Real-time Exterior Quality Assessment of Substation Building Structures Integrating Intelligent Inspection Robots

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Abstract: Traditional construction quality assessment (CQA) methods relying on BIM and 3D laser scanning fail to meet the real-time control requirements of dynamic substation construction due to complex data processing and significant feedback delays. This study establishes a real-time quality assessment framework for substation structures by integrating intelligent robotics with image recognition technology. Utilising YOLO detection to identify twenty key performance indicators across four dimensions, it employs an AHP-fuzzy comprehensive evaluation model to quantify quality scores. Weights are determined through AHP and validated via consistency tests, while FCE quantifies membership degrees, enabling systematic construction quality evaluation.

Keywords: Construction Quality Assessment; Intelligent Inspection Robots; Image Recognition; AHP-FCE Mode; Substation

1. Introduction

As the core hub of the power system, the construction quality of substation structures directly determines the safety, stability and durability of power transmission. With the continuous expansion and increasing complexity of power engineering projects, construction quality management has assumed a critical role in project execution. Substation structures present distinctive challenges: diverse component types, unique construction environments (frequent elevated work, intense electromagnetic interference, compact spatial layouts), and stringent quality standards. Their characteristic multi-opening design with numerous embedded components demands far greater scrutiny of visible construction quality than conventional buildings [2][3]. Traditional quality control methods suffer from limitations including inefficiency, fragmented data, and difficulty in retrospective analysis, particularly when applied to structures with numerous openings, embedded components, and high electromagnetic interference environments. Failure to promptly identify apparent quality defects may lead to reduced structural load-bearing capacity or even electrical safety incidents. Apparent quality defects (such as cracks, dimensional deviations, or non-compliant flatness) that remain undetected and unrectified may cause issues including diminished structural load-bearing capacity, leakage, and corrosion. These problems can subsequently compromise the long-term safe operation of substations and potentially trigger electrical safety incidents [5].

Current construction quality assessment for substation structures primarily relies on traditional methods, including manual inspections, BIM model comparisons, and 3D laser scanning technology [6-9]. Manual inspections suffer from limitations imposed by subjective experience and operational environments, resulting in low efficiency, high rates of missed defects, and difficulties in quantifying data. While the combined approach of BIM and 3D laser scanning enables three-dimensional modelling and deviation analysis, it faces drawbacks such as high equipment costs, complex data processing workflows, and a 24-48 hour delay between scanning results and construction progress. This fails to meet the quality control requirements of ‘real-time detection and prompt rectification’ during the dynamic construction process of substations. Traditional construction quality inspection methods typically rely on manual checks and single data sources. These approaches not only suffer from inefficiency but are also susceptible to human factors, leading to insufficient accuracy and subjective bias [10-11]. Particularly within complex building structures and construction site environments, achieving efficient and precise construction quality assessment has become an urgent challenge for the industry.

In recent years, advancements in image recognition technology and intelligent construction robotics have provided novel solutions for construction quality inspection [12-14]. Image recognition accurately reflects diverse data categories during construction and operational processes by extracting information from images and video footage. Concurrently, the integration of construction robots with computer vision technology in quality inspection has emerged as a research focus alongside developments in smart construction techniques. Intelligent construction robotics employs sophisticated recognition and analysis to capture geometric information of building structures with high precision, enabling intelligent feedback and analysis [15]. Although both image recognition and intelligent construction robotics have seen research and practical application in construction quality monitoring, effectively integrating these technologies to enable scientific quality assessment during construction remains a significant challenge. This study therefore proposes an integrated method combining image recognition with intelligent inspection robots for evaluating the apparent construction quality of substation building structures. This approach provides technical support for automated, real-time management of substation construction quality, holding considerable engineering application value and theoretical significance.

This study aims to propose a multi-criteria decision-making approach for evaluating the apparent construction quality of substation building structures through the deep integration of image recognition and intelligent construction robotics. This approach combines the Analytic Hierarchy Process (AHP) with the Fuzzy Comprehensive Evaluation method (FCE), comprehensively considering multidimensional factors of construction quality. It provides a holistic evaluation of structural construction quality across aspects such as geometric precision, component quality, construction deviation control, and construction visualisation quality. This approach enhances assessment accuracy while strengthening the scientific and systematic nature of construction quality management, providing novel technical means and methodologies for construction quality monitoring within the building industry. The innovations of this research are as follows:

1) Proposing a construction quality assessment framework for inspection robots tailored to the complex construction environments of substations;

2) Developing a perception analysis model and image recognition method suitable for robotic construction scenarios in substations;

3) Establishing an AHP-FCE model by integrating the Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation (FCE), thereby introducing an evaluation methodology for substation construction indicators.

2. Literature Review

With the advancement of image recognition technology, construction robotics, the Analytic Hierarchy Process, and the Fuzzy Integrated Evaluation Method, the integration of these technologies offers more precise, scientific, and efficient solutions for construction quality assessment. This study will explore how these cutting-edge technologies play a pivotal role in evaluating construction quality, analyse their respective application advantages and challenges, and provide a theoretical basis for subsequent technological convergence and innovation.

2.1 Application of Image Recognition Technology in Construction Quality Evaluation

Construction quality evaluation constitutes an indispensable phase throughout the entire engineering construction process, directly impacting both the superiority of engineering quality and operational safety. Burati and Farrington [16] note that rectifying quality defects during the final stages can account for up to 16% of a project's total cost. Current practice relies primarily on manual collection of geometric data from measuring tapes, levels, or total stations for construction quality inspection. These methods prove highly time-consuming in acquiring and interpreting geometric data [17-18], whilst inspection outcomes fail to reflect the structure's complete actual condition, as they measure only discrete points on component surfaces. In recent years, image recognition has garnered significant attention for its application in construction quality assessment due to its high precision, non-contact data acquisition capabilities, and rich multidimensional information representation. Image recognition has been extensively applied across numerous civil engineering domains [19-24], notably in crack and surface defect detection [25,26], construction progress and compliance monitoring [27], and material/component identification within building information models for completed structures [28]. By processing image or video data, image recognition provides technical support for precise structural measurement and intelligent quality control.

2.2 Application of Intelligent Inspection Robots in Construction Quality Assessment

With the advancement of intelligent construction, the application of such robots in quality assessment demonstrates significant advantages and innovations, injecting new vitality into engineering quality management. As mobile platforms equipped with imaging sensors (visible light, thermal imaging, LiDAR, etc.), intelligent inspection robots enable close-range, comprehensive quality inspections in areas difficult for humans to access [29,30]. Particularly within substation environments, these robots facilitate comprehensive inspections of architectural, structural, and aesthetic details, enabling holistic verification of design specifications. This integration encompasses geometric attributes, materials, spatial positioning, compositional relationships, and component quantities [31]. Furthermore, by comparing design information with actual construction data, image recognition can directly identify deviations in construction quality [32,33].

