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3D reconstruction and measurement of surface defects in prefabricated elements using point clouds

Zhao Xu^{1*}, Rui Kang², Ruodan Lu³

Abstract: Due to higher efficiency and lower cost, prefabricated construction is gradually gaining acceptance within the market. Laser scanning has already been adopted in civil engineering to reconstruct 3D model of structure and monitoring the deformation and so on. This paper seeks to explore a more automated and accurate quality control process focusing on the surface defects in prefabricated elements. Laser scanning is adopted for data collection and the 3D reconstruction of the prefabricated components. Besides, a new point cloud pre-processing, involving the KNN algorithm, reduction of data dimension and data gridding, is developed to improve the efficiency and accuracy of subsequent algorithms. The Delaunay triangle is used to extract the contour of the point cloud, then the contour is fitted to further determine the geometric data. Meanwhile, a comprehensive quality control system of prefabricated components based on relevant specifications is proposed, and the quality of prefabricated components is monitored intuitively by the values of indicators. In order to integrate into the BIM platform and better store the obtained quality information, the production quality information is designed to be extended to the IFC standard. The proposed approach will be applied to analyze the causes of quality problems in the production process and strengthen the quality control. This study designs a more efficient and accurate quality evaluation process, including data collection, data processing, indicator calculation and quality evaluation. Moreover, the results forward can feedback to the cause of the quality issues, and further improve the production quality of prefabricated elements.

Keywords: prefabrication, point cloud, surface defect, 3D reconstruction, measurement

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25 **1 Introduction**

26 Due to higher efficiency and lower cost, prefabricated construction is gradually gaining acceptance within the
27 market (Shahzad et al. 2014; Jaillon et al. 2009). The market share of prefabricated buildings is increasing rapidly
28 Quality issues caused by precast elements always lead to delay and additional cost for fixing. The dimensional error
29 and surface defect are the two significant quality issues of prefabricated components, which lead to costly and time-
30 consuming rework. Thus, these two prominent quality issues should be addressed at an early stage.

31 The relevant standards, such as the guidelines for the construction, the quality control manual for the plant and
32 the production of precast and prestressed concrete elements provide a basis for the quality judgment in the
33 production and construction of prefabricated buildings. At the same time, during the construction of prefabricated
34 buildings, the application of BIM strengthened the precise control of on-site construction. (Graham et al. 2018).
35 Although some related studies have paid attention to the quality control methods of prefabricated buildings, the
36 quality evaluation of size errors and surface defects are mostly implemented manually by measuring tapes,
37 straightedges and so on, which leads to inaccurate and inefficient quality evaluation (Latimer et al. 2002).
38 Meanwhile, manually measured data cannot be automatically linked to the BIM platform, which will cause
39 additional data conversion steps and take up another data storage space. Hence, it is urgent to propose an accurate
40 and automatic method to meet the quality control needs of prefabricated components and determine a unified data
41 format. This article uses the IFC standard which is common to the BIM platform.

42 Advanced 3D reconstruction technology can collect detailed data such as geometric information of
43 prefabricated components. Combining these data with relevant standards for interpretation can make more effective
44 use of these data for analysis. Through these analyses, the quality management level of prefabricated components
45 can be improved, thereby promoting the development of the industry. In the existing research, many studies have
46 demonstrated the feasibility of 3D reconstruction for quality management applications. Laser scanning has already
47 been adopted in civil engineering to reconstruct 3D model of structure (Bernardini and Rushmeier, 2002) and

monitoring the deformation (Park et al. 2007) and so on. However, laser scanning is less used in prefabricated buildings, and the algorithm applied for the combination of point clouds and prefabricated components is complicated to achieve (Kim et al. 2014). Thus, a user-friendly method is needed to promote the widespread use of 3D reconstruction.

In order to overcome the above-mentioned limitations, this research proposes a quality information extraction method for the point cloud of prefabricated components. At the same time, this method refers to relevant specifications, and finally integrates into the BIM platform through the IFC data standard. First, this paper focuses on the relative standards to make sure what kinds of data quality control needs. Then, the core processing algorithm is applied to deal with point cloud of prefabricated components. Finally, the study conducts compliance verification to evaluate the processed data and stores it in BIM compatible way. This paper proposes an accurate and efficient automation to achieve prefabricated components quality control.

2 Literature review

Laser scanning and Building Information Model

3D reconstruction technologies can perform Non-Destructive Tests (NDT) (Rodríguez-Gonzálvez et al. 2017) and measure necessary data for quality control. As previously mentioned, there are many methods for surface non-contact detection such as image identify (Cha et al. 2017), infrared detection (Cheng et al. 2008), ultrasonic flaw detection (Sambath et al. 2010), and point cloud detection. Some studies have attempted to apply methods of surface non-contact detection to the construction industry. For example, infrared scanning can be used to find important defects such as cracks on the walls or other parts of buildings (Edis et al. 2015). It is widely applied in defect detection, but it does not do well enough in terms of measurement. Besides, photogrammetry can use images to rebuild terrain or buildings (Eulitz and Reiss, 2015). It is suitable for large scale data collecting, but it can hardly satisfy the high accuracy requirement when altered for the micro level. Moreover, it is easily affected when the environment is not ideal. Because of these limitations, these methods have not yet been widely applied to

prefabricated components. However, laser scanning is a more stable and adaptable measurement compared with infrared scanning and photogrammetry. Recording data by laser scanning makes the data processing more convenient. Furthermore, an advanced laser scanner can provide high accuracy.

Laser scanning is not the only technology that impacts on the development of Architecture, Engineering & Construction (AEC). With the increase of data and management requirement, building information model (BIM) arises to storage and exchange information. BIM has made the information exchange and management smoother in the AEC field. Many scholars in the industry are working on semantic enrichment to describe more complete information (Belsky et al. 2016). And BIM is playing an increasingly important role in the life cycle of building owing to its expandability. Some technologies have been developed around BIM such as RFID (Demiralp et al. 2012) which makes the information traceable. Among the many data exchange formats used in the BIM platform, IFC (Industry Foundation Classes) is the most widely used and the most compatible. IFC is the standard for product data exchange and sharing. The language it uses is EXPRESS, which is an object-oriented, standardized data description language that focuses on the description and definition of data and its relationships. Venugopal et al. (2012) and Aram et al. (2013) have already proved the interoperability of IFC but focus less on quality control information. Applying laser scanning and enrich the IFC format can further improve the performance of quality control.

