

1 **As-Built Data Acquisition and Its Use in Production Monitoring and**
2 **Automated Layout of Civil Infrastructure: A Survey**

3
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7
8 **Abstract**

9 The collection and analysis of data on the three-dimensional (3D) as-built status of large-
10 scale civil infrastructure—whether under construction, newly put into service, or in operation—
11 has been receiving increasing attention on the part of researchers and practitioners in the civil
12 engineering field. Such collection and analysis of data is essential for the active monitoring of
13 production during the construction phase of a project and for the automatic 3D layout of built
14 assets during their service lives. This review outlines recent research efforts in this field and
15 technological developments that aim to facilitate the analysis of 3D data acquired from as-built
16 civil infrastructure and applications of such data, not only to the construction process per se but
17 also to facility management—in particular, to production monitoring and automated layout. This
18 review also considers prospects for improvement and addresses challenges that can be expected
19 in future research and development. It is hoped that the suggestions and recommendations made
20 in this review will serve as a basis for future work and as motivation for ongoing research and
21 development.

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23 Production Monitoring, Terrestrial Laser Scanning

24

25 **1. Introduction**

26 Advancements in on-site spatial survey technologies (e.g., photo/video-grammetry and
27 terrestrial laser scanning) enable more efficient acquisition of 3D data on as-built civil
28 infrastructure (hereinafter referred to as “as-built data”) than is possible with traditional manual
29 techniques. In this review, the term *as-built* refers to either the actual state of an entire facility or
30 one of its constituent components at the completion of construction, or to the actual state of a
31 built asset at any time during its life cycle, particularly during its service life. Three-dimensional
32 as-built data acquired from civil infrastructure have been used to establish geometric properties
33 of entire facilities and their constituent components. More recently, such data have come to be
34 regarded as a tool to be utilized for managerial purposes at various points in the life cycle of a
35 project: during construction, upon completion of construction, and during operational and
36 maintenance phases relevant to the civil engineering field.

37 For purposes of on-site dimensional quality control, progress tracking, and inspection, one
38 particularly important application of as-built data in the construction phase is production
39 monitoring, which entails making comparisons of the actual (“as-built”) state of a project with
40 the “as-designed” state defined in the contractual agreement. Examples of research studies in this
41 area include proactive on-site tracking of the physical progress of construction activities by
42 comparing 3D as-built data acquired on the site of a facility under construction with the design
43 information embedded in the building information model (BIM) (e.g., [1–11]).

44 There are several reasons why it is so important—indeed, vital—for researchers and
45 practitioners to develop new methods and technologies for use in production monitoring. For
46 starters, the design documents may not provide complete details of a planned facility, leaving
47 some aspects thereof to the owner and the contractor to decide later. Because of such delayed
48 decisions, it can be difficult if not impossible to adequately record the as-built condition of an
49 entire facility or of one of its constituent components within the as-built documentation. Such
50 situations are particularly common in the case of mechanical, electrical, and plumbing (MEP)
51 systems that are not fully designed (e.g., those whose characteristics are specified in only
52 rudimentary form, such as via line sketches) [9,10]. In addition, it is sometimes difficult to
53 adequately track and record (within the as-built documentation) changes based on conscious
54 decisions that are made during construction and hence could yield a final product that deviates
55 from the as-designed state. Finally, it can be even more difficult to adequately track and record
56 (in the as-built documentation) deviations that are more subtle and are not the results of
57 conscious decisions (e.g., deviations due to poor workmanship).

58 Another important aspect of the construction, operation, and maintenance phases of civil
59 infrastructure is automated layout. The Oxford English Dictionary defines *layout* as “the way in
60 which the parts of something are arranged or laid out.” The Collins English Dictionary defines
61 *layout*, in its technical sense, as “a drawing showing the relative disposition of parts in a machine,
62 etc.” In this review, the term *automated layout* is used to mean the process of automatically
63 determining geometric properties (dimensions, shape, and 3D position (location and orientation))
64 and other semantic (real-world) attributes of individual components of a structure, as well as the
65 relationships between them, from 3D as-built data.

66 Automated layout is used for documentation purposes, such as in the preparation of a
67 contractual agreement that must be delivered by the contractor to the owner—that is, a package
68 that contains all the pertinent as-built information, particularly CAD drawings. Automated layout
69 is also used for purposes of facility management, to record and update the status of the built
70 assets. Some studies have focused on transforming 3D as-built data acquired from a facility into
71 3D structured or object representations, such as CAD models, in order to better illustrate the as-
72 built conditions (e.g., [12–16]). Such representations or models can then be used as the basis for
73 making managerial decisions (e.g., on repairs and maintenance).