2.3 Application of Analytic Hierarchy Process and Fuzzy Comprehensive Evaluation Method

The Analytic Hierarchy Process (AHP) is a mathematical tool that decomposes complex problems into multiple levels, employing a combination of qualitative and quantitative methods for decision-making. Its core lies in constructing a judgement matrix and calculating hierarchical weights, enabling decision-makers to systematically analyse intricate issues. The Fuzzy Comprehensive Evaluation (FCE) method is a multi-factor decision-making approach grounded in fuzzy mathematics, suited for evaluating problems with blurred boundaries and high uncertainty. This method quantifies the evaluation object and indicator system, synthesising the influence of various factors through fuzzy matrices and membership functions to yield an overall evaluation result. The core of FCE lies in fuzzy transformation and weight allocation.

Current research has applied both AHP and FCE methods to construction quality management and evaluation. Aladayleh et al. [34] explored integrating Building Information Modelling (BIM) technology into construction project risk management practices, employing AHP to prioritise BIM-based strategies across multiple risk management dimensions (including technical, financial, sustainability, and time management). Wu et al. [35] enhanced decision-making efficiency for Engineering, Procurement, and Construction (EPC) projects by applying image recognition technology alongside a combined evaluation method integrating AHP and FCE. Their work underscores the significance of this integrated approach in improving decision-making efficiency for construction developers' management personnel. Ma et al. [36] employed the Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation (FCE) to conduct a comprehensive assessment of construction quality risks in metro engineering projects. They determined the weights of secondary indices and ultimately utilised an integrated AHP-FCE approach to evaluate the importance of sub-indicators. Hou et al. [37] employed the AHP-FCE assessment method to analyse student residents' perceptions of the building environmental performance within student complexes. This approach not only reflected the weighting of each building environmental performance attribute at every level within the hierarchical framework but also revealed the interrelationships among these performance attributes.

In recent years, with advances in image recognition technology and intelligent construction robots, researchers have begun exploring the integration of these cutting-edge technologies with the AHP-FCE methodology to enhance the precision and efficiency of construction quality assessment. However, within the complex construction scenarios of substations, combining image recognition with inspection robotics enables the comparison of design specifications against actual construction conditions. This facilitates the timely detection of construction deviations, thereby ensuring construction quality. Further research is required to effectively integrate the AHP and FCE methods with image recognition and point cloud technology, thereby establishing a comprehensive evaluation system. Addressing these challenges, this paper proposes an evaluation method for the apparent construction quality of building structures based on image recognition and intelligent construction robots. Integrating AHP and FCE methodologies, it aims to enhance the precision and efficiency of construction quality assessment. By establishing a scientifically sound evaluation indicator system, utilising image recognition and point cloud technology to obtain high-precision construction data, and conducting comprehensive evaluations through AHP and FCE, this approach overcomes the subjectivity and limitations inherent in traditional evaluation methods.

3. Framework for Evaluating the Apparent Construction Quality of Substations Using Intelligent Inspection Robots

3.1 Framework for Evaluating the Apparent Construction Quality of Substations

A comprehensive framework for evaluating the apparent construction quality of substations has been established to address complex construction scenarios. This framework employs intelligent construction robots as mobile data acquisition platforms, utilises high-definition machine vision and multi-sensor fusion for data perception, and centres on the YOLO object detection algorithm as its core recognition technology. machine vision measurement principles as the basis for indicator quantification, and substation construction quality acceptance standards as the evaluation criteria. Integrating an edge computing-cloud collaboration computing architecture with digital quality control management logic, this forms a fully automated, end-to-end apparent construction quality evaluation system, as illustrated in Figure 1. This approach overcomes the limitations of traditional manual inspection—characterised by high subjectivity, low efficiency, and significant safety risks—by enabling the quantitative, standardised, and intelligent assessment of core surface quality indicators. These include surface cracks, dimensional deviations, and flatness across diverse substation components such as structural frameworks, equipment foundations, and switchgear cabinets.

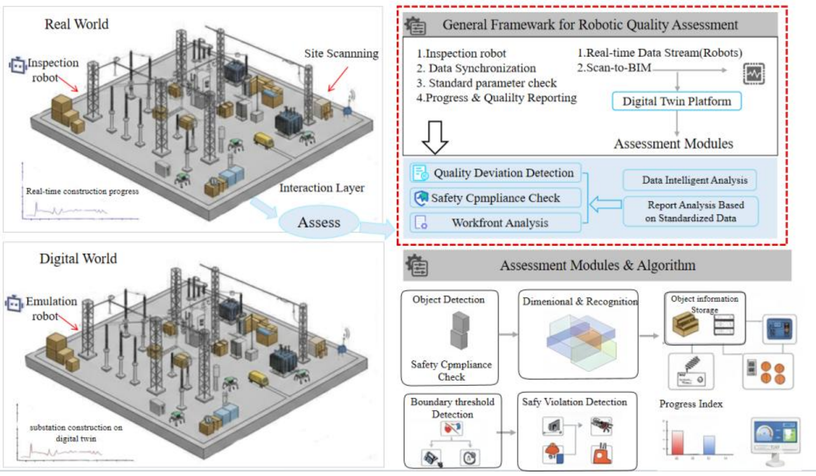

Figure 1. Construction Quality Evaluation Framework for Inspection Robots in Complex Substation Construction Sites

3.2 Development of an Evaluation Indicator System and Identification Methodology for Substations

3.2.1 Integrated image recognition system for substation construction quality assessment

To accommodate substation construction scenarios characterised by numerous embedded components, complex lighting conditions, and diverse topography; this system achieves hierarchical functional decomposition and standardised data exchange from underlying hardware acquisition to top-level application output. Progressing sequentially through data acquisition planning, multi-dimensional data collection, image pre-processing and feature recognition, indicator quantification and grading evaluation, to result output and defect closed-loop control, this system achieves end-to-end closed-loop management from raw image capture to rectification and closure of quality issues, as illustrated in Figure 2. It combines real-time detection with high-precision evaluation. Furthermore, all quality data interfaces with the substation BIM model and the intelligent construction management platform, enabling full lifecycle data traceability. This provides detailed data support for optimising construction techniques and facilitating project acceptance.

