and risk control.

## 11. Research Limitations and Future Direction

This study still has certain limitations in the selection of risk assessment indicators for large-scale public building projects, and there are still many deficiencies in the depth and breadth of the research on major risk factors of large-scale public building projects. The risk indicator system can be further improved.

Future research will focus on different types of large-scale public building projects, such as hospitals, exhibition halls, and other functional building forms. In the index system, more dimensional factors will be considered in combination with the functions and characteristics of different building projects, and more extensive expert research and project demonstration will be conducted. In addition, considering the dynamic nature of risks in the whole life cycle of large-scale public building projects, dynamic indicators can be incorporated into the model for training, which is more conducive to proposing effective and feasible risk countermeasures at different stages.

Based on the risk management model using BIM and BP neural networks, reliable foundations are provided for all decisions throughout the life cycle of green buildings, from decision-making to operation and maintenance. This improves decision-making efficiency and reduces the occurrence of risk events. However, it is important to note that in practical implementation, it is necessary to gather a large amount of information on similar completed green building cases. Training with a large number of sample data is essential to promote continuous learning and maturation of the model.

## Data Availability Statement

All data generated or analyzed during this study are included in this published article.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Author Contributions

All the authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Shihong Huang, Chengye Liang, Jiao Liu. The first draft of the manuscript was written by Chengye Liang, and all authors commented on the previous versions of the manuscript. All the authors read and approved the final manuscript.

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