74 Recording of information on the as-built status of individual components of a facility is
75 needed, because the as-designed state, such as CAD drawings or early component selections
76 made by the design team, may not correspond to the infrastructure actually produced. This could
77 be due to contractors (for the initial construction or for subsequent add-ons or modifications)
78 either not adequately and fully capturing the state of the facility as built, not building precisely to
79 design, or handing over the design documentation without fully communicating that the asset
80 was not built as designed. Regardless of the reason for discrepancies between the as-built state
81 and the as-designed state, an aggravating factor is the owner’s potential lack of control over the
82 as-built information. Even if an accurate 3D as-built layout of the facility is produced—whether
83 after the construction phase, in the case of new construction; or after a renovation, upgrade, or
84 remodeling of part/all of the facility; or after replacement of one or more of its constituent
85 components—the original as-built layout must be modified on a timely basis to reflect and
86 update the state of the facility.

87 Situations such as the ones described above have created a need for methods and
88 technologies that enable the robust, efficient, and cost-effective acquisition of as-built data on

89 demand, and subsequent processes for the extraction of the valuable as-built information by
90 construction professionals and facility managers. For this reason, methods for acquisition of such
91 data through on-site surveys and the extraction of valuable information—to be used for
92 production monitoring during the construction phase, and for automated layout during the
93 construction, operational, and maintenance phases—have been investigated by researchers and
94 practitioners in the civil engineering field.

95 This review provides an extensive survey of the technological advancements that have made
96 it possible to extract and process valuable as-built information for purposes of production
97 monitoring and automated layout. Existing research efforts in this area are outlined in Section 2,
98 and efforts by practitioners are discussed in Section 3. Areas in which further developments are
99 needed are summarized in Section 4.

100

101 **2. Review of Existing Research**

102 The acquisition of as-built data is especially useful in the civil engineering field, where it
103 aids in control/verification of the quality of civil infrastructure—via analysis of deviations
104 between as-built and as-designed structures—and in monitoring of progress on a project. Another
105 practical application is the production of as-built drawings, where it facilitates the determination
106 and documentation of as-built layout. Two types of non-contact spatial survey technology have
107 recently made it possible to efficiently acquire as-built data: those based on photo/video-
108 grammetry (image-based technologies) and those based on terrestrial laser scanning (range-based
109 technologies) [17]. With either of these types of survey technology, as-built data can be acquired
110 by capturing the shape and structure (i.e., spatial coordinates) of an object in point-cloud format
111 [18]. This section presents an extensive review of recent research into the analysis and

112 application of collected 3D data on as-built civil infrastructure for purposes of production
113 monitoring and automated layout.

114

115 2.1. Production Monitoring

116 Acquisition of 3D as-built data via photo/video-grammetry and terrestrial laser-scan surveys
117 has led to automated quality assessment of construction projects, with a focus on dimensional
118 compliance of structural components [19], tracking of progress on individual structural
119 components [1–8,11], dimensional compliance of MEP systems [20], tracking of progress on
120 MEP systems [9,10], and inspection tasks, especially for surface flatness [21].

121

122 2.1.1. Dimensional Quality Control of Structural Framing Work

123 Bosché [19] proposed a method for automated recognition of structural components that are
124 designed in 3D CAD from 3D point clouds obtained at the building construction site. A point-to-
125 point matching approach is used, and registration is performed with an iterative closest point
126 (ICP) algorithm. Once the registration between 3D CAD models of structural components and
127 3D point clouds is completed, a similar ICP-based registration algorithm is used to calculate the
128 poses of models of structural components. These as-built poses are then used to automatically
129 control the compliance of the project with respect to the corresponding dimensional tolerances
130 (see Fig. 1). Specifically, the differences between the as-built and as-designed dimensions
131 (within and between objects) are calculated and compared to their corresponding tolerances
132 defined in the project specifications, which may be specific to the project or refer to industry
133 standards such as MNL 135-00 [22] and AISC 303-05 [23].

134

Fig. 1.

135 *2.1.2. Progress Tracking for Structural Framing Work*

136 *2.1.2.1. Permanent structural work*

137 A decade ago, Shih and Wang [24], Akinci et al. [25], and Shih and Huang [26] proposed
138 methods for quantifying as-built structural progress by comparing differences between the actual
139 work done on the construction site and the original construction schedule. For this purpose, they
140 proposed the use of a 3D point cloud acquired by terrestrial laser scanning and a 4D (3D + time)
141 building information model that represents the original building design and construction
142 schedule. Although the differences were identified manually and visually under this scan-versus-
143 BIM framework at the time of the study, research has enabled this process of construction
144 progress tracking to advance to the point where it can now be automated.