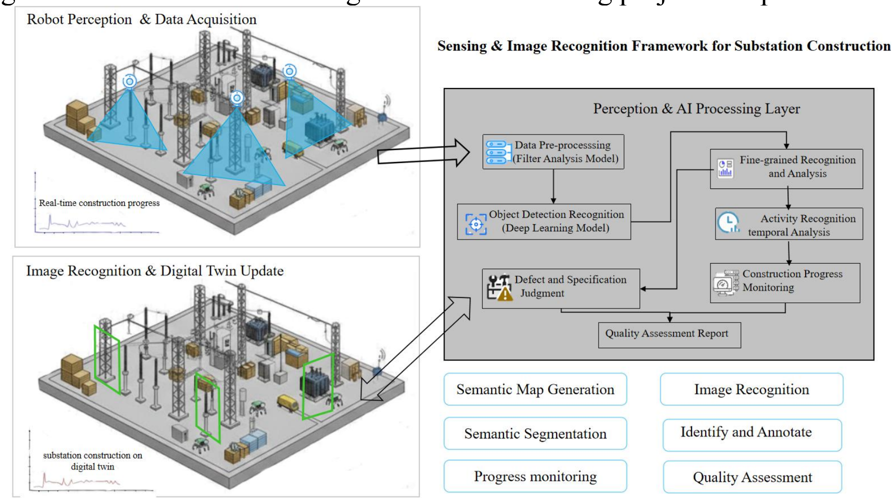

Figure 2. Substation Construction Quality Evaluation with Fusion Image Recognition

3.2.2 Development of quantitative quality assessment indicators for substation construction

The apparent construction quality evaluation metrics for building structures based on intelligent inspection robots should comprehensively cover key aspects of structural construction quality, including geometric accuracy, component quality, construction deviation control, and visualisation quality. The construction quality evaluation model proposed in this study was developed using data from the CBD 500kV substation and expert questionnaire survey results. The CBD 500kV Substation project is a key construction initiative in Beijing's Chaoyang District, involving complex architectural design, structural construction, and multi-disciplinary coordination.

The indicator system employs a hierarchical design methodology, progressively refining from the ‘objective layer’ through the ‘criterion layer’ to the ‘indicator layer’, forming a logically coherent evaluation framework. The objective layer primarily concerns the comprehensive assessment of apparent construction quality in building structures. The criterion layer reflects key aspects of construction quality, including geometric accuracy, component quality, construction deviation control, and visual construction quality. The indicator layer further refines each criterion into specific quantifiable metrics.

Through systematic analysis of relevant research literature [42-45] and construction quality standards for building structures [46], SPSS correlation analysis was conducted on the indicators. This process yielded evaluation metrics for assessing the construction quality of building structures by intelligent construction robots in substation construction scenarios, as shown in Table 1.

Table 1. Evaluation Index of Construction Quality of Building Structure Based on Image Recognition and Intelligent Construction Robot

Serial Number	Criterion Layer	Indicator Layer
1	Geometric Accuracy A1	Component Dimensional Accuracy B1
2		Component Positional Accuracy B2
3		Geometric Shape of the Overall Structure B3
4		Component Installation Spacing Accuracy B4
5		Consistency Between Construction Model and Reality B5
6	Component Quality A2	Concrete Component Apparent Quality B6
7		Steel Structure Component Apparent Quality B7
8		Prefabricated Component Apparent Quality B8
9		Component Surface Flatness and Verticality B9
10		Crack and Surface Defect Inspection B10
11	Construction Deviation	Formwork Installation Deviation B11

12	Control A3	Reinforcement Installation Deviation B12
13		Concrete Pouring Deviation B13
14		Component Assembly Quality Deviation B14
15		Component-to-Design Model Matching Degree B15
16	Visual Construction Quality A4	Component Assembly Quality B16
17		Component Gap and Joint Inspection B17
18		Component Appearance Integrity B18
19		Construction Completeness Inspection B19
20		Appearance Geometric Deviation Analysis B20

Geometric accuracy A1 encompasses component dimensional accuracy B1, component positional accuracy B2, overall structural geometry B3, component installation spacing accuracy B4, and conformity between the construction model and actual conditions B5. Component dimensional accuracy B1 can be rapidly verified through comparison with an image recognition model, detecting deviations in length, width, and height to ensure components meet design specifications. Component positional accuracy B2 can be verified by comparing against the design coordinate system within the image recognition model, detecting deviations in component axis positioning, elevation, and horizontal alignment to ensure compliance with design specifications. Overall structural geometry B3 can be verified by intelligent construction robots capturing the building's planar form data. This data is compared against the image recognition model to check the verticality of vertical components (e.g., columns, walls) and the flatness of horizontal components, ensuring overall geometric accuracy. Component installation spacing accuracy (B4) can be measured efficiently using intelligent construction robotics to capture distance data between adjacent components. This data is then compared against the image recognition model to rapidly identify excessive or insufficient spacing deviations. Construction model consistency with actual conditions (B5) can be assessed by aligning and comparing point clouds with the image recognition model. This evaluates geometric consistency between the construction site and the design model, analysing localised or overall errors.

Component quality A2 encompasses: - Concrete component surface quality B6 - Steel component surface quality B7 - Prefabricated component surface quality B8 - Component surface flatness B9 - Crack and surface defect detection B10 Concrete component visual quality B6 can be assessed by collecting point cloud data from concrete surfaces using intelligent construction robotics. Combined with image processing techniques, this detects surface defects such as air bubbles and honeycombing, evaluating overall concrete quality to ensure compliance with design and construction requirements. Steel component visual quality B7 employs high-definition photography and image recognition to detect surface defects (e.g., scratches, corrosion) and assess weld surface quality. Scanned data facilitates comparison against design dimensions within image recognition models. Prefabricated component visual quality B8 utilises intelligent construction robotics to inspect connection points, joint sealing integrity, and surface flatness of prefabricated components. Component Surface Flatness and Verticality B9: Intelligent construction robots capture comprehensive point cloud data of component surfaces to analyse unevenness, particularly verifying flatness and verticality of critical elements like large-area walls and floor slabs to safeguard subsequent construction and finishing works. Crack and Surface Defect Detection B10: Combining intelligent construction robots with image processing technology to measure crack width, length, and depth on component surfaces. Through high-precision point cloud analysis, crack locations are marked, enabling timely identification and assessment of their severity, with repair recommendations provided.

Construction deviation control A3 encompasses formwork installation deviation B11, reinforcement installation deviation B12, concrete pouring deviation B13, component jointing quality deviation B14, and component conformity to design model B15. Formwork installation deviation B11 may be measured using intelligent construction robotics to assess the actual position, elevation, and verticality of formwork. By comparing scanned data against the formwork's design position within an image recognition model, installation deviations can be rapidly detected, ensuring precise formwork positioning and providing foundational assurance for subsequent construction. Reinforcement installation deviation B12 is detected by capturing point cloud data of reinforcement layout, analysing deviations in spacing, position, and quantity, and comparing these against the design arrangement within the image recognition model. Concrete pouring deviation B13 is measured using intelligent construction robotics technology on the surface of poured concrete, analysing deviations in thickness, compaction, and flatness. Point cloud data visually highlights areas of uneven pouring or insufficient thickness. Component jointing quality deviation B14 can be measured using intelligent construction robotics technology to capture position, angle, and gap data at jointed component interfaces, comparing these against the jointing design in the image recognition model. By analysing point cloud data, deviations at joint locations are rapidly identified, ensuring component jointing quality meets design standards. Component-to-Design Model Conformity B15 employs comprehensive alignment and comparison of point cloud data with image recognition models to inspect the position, shape, and dimensions of completed components. Conformity analysis effectively evaluates the deviation range between actual components and design models during construction, visually displaying construction errors and guiding corrective actions.