3D reconstruction and quality control using point cloud

Point cloud is actually a set of data points exist along with the coordinates within the 3D scanned space. The precision of professional equipment, which can reach 0.01mm level, can meet most industrial needs (Boehler et al. 2003). At the same time, research on the scanning accuracy (Kovacs et al. 2006) and the development of the high precision scanner system (Blais et al. 1988) has also been followed up to ensure accuracy of point cloud. Based on these studies, surface reconstruction using laser scanning can be well performed to achieve multiple purpose (Dey, 2007). The most of the surface reconstruction focus on model smoother surface using triangle meshes. Then, 3D

reconstruction was used to extract information becomes popular to fully use the accuracy of point cloud (Pu and Vosselman, 2009). When using point cloud data to reconstruct a separate structure, some algorithms can be used to extract important information from the reconstructed model for subsequent analysis. This information can be combined with BIM in AEC field for quality inspection to further improve the management of prefabricated buildings.

Due to the advantages of point cloud data in efficiency, safety and economy, laser scanning has been widely used to measure and collect data in the on-site construction stage of prefabricated buildings and the maintenance stage of buildings and bridges. For example, Cong (2018) has used laser scanning for on-site dimensional inspection of industrial plant piping systems. It is significant to extract pipeline from point cloud data and then achieve inspection. Sacks et al. (2018) use laser scanning to obtain the point cloud data of bridge in the operation and maintenance period and further apply digital twin to form models for the purpose of inspection. These studies have proven the feasibility of using laser scanning to obtain point cloud data for quality monitoring.

There are also studies applying laser scanning on the quality control of prefabricated components. Kim et al. (2016) use a coordinate transformation algorithm to achieve non-contact dimensional quality assurance and then analysis the point cloud data to gain quality information; Nahangi et al. (2015) use images to obtain point cloud data and conduct 3D registration with original CAD drawing for automated discrepancy qualification; Wang et al. (2019) uses the scan-to-BIM framework to create an as-is BIM model of a precast panel for geometry quality assessment. These studies applied the existing technology to the quality monitoring of prefabricated components and proposed solutions for automated inspection but did not further analyze them in conjunction with relevant specifications. In this paper, a new point cloud processing method is proposed with reference to the specification, and different algorithms are used in combination with the characteristics of prefabricated components to improve the feasibility and application efficiency of the algorithm.

117 *Point cloud contour extraction*

118 After the scene is scanned and the point cloud data is obtained, before the data format is converted into the
119 BIM technology common format, the source data can be processed to gain the geometric information. After
120 extracting the contour using the existing technology, the data related to the quality control of the prefabricated
121 component can be further calculated.

122 Point cloud contour extraction has been explored widely through a variety of extraction methods. Hackel et al.
123 (2016) scored a contour by a binary classifier, and then looks for points similar to the highly probable point to
124 further determine the contour shape. In this way, the contours in the 3D point cloud of the building can be effectively
125 extracted; Javidrad et al. (2011) sliced the 3D point cloud and filtered the 2D points. Then, the B-spline curve was
126 used for fitting to achieve the contour of the curve, but this study still has limitations on sharp edges or complex
127 curves. Boulaassal et al. (2009) and Awrangjeb (2016) used the Delaunay triangle for contour extraction and both
128 achieved good results.

129 Looking into AEC field, some studies have conducted to use point cloud contour extraction. Malihi et al. (2018)
130 identified the flatness of the surface collected by laser scanning, detailed surface can be captured to support the
131 defect detection; Schnabel et al. (2007) proposed a method to extract building geometries automatically from
132 unorganized point cloud, which reduced manual work to create as-is BIM. Dimitrov & Golparvar-Fard (2015)
133 solved the problem of complex point cloud segmentation in a single scene, provide a solution for building point
134 cloud segmentation; Wang et al. (2015), on the basis of segmentation, further extract the boundary features of the
135 building after the data de-noising and region growing; Zhou et al. (2015) and Kalasapudi et al. (2014) respectively
136 propose the fitting method after boundary extraction, and the alpha shape algorithm used by Zhou is also applied in
137 this paper in another way. All the researches mentioned above have provided theoretical implementation for feature
138 extraction of building point cloud, and provide references for the process of this article.

139 But the quality control of prefabricated components is still limited to manual recording, which does not meet

140 the efficient information management of BIM. Although point cloud contour extraction has been applied in many
141 different fields and solved some issues in the AEC field, it focused on the defect detection area or as-is building
142 rebuild. It remains a research gap in the combination of point cloud contour extraction and prefabricated building
143 quality management.

144 According to the literature review, the research gap of lacking comprehensive prefabricated components quality
145 control in the product process was identified. Furthermore, the research on the cutting-edge technologies of 3D
146 reconstruction has proved that it is feasible to apply laser scanning to replace manual measurement and achieve
147 better quality control. However, it should be noted that point cloud must be combined with appropriate management
148 methods and related requirements to gain more efficient and accurate automatic inspection. Thus, how the point
149 cloud method is applied according to prefabricated component structure features and combined with a management
150 system is the key to filling the gap.

151 **3 Methodology**

152 This paper aims to combine 3D reconstruction with prefabricated component to improve the efficiency and
153 accuracy of production quality control. The methodology starts with the data pre-processing. On the premise of
154 retaining the edge features of data for subsequence calculation and reducing the interference of noises and the
155 number of data points, the K-Nearest Neighbor (KNN) algorithm is adopted. Then in step 1, the data is transformed
156 from 3D into the 2D, by this way the difficulty of complex spatial topological relationships can be reduced. When
157 proceeding to the step 2, two technical routes are needed. First route, the boundary of data is extracted by Delaunay
158 triangle mesh and Alpha Shape algorithm, and then the curve is fitted by least squares method to obtain detailed
159 geometric information in step 3. The other route, the defect in the point cloud data is located by gridding and the
160 Delaunay triangle and subsequent algorithms are used to extract the defect area. In the end, the result is carried out
161 to be verified with prefabricated component standards. The overall research methodology is presented in Figure 1.