145 Bosché and Haas [1] and Bosché et al. [2] proposed methods for automated recognition of
146 structural components that are designed in 3D CAD from 3D point clouds. In their earlier work,
147 the as-planned 3D CAD model was converted to a point cloud model. Using point-recognition
148 metrics, correspondences between the as-planned and as-built models were identified, and the
149 progress on the project was able to be ascertained. In the study by Bosché et al. [2], they
150 introduced an object-surface recognition metric that achieves high precision and recall on
151 structural steel buildings.

152 Golparvar-Fard et al. [3,27] proposed a method for calculating the locations and orientations
153 of construction site images from the images themselves as well as by 3D as-built data acquisition
154 based on photogrammetry. With this method, 3D as-built data can be superimposed on as-
155 planned models. Also, as-built progress can be quantified by registering construction site images
156 in a virtual as-planned environment and analyzing the registered images—and then using the as-
157 planned 4D model as a baseline for progress tracking. The results of comparisons of as-built and

158 as-planned progress are represented in a 4D augmented reality (D4AR) environment.

159 In a later study, Golparvar-Fard et al. [5] proposed a method of progress measurement that
160 compares construction site images acquired daily with a 4D BIM. In this method, an updated as-
161 built point cloud is generated in 4D (3D + time) from the latest images by use of structure-from-
162 motion, multiview stereo, and voxel coloring and labeling algorithms. Then an industry
163 foundation class (IFC)-based BIM is registered with the updated as-built point cloud. Next, a
164 Bayesian probabilistic model-based machine-learning method is used to measure physical
165 progress on the project, which can be represented in D4AR, as illustrated in Fig. 2.

166 Fig. 2.

167 Still another method of progress monitoring was devised by Son and Kim [4], who used an
168 automated 3D method of recognition and modeling of structural components that employs color
169 and a 3D point cloud acquired from a stereo vision system. The data processing first relies on
170 color features to effectively extract information on structural components by employing color
171 invariance, 2D object segmentation, median filtering, and flood fill operation. That information
172 is then utilized to extract the 3D coordinates of each color feature. The final step in the proposed
173 method is the use of the resulting 3D point cloud to generate matching 3D as-built CAD models
174 that have been converted to STL format, which enables project participants to automatically
175 assess project progress.

176 Turkan et al. [6] developed an automated 4D object-oriented progress-tracking system to
177 efficiently update the construction schedule through the use of a 3D CAD model, schedule
178 information found in the original plans for the project, and 3D point clouds acquired via
179 terrestrial laser-scan surveys. In their system, 3D point clouds are registered with a 4D as-
180 planned model in the same coordinate system, in order to extract useful information on the

181 progress of a project. Once registered, progress measurement and schedule updating is
182 automatically performed by recognition of as-built objects. In a later study, Turkan et al. [8], they
183 proposed a 4D-model recognition-driven system for automated tracking of progress on steel-
184 reinforced concrete structures and steel structures that transforms objects to their earned values.

185 Kim et al. [7] proposed a method of progress measurement that uses a 4D BIM in concert
186 with a 3D point cloud obtained by terrestrial laser scanning. The method comprises three phases:
187 alignment of the as-built data with the as-planned model, matching of the as-built data to
188 information in the BIM, and revision of the as-built status. To help identify aspects of the as-built
189 status that are inaccurate, the construction sequence—defined as the sequence-of-activity
190 execution specified in the BIM—is first examined. Then the topological relationships among the
191 structural components—defined as the connectivity between components which is specified in
192 the BIM—are examined. The as-built status-revision phase results in an accurate assessment of
193 the as-built status of the structural components, demonstrating that this methodology can be used
194 to correctly measure construction progress (see Fig. 3).

195 Fig. 3.

196

197 *2.1.2.2. Secondary and temporary work*

198 Turkan et al. [11] developed a method that can be used for tracking of progress on secondary
199 (rebar) and temporary (formwork, scaffolding, and shoring) objects employed in structural
200 concrete work. Previous research had shown that scan-versus-BIM object-recognition systems,
201 which fuse 3D point clouds acquired by photogrammetry or terrestrial laser scanning with a 4D
202 BIM, provide valuable information for tracking of construction work. However, the potential of
203 these systems had been demonstrated for tracking the progress of permanent structures only. The

204 experimental results achieved by Turkan et al. [11] show that it is feasible to recognize secondary
205 and temporary objects in 3D point clouds—and to do so with fairly high accuracy—via either of
206 these two novel fusion techniques (see Fig. 4). However, superior results could be achieved by
207 using additional cues such as color and 3D edge information.