Construction Visualisation Quality A4 encompasses: Component Assembly Quality B16, Component Gap and Joint Inspection B17, Component Surface Integrity B18, Construction Completion Verification B19, and Surface Geometric Deviation Analysis B20. Component Assembly Quality B16 utilises intelligent construction robotics to capture point cloud data of assembled components. This data is compared against assembly designs within image recognition models to analyse component shape, positioning, and connection precision, ensuring assembly quality meets specifications. Component Gap and Joint Inspection B17 measures gaps and joints at component connection points. Precise analysis of joint compactness and gap dimensions via point cloud data enables comparison against design standards, evaluating connection stability and sealing performance. Component Surface Integrity B18 employs intelligent construction robots and high-definition imaging technology to inspect component surfaces for defects such as damage, cracks, or deformation. By comparing high-precision point clouds generated from scans against design models, it comprehensively evaluates surface quality. Construction Completion Inspection B19 Utilises intelligent construction robots to capture comprehensive point cloud data of completed works. This data undergoes thorough comparison against image-recognised design models to evaluate project completion levels. Exterior Geometric Deviation Analysis B20 Analyses the flatness, verticality, and overall shape of building facades. Comparisons against image-recognised design models visually highlight areas of geometric deviation, ensuring exterior quality meets design specifications.

Twenty construction quality evaluation indicators for building structures, compiled based on literature reviews and expert questionnaires. Utilising the YOLO13 object detection algorithm as the core recognition engine, combined with machine vision measurement principles and substation construction quality acceptance standards, a dataset was constructed using substation images. The resulting apparent construction quality evaluation indicators, along with related image-recognised defects and content, are illustrated in Figure 3.

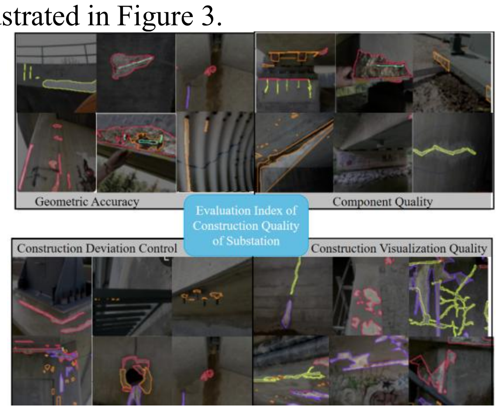

Figure 3. Image Recognition Defect of Substation

4. Calculation of Indicator Weights and Scores Based on the AHP-FCE Model

The Fuzzy Comprehensive Evaluation method is a multi-attribute decision-making approach grounded in fuzzy mathematics theory. It addresses the ambiguity and uncertainty inherent in evaluation subjects through the following steps: first, constructing an evaluation indicator system and a set of evaluation criteria; second, determining the weight vectors for each indicator; then, establishing single-factor evaluation matrices and fuzzy comprehensive evaluation matrices; Subsequently, perform fuzzy operations and normalisation processing; finally, derive the comprehensive evaluation results for the subject.

4.1 AHP-FCE Model Method

Considering the multi-level and complex factors in the assessment of apparent construction quality in building structures, this study employs the Analytic Hierarchy Process (AHP) to determine the weights of each evaluation criterion and subsystem. This is combined with data analysis incorporating expert experience and semi-structured interviews to establish the weights for each indicator. Fuzzy Comprehensive Evaluation (FCE) is a synthetic analysis method grounded in fuzzy mathematics membership theory, effectively addressing multi-variable issues in complex decision-making [38]. However, when confronted with multiple evaluation indicators, FCE often struggles to directly provide precise weight allocations, whereas AHP demonstrates superior performance in this regard [39]. Consequently, this study integrates AHP with FCE. This combination not only mitigates their respective limitations but also enhances the accuracy and comprehensiveness of evaluation outcomes, ensuring effective application in construction quality risk assessment [40-41]. Figure 4 illustrates the specific application process of the AHP-FCE method in evaluating the apparent construction quality of building structures.

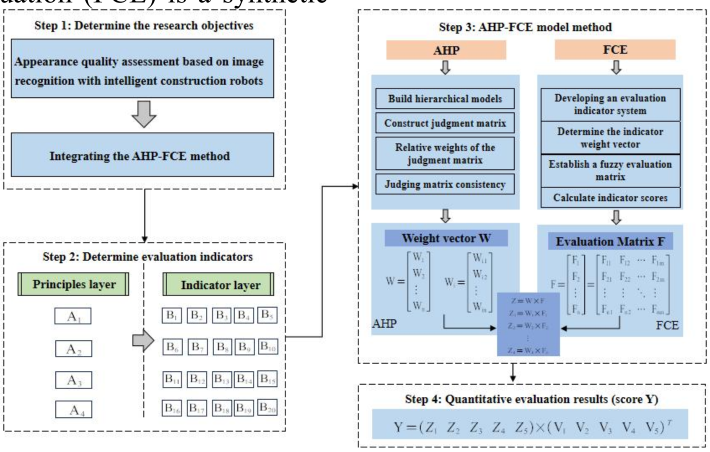

Figure 4. Evaluation Process of Apparent Construction Quality for Building Structures Using the AHP-FCE Model

1) To establish research objectives, an integrated AHP-FCE methodology is employed for evaluating the apparent construction quality of building structures. In this study, we will conduct apparent quality assessments based on image recognition and point cloud technology, combined with AHP and FCE approaches, aiming to provide a systematic and comprehensive evaluation framework to ensure effective control of construction quality throughout the building process.

2) Employ the Analytic Hierarchy Process (AHP) to construct an indicator system for apparent construction quality in building structures. Through expert questionnaires and literature review, we identified indicator layers encompassing geometric accuracy, component quality, construction deviation control, and construction visualisation quality. These criteria will serve as inputs for the AHP model and underpin subsequent decision analysis.

3) Determine the weights of indicators at each level based on the AHP method, and conduct a comprehensive evaluation of each indicator using the Fuzzy Comprehensive Evaluation (FCE) method. During this process, Saaty's 1-9 scale is employed for pairwise comparisons of indicators, calculating the weights for both the criterion and indicator layers. Subsequently, a fuzzy correlation matrix is established incorporating expert ratings. The FCE vector is computed through fuzzy operations to derive the evaluation results.