162

163 ***Prefabricated component quality standard***

164 In order to perform the quantitative analysis of the evaluation indexes for production quality, an evaluation
165 specification should be determined first. By referring to various specifications for quality evaluation of precast
166 concrete components (*Guidelines for the use of structural precast concrete in buildings; Manual for quality control*
167 *for plants and production of precast and prestressed concrete products: PCI MNL-116; Specifications for tolerances*
168 *for concrete construction and materials and commentary: ACI 117M-2010; Tolerances for building part1: precast*
169 *ordinary, reinforced and prestressed concrete components: DIN 18203-1997; PCI design hand book-precast*
170 *prestressed concrete: PCI MNL-120-04; Tolerance manual for precast and prestressed concrete construction: MNL-*
171 *135-00; Specification for tolerances for concrete construction and materials and commentary: ACI 117*), it can be
172 found that the allowable deviations vary in different specifications for components of the same category and the
173 same volume. This paper designed the evaluation indicators based on these existing specifications implemented in
174 AEC industry.

175 In addition to conventional geometric information including length, width, and height, diagonal length is also
176 considered as an important evaluation indicator. Considering the advantages and disadvantages of each specification,
177 this research proposes the allowable deviation for production quality evaluation based on the geometric information
178 automatically extracted from 3D reconstruction of prefabricated concrete components in Table 1 and the defect on
179 the surface (such as honeycomb, surface voids, crack, etc.) in Table 2. Tables 1 and 2 set criteria for evaluating
180 production accuracy and surface defects, so the physical value of quality evaluation index calculated by the
181 algorithm can be quantitatively analyzed.

182 ***Point cloud data pre-processing***

183 The original point cloud is composed of a large number of scattered points, including the noise generated in
184 the acquisition process, which makes it difficult to use an algorithm to process the original point cloud data.
185 Therefore, the data needs to be preprocessed through three steps, namely, the KNN algorithm, reduction of data

186 dimension and data gridding. The KNN algorithm can help reduce noise to eliminate interference, which can
187 facilitate the application of the following algorithm. Next, the original data dimension needs to be reduced,
188 providing the basis for the subsequent studies. After reducing the dimensions of the data to 2D, inspired by Wack
189 and Wimmer (2002), the gridding of point cloud data then be applied, which is also an important step of data pre-
190 processing. Gridding can pinpoint defect and reduce the amount of point cloud data that needs to be calculated.

191 In the first step, KNN (K-nearest neighbors) algorithm (Altman, 1992) is used for point cloud data de-noising
192 and down sampling. In this research, KNN algorithm is used on the raw point cloud data generated directly after
193 laser scanning as a preprocess method. The core of KNN classification algorithm is to predict the classification of
194 a new data point based on a dataset in which the data points are divided into several categories. In other words, a
195 data point is classified by a plurality vote of its neighbors, with the data point being assigned to the class most
196 common among its K nearest neighbors. In this case, there are three classes: boundary points, planar points and
197 noise. Because laser scanning focuses on features such as boundaries, the density of boundary points and the number
198 of neighboring points are much larger than those of planar points and noise. At the same time, through different
199 values of K, KNN algorithm calculates a threshold to judge a data point as an outlier (noise). For a data point in the
200 dataset, if the distance from other points exceeds this threshold, it will be considered as noise and deleted. This is
201 the de-noising process. The neighboring points of the noise are obviously less than the planar points, so the K value
202 used to remove the noise is smaller than that of down sampling the planar points. Under this premise, when the
203 appropriate K value is selected for the down-sampling process which is the process to reduce the number of planar
204 points, the de-noising process is also completed at the same time. It can be seen from the principle of KNN algorithm
205 that the value of K has a great influence on the results. Therefore, when applying the KNN algorithm, the value of
206 K should be considered carefully and determined by comparison.

207 Point cloud data after data cleaning is still three-dimensional data, so the second step for reduction of data
208 dimension is applied. After fully verifying the possibility of data dimension reduction, this research conducted

dimension reduction for the three-dimensional data. Due to the geometric properties of prefabricated components, the collected point cloud forming the surface of the component can be surrounded by a cuboid with tiny height. Therefore, it is in line with the practical application of this research that these data points are extracted after three points determine a certain plane to form a surrounding cuboid so that the three-dimensional can be reduced to two-dimensional. After following verification, the error caused by dimensionality reduction does not affect the defect detection results as shown in Figure 2.

First, three points A, B, and C are not collinear and are extracted and substituted into eq.1. These three points are randomly selected multiple times by the computer according to the principle of non-collinearity. Finally, among the results of multiple selections, the one with the largest number of points is taken. This is because the point clouds on the component surface are roughly distributed on the same plane. If the plane formed by three randomly selected points deviates from the actual plane, then the points on the plane cannot be completely contained in the bounding box. Then the values of a, b, c, d, as well as the plane equation, are obtained.

$$ax + by + cz + d = 0 \quad (1)$$

Subsequently, a rectangular bounding box with the plane represented by the equation as the central plane is established. The height of the bounding box is a tiny value that is adjustable to control the number of data points bounded. The data points in the bounding box are considered to form a plane and separately extracted for subsequent processing as independent plane files. Then the extracted points are rotated so that the plane they form is parallel to the x-y plane to eliminate the z coordinates. One of the rotation matrices that rotates around axis is as follows:

$$R_x(\theta_x) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta_x & \sin \theta_x \\ 0 & -\sin \theta_x & \cos \theta_x \end{bmatrix} \quad (2)$$

After rotating the original three-dimensional data points around the x and y axis by θ_x and θ_y , the (x, y) coordinates in the three-dimensional data are extracted separately to form 2D data, so as to reduce the data dimensionality. In rotation, there is an error angle φ , making the approximate plane of the planar point after rotation

231 cannot be completely parallel to the x-y plane, as shown in Figure 3.

232 With respect to the existence of error angle φ , extracting (x,y) coordinates in the process of dimension
233 reduction to eliminate z coordinates is equivalent to mapping points on the original plane to the x-y plane, resulting
234 in an error between the length L' and the actual length L , which can be calculated as follows:

$$235 \quad \Delta L = L - L' = L(1 - \cos \varphi) \quad (3)$$

236 Take the prefabricated stairs as an example, when the designed length of the shortest side of the prefabricated
237 components is 400mm, if the error angle is controlled at 1° , which can be limited to, the resulting error ΔL is
238 0.06mm, far less than the minimum value in the relevant specification for the evaluation index of dimensional
239 deviation 1mm. Due to transportation and production conditions, most of the prefabricated components that are
240 conventionally used are less than 6 meters in length. When the size is enlarged to 6 meters, the error is still less than
241 1mm. Therefore, the impact of errors in data dimension reduction can be neglected.

242 In the second step, data dimension reduction was completed by using the geometric advantages of prefabricated
243 components and transformed the three-dimensional problem into a two-dimensional data processing problem. After
244 data dimension reduction, surface defect problem is further simplified.