208 Fig. 4.

209

210 2.1.3. *Dimensional Quality Control of MEP Work*

211 Nahangi and Haas [20] proposed a method for monitoring and assessment of fabricated pipe
212 spools using an automated scan-to-BIM registration procedure in which defects are detected
213 through a neighborhood-based ICP algorithm (see Fig. 5). They focused on industrial
214 construction facilities, and targeted assemblies of pipe spool in particular. This method can be
215 employed for the automatic and continual monitoring of such assemblies throughout fabrication,
216 assembly, and erection, thereby enabling timely detection and characterization of deviations.

217 Fig. 5.

218

219 2.1.4. *Progress Tracking for MEP Work*

220 Bosché et al. [9,10] proposed a system that integrates scan-versus-BIM and scan-to-BIM
221 approaches for tracking of the built status of MEP work. This system, which is capable of
222 recognizing and identifying objects that are not built at their as-planned locations (see Fig. 6),
223 enables automated quality control and can even detect discrepancies between the as-built and as-
224 planned states of pipes, conduits, and ductwork. Such discrepancies are due to changes made in
225 the field that either go unnoticed (human error) or are not reflected in the 3D model.

226 Fig. 6.

227 *2.1.5. Automated Inspection and Quality Assurance*

228 Recently, Bosché and Guenet [21] proposed a method that demonstrates the value of
229 integration of techniques for surface-flatness control. The method employed the scan-versus-
230 BIM principle of Bosché and Haas [1] to segment a 3D point cloud acquired on a construction
231 site, by matching each point to the corresponding object in the BIM. Using two different standard
232 flatness-control techniques, Straightedge and F-Numbers, to measure compliance with the
233 designed tolerances, they applied their method to a separate 3D point cloud for each floor. They
234 found the performance of the method to be superior to traditional measurement methods in terms
235 of both quality and efficiency, thereby validating the usefulness of as-built data acquired by
236 terrestrial laser scanning for purposes of standard dimensional control.

237

238 *2.2. Automated Layout*

239 *2.2.1. MEP Systems in Industrial Facilities and Buildings*

240 Because of the increasing demand for automated layout of large as-built 3D pipelines in
241 recent years, several methods for reconstruction of 3D pipelines have been proposed. A 3D
242 layout of an as-built pipeline at an existing plant provides detailed information on each of its
243 distinct elements. Such a model comprises straight pipes, elbows, reducers, and tee pipes with
244 specific diameters, lengths, orientations, and locations. Therefore, it can be used effectively
245 during the ongoing operation, maintenance, and retrofitting of the plant facility [28,29,14]. For
246 example, piping components are periodically renewed during preventive maintenance, and
247 unplanned emergency repairs or replacements may be required after accidents or failures. When
248 a single pipeline (in a network of pipelines) requires maintenance, repairs, and/or replacements,
249 the 3D as-built pipeline layout model allows the facility manager to easily locate the pipeline and

250 ensure that it is correctly repaired and maintained [30]. Moreover, older pipes may need to be
251 retrofitted—or new ones may need to be added—to increase production that stems from capacity
252 expansion and/or process integration [31], which sometimes requires the paths of existing
253 pipelines to be rerouted. In such cases, piping plans (comprising proposed diameters, lengths,
254 and slopes, among others) should be reviewed in conjunction with the 3D as-built environment
255 [32]. Furthermore, the location of the equipment and the surrounding environment should be
256 taken into account.

257 The existing research studies on reconstruction of 3D pipelines range from the development
258 of semi-automated methods (e.g., [33,28,34,31,35]) to fully automated ones (e.g., [12–16]). All
259 of these are based on more efficient survey techniques, such as photogrammetry and laser
260 scanning, than are traditional manual surveys.

261

262 *2.2.1.1. Semi-automated methods*

263 In the case of semi-automated methods (e.g., [33,28,34,31,35]), the reconstruction of 3D
264 pipelines is conducted in an interactive way between the user and the computer. In most cases,
265 the user manually selects the desired portions of pipelines (straight pipes, elbows, tees, etc.) to be
266 modeled. This process involves manual selection of vertices, centerlines, edges, or regions of the
267 desired portions of the pipelines. Next, these manually selected features are used as input for
268 automatic estimation of the poses of the desired portions in 3D space and for the calculation of
269 parameters, such as their radii and lengths, that are needed to reconstruct the desired portions by
270 computer.