4) Quantify the assessment outcomes to analyse and determine the specific level of apparent construction quality evaluation for building structures. Through integrated calculations using AHP and FCE methodologies, comprehensive scores are ultimately derived for each evaluation indicator and sub-objective. These scores

establish the relative quality evaluation levels, thereby providing decision-makers with quantifiable apparent construction quality assessment results.

By collecting construction data for this project alongside various factors influencing construction quality, this study employed a combined approach of the Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation (FCE) to establish an evaluation model. In accordance with the aforementioned weight determination methodology, this paper utilised a questionnaire survey method to invite 20 experts to assign scores for weight determination.

4.1.1 theory of AHP

The Analytic Hierarchy Process (AHP) is a systematic, hierarchical analytical method combining qualitative and quantitative approaches. It demonstrates considerable practicality and effectiveness in addressing complex decision-making problems. The fundamental steps comprise establishing a hierarchical structure model, constructing a pairwise comparison matrix, calculating weight vectors and performing consistency checks, and computing composite weight vectors. The specific procedure for determining indicator weights using AHP is as follows:

1) Establish a hierarchical structure model

This study employs an AHP model comprising three levels: the objective level, the primary indicator level, and the secondary indicator level.

2) Constructing the Judgement Comparison Matrix

The judgement matrix constitutes the fundamental building block of AHP. Within this matrix, elements at the same level are compared pairwise and assigned specific values. Typically, a nine-point scale ranging from 1 to 9 is utilised as the judgement criterion for elements within the matrix, as detailed in Table 2.

Table 2. Judgment Matrix Element Comparison Scale

Serial Number	Scale Meaning	Ratio
1	When comparing the former elementi with the latter element j, i and j are equally important.	aij=1
2	When comparing the former elementi with the latter element j,i is slightly more important than j.	aij=3
3	When comparing the former elementi with the latter element j,i is significantly more important than j.	aij=5
4	When comparing the former elementi with the latter element j,i is strongly more important than j.	aij=7
5	When comparing the former elementi with the latter element j,i is absolutely more important than j.	aij=9
6	The importance of elementi relative to element j falls between the above judgments.	aij=2,4,6,8
7	If the relative importance scale of element i to element j is aij, then the relative importance scale of element j to element i is aji = 1/aij.	Reciprocal

By evaluating each pair of matrix elements according to the scale specified in the table above, we can derive an n-order comparison matrix A.

$$A_{n\times n}=\begin{bmatrix} a_{11} & a_{12} & a_{1..} & a_{1n} \\ a_{21} & a_{22} & a_{2..} & a_{2n} \\ a_{..} & a_{..} & a_{..} & a_{..} \\ a_{n1} & a_{n2} & a_{n..} & a_{nn} \end{bmatrix} \quad (1)$$

3)Combine the expert matrices by applying the geometric mean method [1] to multiply the scoring matrices formed by m experts (m=1,2,...,k) bitwise, then take the m-th root to obtain the unique integration matrix A, as shown in the formula below:

$$\overline{A}=(\prod_{k=1}^{m} a_{ij}^{k})^{\frac{1}{m}} \quad (2)$$

4)To determine the relative weights of the judgment matrix, the geometric mean method (root mean square method) is applied to the integrated unique matrix, as shown in the formula below:

$$W_i=\frac{(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}} \quad , \quad i=1,2,3..,n \quad (3)$$

5)Consistency of the judgment matrix

When comparing indicators pairwise, experts may reach conflicting conclusions. To ensure the rationality of indicator weights, it is essential to conduct consistency checks on the existing judgment matrix. The CR (Consistency Ratio) is commonly used as the standard for matrix consistency in academia, calculated as the ratio of the consistency index (CI) to the average random consistency index (RI). A CR value below 0.1 indicates that the matrix meets the requirements and requires no modification. Otherwise, experts should revise the judgment matrix until the calculated CR value falls below 0.1.The calculation formula of CR is shown in Equation (4).

$$CR=\frac{CI}{RI}=\frac{\lambda_{max}-n}{(n-1)RI}<0.1 \quad (4)$$

The CI calculation formula is shown in Equation (5).

$$CI=\frac{\lambda_{max}-n}{(n-1)} \quad (5)$$

λ_{max} is the maximum eigenvalue of the judgment matrix, calculated as shown in Equation (6). Here, A denotes the judgment integration matrix, W is the weight vector, and $[\overline{A}W]_i$ represents the i-th component of the matrix $[\overline{A}W]$.

$$\lambda_{max}=\sum_{i=1}^{n}\frac{[\overline{A}W]_i}{nW_i} \quad (6)$$

The specific values of the RI value are shown in Table 3 below.

Table 3. Average Random Consistency Index (RI) Values of Judgment Matrix

order of matrix	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49	1.52	1.54

4.1.2 theory of FCE

Fuzzy comprehensive evaluation is a multi-attribute decision-making method based on fuzzy mathematics theory, designed to handle the fuzziness and uncertainty of evaluation objects. The process involves the following steps: First, construct an evaluation index system and a set of evaluation criteria. Second, determine the weight vectors for each index. Third, establish a single-factor evaluation matrix and a fuzzy comprehensive evaluation matrix. Fourth, perform fuzzy operations and normalization processing. Finally, obtain the comprehensive evaluation results of the target object.

1) Establish the fuzzy evaluation factor set and weight set. The weights in the indicator system shown below can be calculated using the AHP method, which will not be elaborated here. Prior to conducting fuzzy evaluation, the weights for each indicator must first be determined.

Table 4. Weighting of Construction Quality Evaluation Indicators Based on Image Recognition and Intelligent Construction Robot

Target layer	Principle layer	Weight	Index level	Weight
A	Geometric Accuracy A1	0.411	Component Dimensional Accuracy B1	0.2459
			Component Positional Accuracy B2	0.4895
			Geometric Shape of the Overall Structure B3	0.0804
			Component Installation Spacing Accuracy B4	0.0427
			Consistency Between Construction Model and Reality B5	0.1415
	Component Quality A2	0.181	Concrete Component Apparent Quality B6	0.1323
			Steel Structure Component Apparent Quality B7	0.0741
			Prefabricated Component Apparent Quality B8	0.0385
			Component Surface Flatness and Verticality B9	0.4802
			Crack and Surface Defect Inspection B10	0.2749
	Construction Deviation Control A3	0.166	Formwork Installation Deviation B11	0.0878
			Reinforcement Installation Deviation B12	0.2531
			Concrete Pouring Deviation B13	0.1183
			Component Assembly Quality Deviation B14	0.038
			Component-to-Design Model Matching Degree B15	0.5028
	Visual Construction Quality A4	0.242	Component Assembly Quality B16	0.4555
			Component Gap and Joint Inspection B17	0.2645
			Component Appearance Integrity B18	0.0895
			Construction Completeness Inspection B19	0.1363
			Appearance Geometric Deviation Analysis B20	0.0542