245 In the third step, data gridding is used to pinpoint the location of defect and further extract the defect area for
246 separate calculation as shown in Figure 4. For the planar extraction data of the entire prefabricated component, the
247 surface defect typically only occurs in a small area. In this case, it is not necessary to calculate the whole area.
248 Another method that can be used to locate defect is relative coordinate system of the prefabricated component.
249 However, setting the coordinate system requires additional work, and the defect area is often irregular. Using the
250 coordinate system to extract defect requires relatively complicated calculations. Therefore, this paper adopts data
251 gridding to pinpoint the location of defect.

252 According to the (x, y) coordinates of the point cloud data, proper M and N are select to form a $M \times N$ grid.
253 Considering the area and location of the defect, the grid partition can be adjusted to precisely locate the defect. At

254 the same time, the divided grid is output in blocks, and the defected grid is separately extracted to further calculate.

255 ***Data boundary extraction and fitting***

256 This section is focusing on the dimensional error. Figure 5 shows the processing flow of boundary information.

257 First, Delaunay triangulation algorithm was used to form disjoint triangular grids for the scattered points of point
258 cloud data after dimension reduction. The three vertices of each triangle are extracted for subsequent calculation for
259 boundary judgment. To determine the boundary, the parameter r is calculated by Alpha Shape algorithm. The
260 boundary can be judged by being compared with the parameter developed. Finally, the obtained boundary points
261 are fitted to obtain the dimension and quality information of precast concrete components.

262 (1) Mesh formation based on Delaunay triangulation algorithm

263 As a pre-processing technique, triangulation is the basis of subsequent data processing. Delaunay
264 triangulation algorithm is adopted in this paper to form triangular grids.

265 The Delaunay triangulation algorithm has two important properties. ① Property of the empty circle which
266 means the Delaunay triangle is unique. ② Property of maximizing the minimum angle which determines that the
267 Delaunay triangulation is the closest to regular triangulation. Delaunay triangulation proposes a standard for forming
268 triangular grids, and there are two main ways to implement the algorithm: Lawson algorithm and Bowyer-Watson
269 algorithm. Lawson algorithm is a scatter-based network construction algorithm that has a rigorous theory and good
270 uniqueness. In the process of forming Delaunay triangle using the Lawson algorithm, deletion and movement of
271 points can be performed quickly and dynamically. Due to the advantages mentioned above, the Lawson algorithm
272 is used to calculate the planar triangular grids of prefabricated components in this research. The Lawson algorithm
273 first creates a large triangle to surround all the data points; followed by inserting points into the triangle and
274 connecting them to the vertices of the triangle to form a new triangle; and finally performs the empty circumcircle
275 test one by one, generating initial triangular grids. Meanwhile, the triangulation network is verified as Delaunay
276 triangulation network by switching diagonals.

277 Figure 6(a) shows the principle of Delaunay algorithm. $\triangle ABC$ is the largest triangle surrounding the data point
278 at the beginning, P1, P2, and P3 are the points inside the triangle. P2 is in the circumcircle of $\triangle ACP_1$, so the triangle
279 is not a Delaunay triangle and is removed from the grid. Figure 6 (b) is a Delaunay triangulation grid formed by
280 processing the two-dimensional plane extracted from the prefabricated concrete staircase by the algorithm. As can
281 be seen from the results, the generated triangular grid satisfies the Delaunay triangulation criteria. However, such
282 triangular grid cannot directly extract the dimension information, making boundary judgment and extraction
283 required based on the Delaunay triangular grid.

284 (2) Boundary judgment based on Alpha Shape algorithm

285 Alpha Shape algorithm were first defined by Edelsbrunner et al. (1983), which is an improved algorithm for
286 the convex hull boundary algorithm. In essence, it selects a circle with a fixed radius and judges every pair of
287 possible boundary line on the circle in the data points. If there are no other points in the circle except these two
288 points, it is judged as the boundary. According to different values of the key parameter α , the boundary data points
289 that can be judged by this algorithm are different. Thus, the value of α need to be selected appropriately by
290 comparison. According to the principle of the Alpha Shape algorithm, it is necessary to iteratively check all the
291 possibilities of forming a boundary, which takes a significant amount of time. Therefore, Delaunay triangulation is
292 often performed before applying the algorithm, so as to preprocess the data more effectively.

293 The application of the Alpha Shape algorithm is closely related to the set of triangular points in Delaunay
294 triangular grid. It can be known that each triangle in the grid has its own characteristic radius, which is the radius
295 of the minimum circumscribed empty circle of the triangle. According to the principle of the Alpha Shape algorithm,
296 the question whether there are other points in the circle with fixed radius can be converted into the question whether
297 the minimum circumradius of the Delaunay triangle is larger than the set radius. Therefore, to determine whether
298 the triangle is a boundary triangle, it only needs to determine the size relation between the radius of the minimum
299 circumscribed empty circle and the set radius. Thus, the geometric information of each Delaunay triangle needs to

300 first be obtained. The formulas of the side length and the semi-perimeter of triangle are shown as follows:

301
$$l = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (4)$$

302
$$s = \frac{1}{2}(a + b + c) \quad (5)$$

303 where (x_1, y_1) and (x_2, y_2) are the endpoints coordinates of the calculated side; and a, b, and c are the lengths of the
304 three sides of the triangle. Using this geometric information, the area of the triangle can be calculated with the help
305 of the Heron formula, and the radius of the minimum circumscribed empty circle of the triangle can then be obtained,
306 as shown in the following formulas:

307
$$S = \sqrt{s(s-a)(s-b)(s-c)} \quad (6)$$

308
$$r = \frac{a \times b \times c}{4 \times S} \quad (7)$$

309 Finally, based on the relationship between r and $1/\alpha$, it can be determined whether the triangle is a boundary triangle:

310
$$\begin{cases} r < \frac{1}{\alpha}, \text{ boundary triangle} \\ r > \frac{1}{\alpha}, \text{ non-boundary triangle} \end{cases} \quad (8)$$

311 The result of processing the obtained data by using the Alpha Shape algorithm is shown in Figure 7.

312

313 (3) Data boundary fitting based on least squares method

314 After the boundary points of precast concrete are obtained, the least square method is used for boundary fitting.

315 The least square method seeks the best function matching of the data by minimizing the sum of squared errors. Due
316 to the geometry of the prefabricated elements, the lines are basically straight except for the reserved holes. Except
317 for the hole boundary, the boundary points of the four edges are fitted to the straight-line equations after truncating
318 the end points. The application process of straight-line method is relatively simple, so the boundary fitting of this
319 part is not listed. The process of applying the least square method to a closed curve is complicated, which needs to
320 conduct derivative and find the pole. Therefore, this section will focus on the process and formula for fitting circular
321 curve of reserved hole.