271 Veldhuis and Vosselman [28], Navab and Appel [34], and Reisner-Kollmann et al. [35]
272 proposed semi-automated methods based on photogrammetry, which enables the reconstruction

273 of as-built pipelines from multiple digital images acquired from industrial facilities such as
274 chemical processing plants, oil platforms, nuclear installations, and power plants. Navab and
275 Appel [34] studied only the reconstruction of straight-pipe portions of pipelines. Veldhuis and
276 Vosselman [28] proposed a method that is capable of reconstructing elbows, but they tested their
277 method only on straight-pipe portions. Reisner-Kollmann et al. [35] proposed a method that
278 allows for the reconstruction of entire pipelines, but in the form of tubes without boundaries
279 between the different types of pipe (straight pipes, elbows, tees, etc.).

280 The semi-automated methods based on photogrammetry require correspondences among
281 vertices, centerlines, edges, or regions across multiple images in order to reconstruct the desired
282 portions in 3D. Therefore, the user has to manually measure the edges of every straight pipe [28]
283 or the centerline of every pipeline [35] in a series of digital images. For example, in the
284 computation for the reconstruction process proposed by Veldhuis and Vosselman [28], every
285 straight pipe has to be measured manually in at least four images, the minimum requirement for
286 reconstruction of a straight pipe being that two points on the edges of a straight pipe be present in
287 two images. In an experiment on reconstruction of 16 straight pipes, Veldhuis and Vosselman
288 [28] actually used eight images and manually measured 256 edges (16 edges for each pipe). They
289 recommended using even larger numbers of images and measured edges of each straight pipe in
290 order to improve the quality of reconstruction.

291 In the semi-automated methods based on photogrammetry, there is a primary assumption
292 that a series of digital images is already pre-calibrated, hence these methods rely highly on pre-
293 calibration. For this calibration, markers have to be attached in advance to each of the desired
294 portions of the pipelines to be modeled [34,35] (see Fig. 7). In addition, both intrinsic and
295 extrinsic parameters of the cameras must be provided. These tasks, which include the

296 identification of correspondences of the desired portions across a number of images and pre-
297 calibration that requires extensive manual intervention, are not only time-consuming for the user
298 but also become nearly impossible for entangled pipelines and for enormous facilities that
299 include a large number of pipelines.

300 Fig. 7.

301 Because of improvements in laser scanning, Johnson et al. [33] and Masuda and Tanaka [31]
302 proposed semi-automated methods that allow for the reconstruction of as-built pipelines from a
303 3D point cloud acquired by terrestrial laser scanning on the site of an industrial plant. Compared
304 with photogrammetry, laser scanning provides an explicit, dense 3D point cloud by directly and
305 quickly measuring the 3D positions and shapes of as-built pipelines [14]. Recent advances in
306 laser scanning have made it possible to automatically capture large-scale 3D point clouds from a
307 broad range of areas [31].

308 In the method proposed by Johnson et al. [33], the user manually selects and draws
309 rectangular regions around the portions of the pipelines to be modeled (straight pipes, elbows,
310 tees, etc.) in a series of range images acquired from many different viewpoints. Next, smooth
311 surface-mesh models of those regions are generated, and they are registered to a single, seamless
312 surface-mesh model. In the mesh-generation process, the user specifies the amount of scene data
313 to be processed, and the range image is sub-sampled for mesh generation. The registered surface-
314 mesh models for the regions of interest can be recognized once CAD drawings have been
315 provided for each type of pipe (straight pipes, elbows, tees, etc.). However, if the desired
316 portions differ too much from the given CAD drawings, they cannot be recognized and modeled.
317 Finally, after the regions of interest are identified, each pipe is modeled by manually rotating and
318 orienting it so that its actual position and orientation correspond with those of some pipe in the

319 given CAD drawings.

320 In the study by Masuda and Tanaka [31], smooth mesh models are first generated
321 automatically from a 3D point cloud. Then the portions that are missing in the mesh models—
322 because of the limited number of viewpoints or partial occlusion by a large number of objects—
323 are manually compensated for, based on the reflected images. These reflected images have the
324 form of unit spheres, which can be converted to two types of images: a perspective image for
325 users and a rectangular image via Mercator projection for purposes of computation. The user
326 intuitively selects a seed region (such as one which is included in a desired portion of a
327 perspective image), and then the corresponding pixels in the rectangular image are detected
328 automatically. At that point, the desired portions are modeled by fitting a surface to vertices in
329 the selected seed region. Then when the user specifies the locations and sizes of the desired
330 portions according to the standards, the adjacent vertices that lie on that surface are searched via
331 the region-growing method (see Fig. 8).