Table 5. Factor Set and Weight Set

Factor Set	Weight Set
A=[A1,A2,A3,A4,A5]	A=[0.411, 0.181, 0.166, 0.242]
A1=[B1,B2,B3,B4,B5]	A1=[0.2459, 0.4895, 0.0804, 0.0427, 0.1415]
A2=[B6,B7,B8,B9,B10]	A2=[0.1323, 0.0741, 0.0385, 0.4802, 0.2749]
A3=[B11,B12,B13,B14,B15]	A3=[0.0878, 0.2531, 0.1183, 0.038, 0.5028]
A4=[B16,B17,B18,B19,B20]	A2=[0.4555, 0.2645, 0.0895, 0.1363, 0.0542]

Table 6. Evaluation Grade Score Range Table

Evaluation Criterion,	Excellent	Good	Average	Poor	Very Poor
Median	90	70	50	30	10
Score Range	[80, 100]	[60, 80]	[40, 60]	[20, 40]	[0, 20]

2) Construct the evaluation matrix

The evaluation matrix is a fuzzy relation matrix that maps evaluation indicators to comment levels, where each indicator corresponds to a membership degree matrix for each comment grade. The membership degree F represents the proportion of votes for the j-th evaluation on the i-th factor relative to the total number of participants, which forms the fuzzy relation matrix.

$$F_{ij}=\begin{bmatrix} F_{i1}^{j1} & F_{i1}^{j2} & \cdots & F_{i1}^{j5} \\ F_{i2}^{j1} & F_{i2}^{j2} & \cdots & F_{i2}^{j5} \\ \cdots & \cdots & \cdots & \cdots \\ F_{in}^{j1} & F_{in}^{j2} & \cdots & F_{in}^{j5} \end{bmatrix} \quad (7)$$

The fuzzy evaluation result of the row vector Zi is obtained by fuzzy operation of the weight Wi and the fuzzy matrix Fij.

$$Z_i=W_i\times F_{ij}=[u_i^1\ u_i^2\ u_i^3\ldots u_i^n] \quad (8)$$

$$Z=W\times U_i^j=\begin{bmatrix} U_1^1 & U_1^2 & \cdots & U_1^5 \\ U_2^1 & U_2^2 & \cdots & U_2^5 \\ \cdots & \cdots & \cdots & \cdots \\ U_n^1 & U_n^2 & \cdots & U_n^5 \end{bmatrix} \quad (9)$$

3) Calculate the score

The final fuzzy evaluation results for each level of indicators are obtained by multiplying the membership degree of each indicator with the corresponding comment set to derive scores. These scores are then matched with the evaluation grade score intervals to determine the final evaluation results for each level of indicators. The scoring calculation formula is as follows:

$$Y_{ij}=[z_{ij}^1\ z_{ij}^2\ z_{ij}^3\ldots z_{ij}^n]\times[90\ 70\ 50\ 30\ 10]^T \quad (11)$$

4.2 Construction Quality Evaluation Model Construction and Calculation

To establish an evaluation model, this study collected construction data from the CBD500KV substation project and analyzed various quality influencing factors. By combining Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation (FCE), we determined the weights through a questionnaire survey involving 20 experts. The calculation results are as follows:

4.2.1 Weight Calculation of HAP

Using formulas 3 through 6, we calculate the weights for the primary indicators (A1-A4) and secondary indicators (B1-B20). After confirming that all 20 expert judgment matrices meet the consistency requirement (CR <0.1), we perform matrix aggregation analysis on these matrices. The resulting primary and secondary indicators are illustrated in Figure5-9.

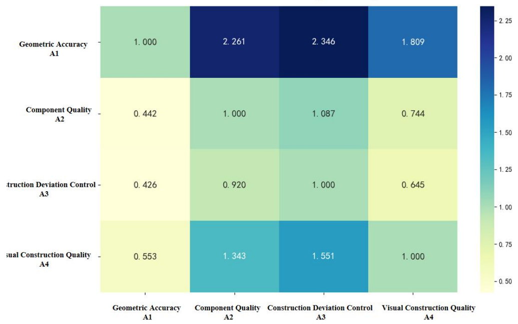

Figure 5 Heatmap of the First-Level Indicator Judgment Integration Matrix

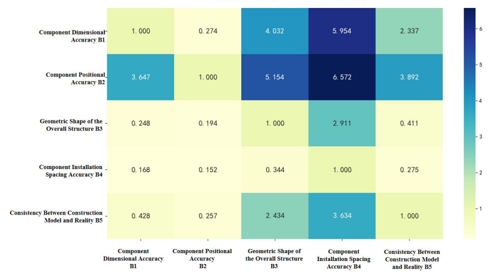

Figure 6 Heatmap of the Secondary Indicators B1-B5 Judgment Integration Matrix

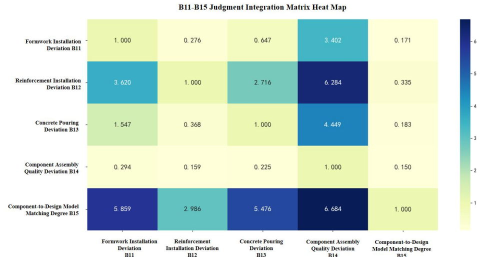

Figure 7 Heatmap of the Secondary Indicators B6-B10 Judgment Integration Matrix

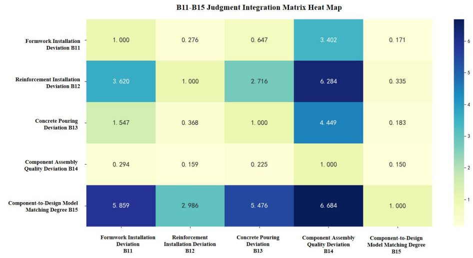

Figure 8 Heat Map of the Judgment Integration Matrix for Secondary Indicators B11-B15

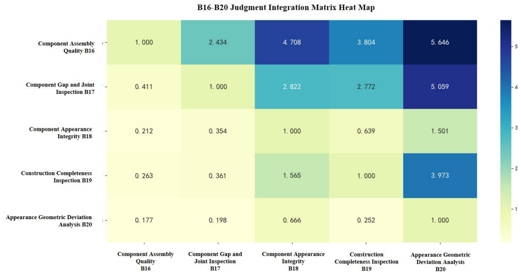

Figure 9 Heatmap of the Secondary Indicators B16-B20 Judgment Integration

Based on the evaluation of the integration matrix and weight calculation results across various indicators, the weights between indicators at different levels are calculated, with the summarized results as shown in the table7.