322 In order to find the best fitting circular curve to extracted boundary points, the sum of distances between these
 323 boundary points and circular curve should be minimized. Since it will cause square root calculation, which is not
 324 conducive to computing, the difference of the distance square is used for comparison. Furthermore, in order to
 325 satisfy calculation principle of least squares method, the difference needs to be squared to ensure the obtained f-
 326 value is a non-negative number. The formula is as follows:

$$f = \sum ((x - A)^2 + (y - B)^2 - R^2)^2 \quad (11)$$

328 Here (A, B) is the center of fitted circle while R is the radius of fitted circle. The actual operation to achieve data
 329 boundary fitting is to calculate (A, B) and R, and minimize f. At the same time, the equation will be too complicated
 330 if the formula (12) is expanded, so a new squared difference formula is obtained by parameter substitution:

$$Q(a, b, c) = \sum (x^2 + y^2 + ax + by + c)^2 \quad (9)$$

332 The point with partial derivative of 0 is extreme point by figuring out the partial derivative of Q(a,b,c). Since the
 333 maximum of the function is infinite, the obtained extreme point is minimum, which satisfies principle of least
 334 squares calculation. The function values of all obtained extreme points are compared, the minimum is the solution.

$$\begin{cases} \frac{\partial Q(a, b, c)}{\partial a} = \sum 2(x^2 + y^2 + ax + by + c)x = 0 \\ \frac{\partial Q(a, b, c)}{\partial b} = \sum 2(x^2 + y^2 + ax + by + c)y = 0 \\ \frac{\partial Q(a, b, c)}{\partial c} = \sum 2(x^2 + y^2 + ax + by + c) = 0 \end{cases} \quad (10)$$

336 The solution can be found by converting the formula to a matrix:

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \sum x^2 & \sum xy & \sum x \\ \sum xy & \sum y^2 & \sum y \\ \sum x & \sum y & N \end{bmatrix}^{-1} \begin{bmatrix} -\sum (x^3 + xy^2) \\ -\sum (x^2y + y^3) \\ -\sum (x^2 + y^2) \end{bmatrix} \quad (11)$$

338 Center and radius of the circle can be calculated based on obtained a, b, c:

339 $A = \frac{a}{-2}, B = \frac{b}{-2}, R = \frac{1}{2} \sqrt{a^2 + b^2 - 4c}$. The geometric information of fitted circle is solved, and then the
 340 boundary linear equation of precast concrete is combined to check positioning information and opening size of the
 341 reserved hole to get complete geometric information.

342 (4) Surface defect area calculation

343 Defect area cannot be calculated merely by data gridding. Because the defect has no fixed shape, it is still
344 surrounded by normal data points. Therefore, it is necessary to further separate the defect data from the normal data.

345 The Vertex Clusters algorithm can separate the defect data points from the normal data points while retaining
346 the geometry feature. The Vertex Clusters algorithm starts from the seed point and diverge outward through a circle
347 of fixed radius. The points contained within the circle are judged to be the same cluster, and these points continue
348 to spread as seed points until the circle no longer contains new points or artificial stops. Due to the application of
349 the KNN algorithm for data cleaning, the density of the defect points exceeds the normal point, which is more
350 conducive to the separation using the Vertex Clusters algorithm. The separation result is shown in Figure 8.

351 Then the Delaunay triangulation algorithm and the Alpha Shape algorithm can be applied to defect points of
352 the output after separating. Nevertheless, the purpose of applying these two algorithms is different from the above.
353 The defect point does not need to be strictly extracted. The defect area is the critical point for the surface defect
354 quality problem. Therefore, in this section, when applying the Alpha Shape algorithm, the value of α is adjusted to
355 form a triangular mesh, so that all the defect points can be connected without misconnecting the points on the
356 boundary. According to the principle of Alpha shape algorithm, the value of α is related to the maximum
357 circumscribed circle radius of the formed triangular mesh. According to the condition of the damaged surface, the
358 radius of the circumscribed circle of the formed triangular network is regular. Select the value of α multiple times
359 to match this radius, compare the results, and choose the optimal α value.

360

361 4 Experimental results and analysis

362 *Data selection*

363 This paper focuses on the practicality of the algorithm, so the data selection combines the actual situation and
364 related policies and strives to represent a wide range of examples with special cases.

365 (1) Data resource

366 The selection of data acquisition objects for concrete prefabricated components should be characterized by
367 strong representativeness, wide application range, and good applicability. Prefabricated interior and exterior wall
368 panels, prefabricated stair slabs, and prefabricated floor slabs (including prefabricated composite floor slabs) -
369 hereinafter referred to as “three slabs” - which are typical prefabricated components, assume important structural
370 and functional functions. The structural importance of “three slabs” in prefabricated construction is self-evident. It
371 can provide reference for subsequent quality monitoring of the element in practical application. Due to functional
372 requirements of the element, there are many embedded parts on board, such as pre-embedded electric boxes and
373 water pipes on prefabricated interior wall, combined with load-bearing structural characteristics of floor, wall, and
374 stairs, so rebar is widely applied in the element. Due to the above characteristics, “three slabs” can make full use of
375 prefabricated properties of the prefabricated elements in the manufacturing process. Therefore, choosing “three
376 slabs” for data collection can ensure the collected data is representative, and the conclusions and measures can be
377 extended to other prefabricated elements, which is universal.

378 (2) Data acquisition equipment

379 The data acquisition equipment used in this is HandySCAN BLACK. The light source are 7 blue laser crosses and
380 the measurement rate is 800,000 measurements/s. The accuracy of this equipment can reach 0.035mm and the
381 volumetric accuracy (based on part size) is 0.020 mm + 0.060 mm/m. This device can meet the needs of collecting
382 information quickly and with high accuracy. Such accuracy can meet the needs of dimensional measurement and
383 defect area calculation in this paper. For cracks with higher requirements, it is beyond the scope of this paper.