332 Fig. 8.

333 A great deal of user input is involved in the semi-automated layout process. With most
334 methods based on either photogrammetry or laser scanning, such input is available only if all of
335 the straight pipes or pipelines are visible (i.e., nearly free of occlusion by other objects). Another
336 inherent drawback of these methods is that the reconstruction is error-prone if the user makes a
337 mistake or the user input is not sufficiently accurate [35]. Furthermore, methods based on
338 photogrammetry have other, more limitations: Their use is limited to portions of straight pipes or
339 to entire pipelines that can be modeled as tubes without boundaries between different types of
340 pipe. Therefore, it is difficult to use them for reconstruction of an entire 3D pipeline, since most
341 pipelines are composed of a series of straight pipes connected to one another by elbows, tees, etc.

342 Although the aforementioned techniques based on laser scanning represent a major step forward
343 in terms of their capacity for reconstruction of an entire 3D pipeline, they still entail a large
344 number of manual processes. From a practical point of view, recognizing each type of pipe from
345 a noisy, incomplete, and enormous 3D point cloud that includes a large number of pipelines
346 becomes nearly impossible if it has to be done in a semi-automated way with manual
347 intervention.

348

349 *2.2.1.2. Fully automated methods*

350 Several research studies (e.g., [12–16]), have investigated the possibility of automatic
351 modeling of 3D as-built pipelines. These studies have all yielded similar advancements in terms
352 of automatic performance.

353 Bosché [12] proposed an automated method that enables reconstruction of as-built straight
354 and curved pipes from a 3D point cloud acquired from pipe spools that surround buildings (see
355 Fig. 9). Bosché’s method iteratively fits and matches all cylindrical pipes by adopting the method
356 proposed by Kwon [36]. Once that is done, two or more adjacent straight pipes are analyzed to
357 compare their relative positions and orientations in an effort to determine how they are likely to
358 be connected. In this way, the positions of the elbows are inferred, and the positions of some of
359 the straight pipes that are connected to other straight pipes or elbows are corrected accordingly.

360

Fig. 9.

361 Rabbani et al. [13] proposed an automated method that enables reconstruction of as-built
362 cylindrical pipes from a 3D point cloud acquired at an industrial plant (see Fig. 10). In this
363 method, segmentation of the point cloud is performed using a smoothness constraint based on a
364 combination of surface-normal similarity and spatial connectivity. This segmentation is followed

365 by an object-recognition stage based on a variation of the 3D Hough transform, which requires a
366 5D Hough space for detection of the orientations of cylindrical objects and estimation of their
367 radii and positions in the point clouds. Then cylindrical 3D-object models are fitted using models
368 from a catalogue of commonly found CAD objects as templates.

369 Fig. 10.

370 Kawashima et al. [14] also proposed an automated method for reconstruction of as-built
371 pipelines from a 3D point cloud acquired at an industrial plant. In their method, the entire 3D
372 pipeline is reconstructed by automatically recognizing the type of each pipe (such as straight,
373 elbow, or tee) and the connections between pipes. First, points on straight pipes are extracted by
374 eigenvalue analysis of the point clouds and the surface-normal vectors. Then the radii, positions,
375 and axes of the straight pipes are calculated using the point clouds. At that point, the connection
376 relationships among the extracted straight pipes are determined by checking the relative positions
377 and orientations of their axes. Based on these connection relationships, other types of pipes, such
378 as elbows and tees, are modeled.

379 Lee et al. [15] proposed an automated method that enables reconstruction of as-built
380 pipelines composed of straight pipes, elbows, and tee pipes from a 3D point cloud. In their study,
381 Voronoi diagrams are used to generate skeleton candidates for individual pipelines from the point
382 cloud. Then extraction of skeletons from the skeleton candidates is performed using topological
383 thinning. The extracted skeletons are segmented into their individual components, and a set of
384 parameters for each component is calculated (see Fig. 11).

385 Fig. 11.

386 Ahmed et al. [16] proposed a method based on the Hough transform and the judicious use of
387 domain constraints that can automatically find, recognize, and reconstruct 3D pipes from a 3D

388 point cloud. The core algorithm utilizes the Hough transform's efficacy in detecting parametric
389 shapes in noisy data by applying it to projections of orthogonal slices to grow cylindrical pipe
390 shapes within a 3D point cloud. They considered that most of the pipes, conduits, and ducts are
391 built orthogonal to one another and along the main axes of a building. In this way, searching in
392 planes perpendicular to these axes for standard reference pipe diameters reduces the problem
393 from three to two dimensions (see Fig. 12).