The weight aggregation table reveals the following ranking of primary indicators: geometric accuracy (A1, 0.411), construction visualization quality (A4, 0.242), component quality (A2, 0.181), and construction deviation control (A3, 0.166). Among secondary indicators, the top five by comprehensive weight are: component positional accuracy (B2, 0.2012), assembly quality (B16,0.1102), dimensional accuracy (B1, 0.1011), surface flatness and verticality (B9, 0.0869), and component-to-design model matching (B15,0.0835).

Table 7. Weight Summary Table

Target Layer	Primary Indicator	Relative WeightW1	Secondary Indicator	Relative WeightW2	Composite Weighting=W1*W2
A	Geometric Accuracy A1	0.411	Component Dimensional Accuracy B1	0.2459	0.1011
			Component Positional Accuracy B2	0.4895	0.2012
			Geometric Shape of the Overall Structure B3	0.0804	0.0330
			Component Installation Spacing Accuracy B4	0.0427	0.0175
			Consistency Between Construction Model and Reality B5	0.1415	0.0582
	Component Quality A2	0.181	Concrete Component Apparent Quality B6	0.1323	0.0239
			Steel Structure Component Apparent Quality B7	0.0741	0.0134
			Prefabricated Component Apparent Quality B8	0.0385	0.0070
			Component Surface Flatness and Verticality B9	0.4802	0.0869
			Crack and Surface Defect Inspection B10	0.2749	0.0498
	Construction Deviation Control A3	0.166	Formwork Installation Deviation B11	0.0878	0.0146
			Reinforcement Installation Deviation B12	0.2531	0.0420
			Concrete Pouring Deviation B13	0.1183	0.0196
			Component Assembly Quality Deviation B14	0.038	0.0063
			Component-to-Design Model Matching Degree B15	0.5028	0.0835
	Visual Construction Quality A4	0.242	Component Assembly Quality B16	0.4555	0.1102
			Component Gap and Joint Inspection B17	0.2645	0.0640
			Component Appearance Integrity B18	0.0895	0.0217
			Construction Completeness Inspection B19	0.1363	0.0330
			Appearance Geometric Deviation Analysis B20	0.0542	0.0131

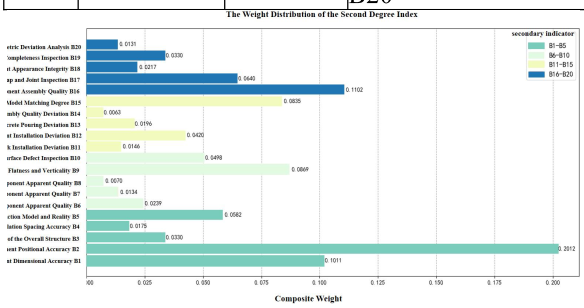

Figure 10. Distribution of Comprehensive Weight of Secondary Indicators

4.2.2 Application of FCE

The steps and procedures for constructing the evaluation index system have been introduced in the Analytic Hierarchy Process (AHP). Further research is conducted on the fuzzy comprehensive evaluation method based on AHP. According to the expert scoring of indicators, the membership degrees of each indicator are obtained, and the summarized results are shown in the table 8.

The multi-level fuzzy evaluation of geometric accuracy A1 layer is carried out, and its index layer is analyzed: component size accuracy B1, component position accuracy B2, geometric shape of the whole structure B3, component installation spacing accuracy B4 and construction model and actual consistency B5. The score of index layer is obtained by combining the comment membership degree with the relevant score, and the result is analyzed.

Table 8. Summary of Membership Degrees for Each Indicator

Evaluation Criterion,	Excellent	Good	Average	Poor	Very Poor
Component Dimensional Accuracy B1	0.4	0.3	0.3	0	0
Component Positional Accuracy B2	0.5	0.35	0.15	0	0
Geometric Shape of the Overall Structure B3	0.25	0.5	0.1	0.15	0
Component Installation Spacing Accuracy B4	0.1	0.25	0.4	0.25	0
Consistency Between Construction Model and Reality B5	0.6	0.2	0.2	0	0
Concrete Component Apparent Quality B6	0	0.3	0.4	0.25	0.05
Steel Structure Component Apparent Quality B7	0	0.25	0.2	0.45	0.1
Prefabricated Component Apparent Quality B8	0	0.2	0.2	0.55	0.05
Component Surface Flatness and Verticality B9	0.4	0.35	0.15	0.25	0
Crack and Surface Defect Inspection B10	0.25	0.45	0.2	0.1	0
Formwork Installation Deviation B11	0.05	0.2	0.25	0.4	0.1
Reinforcement Installation Deviation B12	0.1	0.25	0.4	0.2	0.05
Concrete Pouring Deviation B13	0	0.25	0.2	0.4	0.15
Component Assembly Quality Deviation B14	0	0.15	0.15	0.5	0.2
Component-to-Design Model Matching Degree B15	0.1	0.5	0.2	0.2	0
Component Assembly Quality B16	0.5	0.25	0.15	0.25	0
Component Gap and Joint Inspection B17	0.15	0.45	0.3	0.1	0
Component Appearance Integrity B18	0.05	0.2	0.5	0.25	0
Construction Completeness Inspection B19	0	0.2	0.55	0.15	0.1
Appearance Geometric Deviation Analysis B20	0	0.1	0.15	0.6	0.15

Table 9. Statistical Results of Primary Indicators

Target Layer	Score	Evaluation Results
Geometric Accuracy A1	74.128	Good
Component Quality A2	65.844	Good,
Construction Deviation Control A3	53.626	generally
Visual Construction Quality A4	64.78	good