384 (3) Principle of data acquisition

385 The main application algorithm of the laser scanner used in this data acquisition is laser triangulation method.
386 The principle is shown in Figure 9. During the data acquisition process, the laser beam has a certain γ angle to the
387 surface of object, which applies oblique laser triangulation method. Reflected light is at α angle to surface normal,

388 and at β angle to light sensor. The distance to be measured is S, spot moving distance is S', object distance is L, and
389 image distance is L'. Combined with focal distance f, the distance S to be measured:

390
$$S = \frac{S'(L - f) \sin \beta \cos \gamma}{f \sin(\alpha + \gamma) \mp S'(1 - \frac{f}{L}) \sin(\alpha + \beta + \gamma)} \quad (12)$$

391 The coordinates of the points located on the surface of the component are two-dimensional data. Together
392 with the distance S to be measured, complete three-dimensional data can be generated. The accuracy of the data
393 acquisition can fully meet the need of quality evaluation in this way.

394 ***Implementation and results***

395 Based on the above theoretical analysis, the dimensional deviation and defect area, namely the value of quality
396 evaluation indicators, can be calculated and further compared with the standards. In this paper, the precast concrete
397 stairs and external walls collected through field investigation were taken as examples to calculate dimensional
398 deviation and defect area. The example calculation process covers three steps: data pre-process, boundary extract
399 calculation and defect calculation. The reserved holes of precast concrete staircase are representative, which was
400 used to verify the size calculation. Defect area was calculated according to the surface pockmark of prefabricated
401 exterior walls and the angular collapse of prefabricated stairs

402 (1) Data pre-process result

403 Using KNN algorithm to reduce number of points was the first step of data pre-processing. Since the value of
404 K has a great influence on the results, different K values were adopted in this research to process the point cloud
405 data of precast concrete stairs. The results are exhibited in Table 3. According to the characteristics of the KNN
406 algorithm, it reduced the number of points and noise under the premise of retaining features. The experimental
407 results obtained by different K values show that when $K = 4$, the number of points reached the minimum. Figure 10
408 shows the change of the original point cloud data after down sampling.

409

410 It can be found that KNN algorithm retained the geometric features of the original data, and only reduced the
411 density of excessively dense points after down sampling. The point cloud data obtained after applying KNN
412 algorithm removed the noise, facilitating the next step of data processing. Then dimension reduction was applied to
413 convert point cloud data to 2D, the result is shown in Figure 11.

414 Next, grid was generated to locate defects. From the divided grid map, the circular defect in Figure 12 (a) of
415 prefabricated stair components in grid (1,1) and the surface defect in Figure 12 (b) of prefabricated exterior walls
416 in grid (1,7), (1,8), (1,9), (1,10), (1,11) etc. could be clearly observed. Reasonable gridding ensures that the quality
417 defect information can be output completely without including the normal surface in the defect information, thus
418 providing good data for subsequent calculations of defect parameters.

419 (2) Data boundary extraction result

420 Alpha Shape algorithm was used to extract data boundary. It shows that the results obtained after using the
421 algorithm are significantly different from the Delaunay triangular grid formed before. Meanwhile, the precast
422 concrete components have a large number of holes which are reserved for transportation and installation. These
423 reserved holes are required to be accurately positioned to ensure the quality of installation, which means that the
424 extraction of the internal boundaries is extremely important for quality detection.

425 However, it can be seen from Figure 13 that after using Alpha Shape algorithm, due to the excessively dense
426 data points of the point cloud of prefabricated components and the lack of rigorous discussion for the value of α ,
427 the extracted boundary has excessive thickness and independent interference points. Therefore, a careful comparison
428 of different α values was carried out as shown in Figure 14.

429 It is inevitable that redundant boundary points were extracted due to the limitation of data itself. Therefore,
430 this paper was devoted to minimize interference points to ensure that the boundary lines can be extracted as
431 completely as possible. Relatively speaking, when $\alpha=0.85/0.8$, the boundary lines could be completely extracted.
432 Moreover, because a smaller α is likely to cause more computation cost and interference points, the value of α was

433 finally set as 0.85. The final quality data can be obtained by fitting the extracted boundary points.

434 Then least square method was applied for boundary fitting. The four linear fitting curves on the four sides of
435 prefabricated stair plane were obtained as follows: $X_1 = -220.11$, $X_2 = 962.11$, $Y_1 = 201.86$, $Y_2 = 601.69$.

436 Therefore, the length L of top plane of the point cloud reverse reconstruction model could be obtained as
437 $L=188.22\text{mm}$ and the width $H=399.83\text{mm}$. Data error with calibration of design CAD drawings was
438 $\Delta L = 1182.22 - 1180 = 2.22\text{mm}$, $\Delta H = 399.83 - 400 = -0.017\text{mm}$.

439 At the same time, the circle center(A, B) of the two reserved openings obtained after fitting as $(-38.90, 500.53)$,
440 $(780.24, 499254)$. Combined with boundary positioning line, the distance between circle center and the left and right
441 sides were 181.21mm and 181.87mm , and the distance from top edge were 101.16mm and 102.15mm . The radius
442 of circles were $R_1 = 29.47\text{mm}$, $R_2 = 29.45\text{mm}$, $\Delta R_1 = 0.53\text{mm}$, $\Delta R_2 = 0.55\text{mm}$. Since the prefabricated stairs for
443 scanning experiments are not perfect in size, the radius of the reserved hole is actually smaller than the design value,
444 resulting in that the calculated data after fitting the curve is also smaller than the corresponding actual size. The
445 original size information and the size information calculated by actual collection are marked on the map in Figure
446 15.

447 (2) Defect area calculation results

448 In addition to dimensional deviation in appearance quality defects, defect area is the other important evaluation
449 index. The defect area in the surface pockmark of prefabricated exterior walls and the angular collapse of
450 prefabricated stairs were calculated as an example. The position and size of appearance defects in the three-
451 dimensional reconstruction model both are shown in Figure 16.

452 By extracting the plane where defect occurs, adjusting division size of the planar grid, exporting defect grid to
453 finally separate defect data from normal data, the defect points after separation were obtained finally. The triangular
454 grid formed with certain α based on the defect points is shown in Figure 17. The detailed processing result is
455 exhibited in Figure 18.

As shown from the comparison in Figure 18 the generated triangular grid of defect points substantially restored the actual defect region, and scattered defect was separated from large defect, which is a prerequisite for the subsequent accurate calculation of the defect region area. The triangle of the damage point constitutes the entire area of the damage. Therefore, the area of each triangle was calculated separately and then summed as eq.9 above.