394 Fig. 12.

395 The previous methods are limited to parts of an entire 3D pipeline, for example, straight
396 pipes, elbows, and tees in the most recent study by Lee et al. [15]. Although the study by
397 Kawashima et al. [14] attempted to achieve an improvement in terms of the completeness of the
398 modeled 3D pipeline layout, only 55% of the individual pipes (other than the straight pipes) were
399 accurately modeled from their actual pipe forms. In addition, in the studies by Kawashima et al.
400 [14] and Lee et al. [15], the detection of as-built pipelines from a 3D point cloud was performed
401 manually before the proposed reconstruction process was initiated.

402 Previous attempts to address this problem range from the development of semi-automated
403 methods to assist users in a tedious manual reconstruction process to the development of fully
404 automated methods that eliminate any user involvement. The results of these efforts have shown
405 that the repetitive, tedious, and even trivial tasks typically performed in the manual 3D
406 reconstruction of as-built pipelines can be eliminated by using automated approaches. However,
407 there is still a need for an effective, fully automated 3D reconstruction method that can model an
408 entire pipeline, irrespective of the types of its constituent parts. Specifically, as-built pipelines,
409 though generally cylindrical, present a challenge to automatic detection because of the variety of
410 types (shapes) and diameters of pipes and the arbitrariness of their poses. Additionally, the

411 incompleteness and unstructured nature of a point cloud complicates automation [16,37]. For
412 automatic performance, algorithms must be improved to the point of being able to handle point
413 clouds that are somewhat less than complete and to predict, extrapolate, semantically relate, or
414 otherwise represent the parts that are occluded or missing [16].

415

416 2.2.2. *Buildings*

417 Jung et al. [38] proposed a method for modeling of a semantically rich 3D indoor building
418 layout from a 3D point cloud acquired by terrestrial laser scanning. Their method, which is a
419 semi-automatic approach that accounts for the high degree of complexity of indoor environments,
420 comprises three main steps: segmentation for plane extraction, refinement for removal of noisy
421 points, and boundary tracing for outline extraction. After these steps are performed, the resulting
422 3D indoor building models are used in conjunction with the points that were not processed in the
423 three main steps to create manual models. With the extracted boundary lines as guides, each
424 object and its relationship each other can easily be identified and modeled (see Fig. 13).

425

Fig. 13.

426

427 **3. Commercial and State-of-the-Art Tools**

428 Currently, modeling which is done to represent the existing state of an as-built pipeline or
429 the 3D layout of an as-built building is mostly performed manually—in an interactive manner—
430 by the user. Especially, 3D layout of as-built pipelines from 3D point clouds has been extensively
431 investigated, and several commercially available software programs have been developed to
432 assist the current manual process of 3D layout.

433 Most providers of laser-scanning systems (e.g., Leica Geosystems and Trimble) have
434 developed software that enables the 3D layout of as-built pipelines from 3D point clouds. For
435 example, the latest version of Leica Cyclone (version 8.1) by Leica Geosystems provides a user
436 interface for 3D layout of as-built pipelines that includes functions for tasks such as automatic
437 pipe finding, region growing from selected 3D points for cylindrical objects, cylinder fitting, and
438 generation of models from the selected 3D point clouds. With this software, models of objects of
439 various geometric types pertinent to the 3D layout of as-built pipelines, for example, cylinder,
440 elbow, reducing elbow, cone, torus, reducer (eccentric and concentric), and pipe tee, can be
441 created by a semi-automatic layout process.

442 Chunmei et al. [39] and Qiusheng et al. [40] used Cyclone (version not specified) by Leica
443 Geosystems to model the 3D layout of as-built pipelines from a 3D point cloud. In the study by
444 Chunmei et al. [39], the noise-removal function was used to eliminate some noise prior to the
445 modeling. Then users manually segmented the complicated pipeline network into individual
446 pipelines and used the cylinder-fitting function to model the layout of the various segments,
447 which could contain both straight and bent parts. Chunmei et al. [39] remarked that with their
448 method, prior knowledge (design data) is required if some parts of the as-built pipelines are
449 missing in the acquired 3D point clouds on account of self-occlusion or occlusion by other
450 objects. In the study by Qiusheng et al. [40], users manually selected 3D point clouds
451 corresponding to the individual pipelines in a network and used the region-growing function to
452 determine the boundary of each pipeline. After the boundaries were found, the cylinder-fitting
453 function was used to model the pipeline layout.

454 Trimble RealWorks provides the EasyPipe tool for modeling of pipeline layout, which
455 extracts 3D points for cylindrical objects and fits cylinders to them. Then models of the elbows

456 can be aligned and connected to the models of the cylindrical pipes.