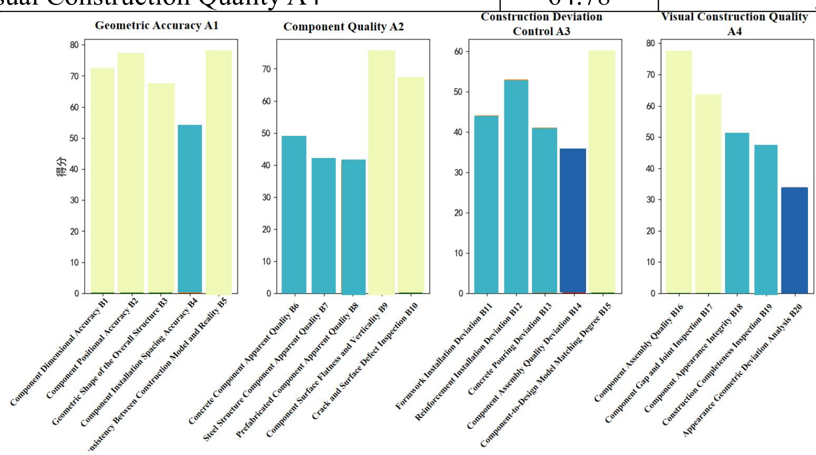

Figure 11. Distribution of Fuzzy Comprehensive Score for Secondary Indicators

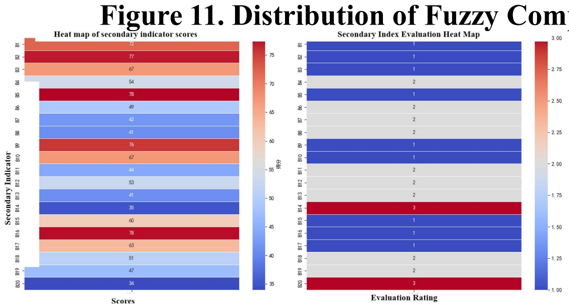

Figure 12. Heatmap of secondary Indicator Scores and Comments

4.2.3Analysis

1) Analysis of primary indicator results：

Geometric Accuracy (A1, 74.1 points): Geometric control is the core dimension of construction quality, accounting for 41.1%. Construction Visualization Quality (A4, 64.8 points): The importance of comparing digital models with on-site data ranks second, contributing 24.2%. Component Quality (A2, 65.8 points): Material and surface quality carry relatively low weight (18.1%), likely due to reliance on standardized production processes. Construction Deviation Control (A3, 53.6 points): Dynamic error management has the lowest weight (16.6%), indicating experts prioritize pre-design precision over in-process corrections.

2) Key analysis of secondary indicators:

Geometric accuracy (A1) core metrics: Component positional accuracy (B2, 77 points) carries the highest weight (48.95%), followed by dimensional accuracy (B1, 24.59%), indicating spatial positioning precision significantly surpasses component form control. Secondary metrics: Installation spacing (B4, 5.4 points) and overall geometric shape (B3, 6.7 points) have the lowest weight (<10%), reflecting their diminished importance.

In component quality (A2), the apparent quality is the primary focus: surface flatness (B9, 75.5 points) accounts for 48.02% of the weight, while crack detection (B10,67 points) contributes 27.49%. The guidelines emphasize that visible defects should be prioritized over material properties (with B6-B8 each contributing <15% of the weight).

In Construction Deviation Control (A3), the component-to-design model matching score (B15,60 points) carries a 50.28% weight, significantly higher than other indicators. This suggests that controlling 'construction per drawings' is considered more critical than process deviations (e.g., formwork installation B11,8.78%).

In the construction visualization quality (A4) assessment, component assembly quality (B16,77.5 points) carries 45.55% weight, while joint inspection (B17,63 points) accounts for 26.45%. This highlights that the standardization of prefabricated construction requires heightened attention.

In this study, all judgment matrices passed the CR test (<0.1), indicating high consistency in expert opinions and credible weight results. Meanwhile, the top five weight indicators (B2, B16, B1, B9, B15) accounted for 52.3% of the total weight, demonstrating that AHP-FCE can effectively extract core elements from expert consensus.

5. Results and Discussion

This study developed an integrated framework for evaluating apparent construction quality by combining intelligent inspection robots with image recognition technology. By integrating Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation (FCE), we constructed an AHP-FCE model to conduct empirical analysis on the CBD 500kV substation project. Through the deep integration of qualitative decision-making and quantitative perception, the following key findings were obtained:

5.1 Indicator Weight Analysis

Primary Indicator Distribution: Based on evaluations by 20 industry experts, geometric accuracy (A1) was assigned the highest weight (0.411), confirming that spatial positioning and dimensional control of components are the primary quality control dimensions in power hub projects. Construction visualization quality (A4, 0.242) ranked second, demonstrating that the consistency between on-site construction data and digital models has become a critical criterion for assessing construction quality in the digital twin era.

The secondary indicator's keyness analysis: The comprehensive weight ranking confirms that' component positioning accuracy '(B2, 0.2012) is the most sensitive factor affecting overall quality, followed by' assembly quality '(B16,0.1102) and' dimensional accuracy' (B1, 0.1011). This indicates that controlling axis deviations and elevation errors during construction is the core guarantee for preventing equipment installation conflicts in substations.

5.2 Technical Advantages Analysis

(1) Through the integration and consistency test (CR<0.1) of the 20-expert judgment matrix, the relative weights of indicators at each level were determined. Among the primary indicators, geometric accuracy (A1) carries the highest weight (0.411), highlighting the priority of component positioning and dimensional control. Construction visualization quality (A4, 0.242) ranks second, underscoring the importance of digital model-site data comparison. Component quality (A2, 0.181) and deviation control (A3, 0.166) have relatively lower weights, though their sub-indicators still require close monitoring.

(2) Among the secondary indicators, the top five in comprehensive weight ranking are: component position accuracy (B2, 0.2012), assembly quality (B16,0.1102), dimensional accuracy (B1, 0.1011), surface flatness and

verticality (B9, 0.0869), and component-to-design model matching (B15,0.0835). The highest-weight indicator is component position accuracy (B2, 0.2012), indicating that spatial positioning deviations during construction (e.g., axis offset or elevation errors) have the most significant impact on overall quality.

(3) The comparison between high-density point cloud data obtained through intelligent construction robot technology and image recognition models enables quantitative assessment of geometric accuracy (e.g., component position accuracy B2 score 77, construction model consistency B5 score 78), demonstrating significant superiority over traditional manual sampling methods. The deviation detection resolution reaches millimeter-level precision, making it particularly suitable for refined quality management of complex structures. The established 20 indicators cover four dimensions: geometry, components, deviation control, and visualization, addressing the limitations of traditional methods that focus solely on single metrics. The construction visualization quality A4 (score 64.78) indirectly reflects the standardization of construction processes through quantitative analysis of component assembly quality B16 (77.5) and gap detection B17 (63).

5.3 Research Limitations and Prospects

While the proposed construction quality evaluation method demonstrates certain advantages, several areas for improvement remain. Future research could focus on the following dimensions:Data Processing and Automation: The evaluation process can be further optimized for efficiency and real-time performance by adopting more efficient data processing algorithms and automated analysis tools. Multi-source Data Integration: Beyond image recognition and intelligent construction robot data, incorporating additional sensor data (e.g., temperature/humidity sensors, stress sensors) through multi-source data fusion could enhance the comprehensiveness and accuracy of construction quality assessment.

In conclusion, this study not only introduces innovative quality assessment tools and methodologies for the construction industry, but also establishes a foundation for the digital, precise, and intelligent advancement of building quality management. With continuous technological progress, the evaluation methods for structural appearance quality based on image recognition and intelligent construction robotics will play an increasingly vital role across broader fields and application scenarios.

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