The results show that the selection of $\alpha=0.4$ for surface pockmark of prefabricated exterior walls to form triangular grid could meet the requirement of calculation area. The calculation results were $S_1 = 56609.39 \text{ mm}^2$ and area percentage $p_1 = \frac{S_1}{S} = 1.369\%$; the selection of $\alpha=0.5$ for angular collapse of prefabricated stairs to form triangular grid, $S_2 = 2266.24 \text{ mm}^2$ and area percentage $P_2=0.446\%$.

Verification with prefabricated component standards

Through the establishment of index evaluation criteria and the determination of corresponding weight, the calculated results were evaluated in combination with specific criteria in Table 4. According to the weight and the evaluation value of each sub-index, namely the corresponding 0/1 value, the comprehensive evaluation index value was calculated as shown in Table 5. Only when the comprehensive evaluation index is 1, the production quality of the element is judged to be qualified. The lower comprehensive evaluation index is, the worse the production quality of the element, and the more aspects that need to be improved.

The comprehensive quality evaluation index of precast concrete stairs was 0.96, and the quality was judged to be unqualified. The angular collapse occurred during the removal of frame exerted a great negative impact on the results of quality evaluation. Although the area ratio of angular collapse met the requirements, the number of angular collapses caused by violent construction was excessive, which led to the unqualified results of the quality evaluation.

The results of production quality comprehensive evaluation index can directly reflect whether the quality of prefabricated elements satisfy the requirements of standard, which provide a quick and intuitive information for workers to deal with in time. At the same time, the detailed measurement data of each indicator can provide support for finding the cause of the quality issues and improving production quality.

479 *Data storage and IFC extension*

480 In order to meet the compatibility of the BIM platform and better store the obtained quality information, the
481 production quality information of the prefabricated components should be extended to the IFC standard. The
482 extension of IFC is divided into three ways: ① Extension based on adding new entity; ② Extension based on
483 IfcProxy entity; ③ Extension based on property set. The last, which does not generate new entities nor modify the
484 original entity with small and targeted scope of modification, was adopted in this paper. The new property sets, and
485 property definitions were extended under the original property set definition. To perform property set definition, it
486 is necessary to improve the property set name (PsetName), applicable entity (Entity), applicable type value
487 (PropertyType) and property set description (PropertyDescribe). The definition of the property includes the property
488 name (PropertyName), property value (PropertyValue) and property value type (Type). The Tables 6 and 7 describe
489 the property sets definition and property sets of concrete prefabricated wall.

490 The EXPRESS structure diagram can intuitively express the IFC extension as shown in Figure 19. After the
491 completion of the production quality property expansion of the concrete prefabricated components, the information
492 collected by the previous algorithm were stored in the IFC standard, which not only enriched the semantic
493 information of the BIM model, but also integrated the production quality information into a BIM platform as a
494 reference property.

495

496 **5 Discussion**

497 The main purpose of this paper is to use high-precision scanning reconstruction technology to detect and
498 digitize the quality problems of prefabricated components in the process of assembly and construction, to achieve
499 higher efficiency and higher precision. In order to achieve this goal, the experiment designed in this paper uses the
500 Delaunay triangle to extract the contour of the point cloud, and further linearly fits to determine the geometric data.
501 Taking prefabricated stairs and prefabricated exterior walls as examples, this paper successfully extracted the hole

502 position, shape information and appearance defect. After comparing with the design information of the prefabricated
503 building, the obtained difference value can more suitably reflect the quality problems of the prefabricated
504 components in the production process. According to the error analysis and the technical precision adopted in the
505 experiment, it can be proven that the algorithm proposed in this experiment can meet the needs of the quality
506 management of the prefabricated building.

507 In order to achieve the purpose of practical application in combination with cutting-edge technology, it is
508 necessary to consider the actual situation. Combined with the requirements in the quality assessment standards
509 related to prefabricated buildings, this paper also established a comprehensive evaluation system. Using reasonable
510 weight distribution, the data values are analyzed to obtain meaningful evaluation indicators. With these indicators,
511 it is possible to analyze the causes of quality problems in the production process and strengthen the quality control.
512 This will not only provide detailed data for subsequent construction, but also forward feedback to the cause of the
513 problem, improving the quality of the prefabricated building from two aspects.

514 As shown in Figure 20, considering point cloud data and the design document from the structural designer as
515 input, then extract the key information, such as geometric information, to check and calculate the needed data. The
516 error data and defect data can then be used for quality inspection using the quality standard, for which the quality
517 manager provided. If the prefabricated component passes the inspection, then the information is transferred to
518 construction workers on site, otherwise it will be transferred to factory workers to further analyze the causes and
519 improve the performance.

520 **6 Conclusion**

521 At present, the quality management of prefabricated components is still limited to manual measurement,
522 resulting in poor efficiency and accuracy. In response to such deficiencies, this paper aimed to explore a more
523 automated and accurate quality control process through the research on 3D reconstruction technology. After
524 comparing a variety of 3D reconstruction techniques, the laser scanning technology that retains more complete data,

525 is more adaptable. The Delaunay triangle was adopted as the core of the algorithm. The comprehensive prefabricated
526 component quality evaluation system based on relevant specifications was established. Besides, a new process for
527 extracting quality information was developed, which greatly improved the efficiency and accuracy.

528 In this process, the KNN algorithm was used to reduce the data density, successfully compressing the data to
529 60.20% of the original volume while retaining the data characteristics. This operation reduced the size of the data
530 set while also increased the computational speed of subsequent algorithms. In order to realize the contour extraction
531 of point cloud data, the Alpha Shape algorithm was applied flexibly to overcome the problem of concave plane
532 extraction, and finally effectively separated the inner and outer boundaries. In addition, the defect information was
533 extracted using data grid positioning integrated with the Vertex Clusters algorithm, which also provided data support
534 for determining the values of indicators. The comprehensive data can provide detailed parameters for on-site
535 construction, and guide the management system in the pre-production process.

536 This paper presented the general flow of quality management of prefabricated components, which involves
537 point cloud acquisition, contour extraction and calculation parameters. Although the feasibility of practical
538 application was demonstrated by typical examples, some limitations were still presented in practical application.
539 First, the diversity was not fully considered. Because the current steps of dimensionality reduction were limited to
540 plane extraction, and it was impossible to perform dimensionality reduction on the surface. Next, the shape of the
541 reserved holes was also set to a regular shape, such as a perfect circle or a rectangle. However, in the case of
542 prefabricated buildings with higher assembly rates, prefabricated components tend to diversify. Lastly, the
543 automation operation is not fully realized, and multiple parameters need to be manually adjusted according to the
544 actual situation, which reduced the efficiency of the process. Although a simple dimensionality reduction algorithm
545 was adopted to improve the applicability of data calculation, a lot of work need to conducted to enhance the
546 automation of operation in the future research. Nonetheless, this study is still valuable for improving the quality
547 detection efficiency of prefabricated elements and filling the research gap in this area.

548 **Data Availability Statement**

549 Some or all data, models, or code that support the findings of this study are available from the corresponding
550 author upon reasonable request.

551

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557

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Table 1: Allowable deviation of the dimensions of precast concrete component

Prefabricated column	Length	±3	±5	±7	±10
	Width	±3	±5	±7	±10
	Height	±2	±3	±4	±6
Prefabricated beam	Length	±3	±5	±7	±10
	Width	±3	±5	±7	±10
	Thickness	±2	±3	±4	±6
Prefabricated slab	Length	±3	±5	±7	±10
	Width	±3	±5	±7	±10
	Thickness	±2	±3	±4	±6
	Diagonal length	±6	±8	±10	±12
Prefabricated interior wall	Length	±3	±4	±5	±6
	Width	±3	±4	±5	±6
	Thickness	±2	±3	±4	±5
	Diagonal length	±3	±4	±5	±5
Prefabricated external wall	Length	±3	±3	±4	±4
	Width	±3	±3	±4	±4
	Thickness	±2	±2	±3	±3
	Diagonal length	±3	±4	±5	±5
Prefabricated stair	Length	±3	-	-	-
	Width	±3	-	-	-
	Thickness	±2	-	-	-
Reserved hole	Offset of center line	5	-	-	-
	Size	±5	-	-	-

Table 2: Allowable surface defect for prefabricated concrete components

Defect type	Allowance
Crack	Width < 0.02mm & Length < 100mm
Honeycomb	The area in the secondary part < 10000mm ² or the proportion of the area < 0.5%
Collapse of edge	The proportion of the plane area < 0.5% or the number < 3
Surface voids	The proportion of the plane area < 1%
Reinforcement exposure	Should not exist
Defect of the connection	Should not exist

Table 3: Comparison of different K values

The K value	1(The original data)	2	3	4	5	6
The number of points	582,357	380,565	362,596	350,591	368,967	380,848
Compression ratio	100%	65.35%	62.26%	60.20%	63.36%	65.40%

Table 4: Weights of production quality evaluation index for precast concrete

First-class index	Assign weight	Second-class index	Assign weight	Comprehensive weight	Value
Production accuracy	0.6	Length accuracy	0.4	0.24	0/1
		Angle accuracy	0.3	0.18	0/1
		Positioning accuracy of reserved hole	0.2	0.12	0/1
		Shape accuracy of reserved hole	0.1	0.06	0/1
		Crack	0.3	0.12	0/1
Surface quality	0.4	Honeycomb	0.1	0.04	0/1
		Angular collapse	0.1	0.04	0/1
		Surface pockmark	0.1	0.04	0/1
		Leakage reinforcement	0.2	0.08	0/1
		Joint defect	0.2	0.08	0/1

Table 5: Calculation example of comprehensive evaluation index

Type of element	Specific index	Requirements of index		Actual data	Index weight	Index value
Prefabricated stair	Length accuracy	Length	± 3	2.22		1
		Width	± 3	-0.17	0.24	1
		Thickness	± 2	-2.84		1
	Angle accuracy	-		-	0.18	1
	Positioning accuracy of reserved hole	Offset of center line position	5	2.15	0.12	1
	Shape accuracy of reserved hole	Size	± 5	0.55	0.06	1
	Crack	Width is less than 0.02mm and length is less than 100mm		Not detected	0.12	1
	Honeycomb	The secondary part is less than 10000mm ² or the area is less than 0.5%		Not detected	0.04	1
	Angular collapse	Plane area ratio is less than 0.5% / less than 3		0.446%/3	0.04	0
	Surface pockmark	Plane area ratio is less than 1%		Not detected	0.04	1
	Leakage reinforcement	There should be no		Not detected	0.08	1
	Joint defect	There should be no		Not detected	0.08	1

Table 6: Concrete prefabricated wall property set definition

PsetName	PSet_PrefabricateWall
Entity	IfcWall
PropertyType	IfcWall/Userdefined/ PrefabricateWall
PropertyDescribe	Used to describe the quality of concrete prefabricated walls

Table 7: Property sets for quality of concrete prefabricated components

	PropertyName	PropertyValue	Type
1	Length Deviation	IfcPropertySingleValue	IfcReal
2	Width Deviation	IfcPropertySingleValue	IfcReal
3	Height Thickness Deviation	IfcPropertySingleValue	IfcReal
4	Diagonal Deviation	IfcPropertySingleValue	IfcReal
5	Reserved Hole Position Deviation	IfcPropertySingleValue	IfcReal
6	Reserved Hole Size Deviation	IfcPropertySingleValue	IfcReal
7	Crack	IfcPropertySingleValue	IfcReal
8	Honeycomb	IfcPropertySingleValue	IfcReal
9	Corner Breakage	IfcPropertySingleValue	IfcReal
10	Pockmark	IfcPropertySingleValue	IfcReal IfcString
11	Reinforcing Bar Exposed	IfcPropertyEnumeratedValue	(Y/N) IfcString
12	Connection Reliability	IfcPropertyEnumeratedValue	(Y/N)
13	Comprehensive Index	IfcPropertySingleValue	IfcReal

Figure 1

Figure 3

Figure 4

Figure 5

(a) The principle of Delaunay algorithm

(b) Generate the Delaunay triangular grid

Figure 8

Figure 9

(a) Before rarefaction (global view)

(b) After rarefaction (global view)

(c) Before rarefaction (local view)

(d) After rarefaction (local view)

(a) 4x12 grid of prefabricated stairs

(b) 11x11 grid of prefabricated exterior walls

(a) Comparison before and after using the algorithm

(b) Magnify the details of the processing results
after using the algorithm

Figure 14

Figure 15

(a) surface pockmark of prefabricated exterior walls

(b) angular collapse of prefabricated stairs

(a) extraction and grid of surface pockmark of prefabricated exterior walls

(b) extraction and grid of angular collapse of prefabricated stairs

(a) Original defect data point

(b) Triangular grid of defect point

Figure 19

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