457 In addition to Cyclone, Leica Geosystems has released several plug-in tools for 3D layout of
458 as-built pipelines from 3D point clouds: Leica CloudWorx for AutoCAD Pro 5.0, Leica
459 CloudWorx for Revit version 1.0.2, and Leica CloudWorx for MicroStation 4.0. By using these
460 plug-in tools, it is now possible to import and process the 3D point clouds inside AutoCAD,
461 Revit, and MicroStation. There are several functions that are especially useful for 3D layout of
462 as-built pipelines, such as one that generates cylinders based on least-squares fitting from the
463 selected 3D point clouds and one that connects cylinders with elbows.

464 The leading 3D CAD vendors (Autodesk, Bentley, Aveva, and Intergraph) have also
465 developed software that enables the 3D layout of as-built pipelines from 3D point clouds. One
466 example of this is AutoCAD Plant 3D, which can be used with Kubit's PointSense Plant add-in
467 for AutoCAD (see Fig. 14(a)). PointSense Plant by Kubit provides several functions for pattern
468 recognition that can identify pipelines from 3D point clouds. Then users manually model the
469 layout of as-built pipelines by fitting CAD objects to the segmented 3D point clouds.

470 SmartPlant 3D by Intergraph has functionality similar to that of the combination of
471 AutoCAD Plant 3D and Kubit's PointSense Plant add-in for AutoCAD (see Fig. 14(b)).
472 SmartPlant 3D's fitting function automatically calculates the best fit for cylinders from 3D point
473 clouds that have been selected manually. In addition, the cylinders can be placed manually, and
474 then the software calculates the orientation and extent of the cylinders by evaluating the point
475 clouds.

476 Fig. 14.

477 The aforementioned programs are user-friendly tools for the 3D layout of as-built pipelines,
478 as they provide several functions for manipulation of 3D point clouds acquired by laser scanners

479 and have the capability to create and modify pipeline models [39]. However, large 3D point
480 clouds are not easily managed and processed, so they need to be divided into several smaller
481 parts. Recently, Autodesk ReCap provided an efficient mechanism for managing such large 3D
482 point clouds by using different file formats (e.g., RCS and RCP).

483 The recently developed EdgeWise Plant™ (version 4.0) provides a function that
484 automatically detects the straight sections of a pipeline and fits cylinders to them (see Fig. 15).
485 This software is a powerful engine that can handle large 3D point clouds. However, its use is
486 limited to only the straight sections of a pipeline, whereas an entire pipeline can include other
487 forms of pipe. Hence, significant user intervention is required, both to identify pipes that are not
488 straight and to uncover any undetected straight pipes that need to be modeled.

489 Fig. 15.

490 The aforementioned reconstruction programs are in common use but are not fully automated,
491 as they rely on substantial operator input/intervention to model the 3D layout of an as-built
492 pipeline [44]. Although some programs provide semi-automated functions such as region
493 growing, the user still has to mark certain portions of pipeline manually, to indicate that they are
494 to be modeled [45,46]. To exploit the potential advantages of obtaining a 3D layout of an as-built
495 pipeline, it is necessary to accurately measure the dimensions of installed pipelines and
496 efficiently model them [35]. However, marking portions of individual pipelines in an enormous
497 and complicated set of 3D point clouds is very time consuming and labor intensive. Furthermore,
498 it is difficult to identify individual pipelines from a 3D point cloud, because pipelines of various
499 radii, lengths, and orientations can be installed in complex configurations. In a study conducted
500 by Fumarola and Poelman [47], it took 15 days to model the layout of 2,602 objects (planes and
501 cylinders) by a semi-automatic layout process. In a study by Sanders [48] of a Chevron

502 installation that was being revamped, 40% of the total cost of modeling of the layout was spent
503 on data-processing labor [48].

504

505 **4. Conclusions and Recommendations**

506 4.1. Summary and Discussion

507 Over the last decade, efficient acquisition of 3D as-built data from civil infrastructure based
508 on photo/video-grammetry and terrestrial laser-scan surveys has been a matter of increasing
509 interest in the civil engineering field. Researchers and practitioners alike have engaged in efforts
510 to develop semi- or fully automatic data processing methods and technologies to assist in and
511 support the tasks of production monitoring and facility management.

512 These efforts demonstrated that such tasks can be automated to some degree. In particular,
513 several methods for dimensional compliance or progress tracking have been demonstrated to be
514 applicable to work on permanent structural components, such as frames of buildings [1–
515 3,19,4,27,5–8], brick façades [27], and MEP systems [9,10,20]. Recently, the study by Turkan et
516 al. [11] demonstrated the applicability of their method to secondary components (e.g., rebar) and
517 temporary components (e.g., formwork, scaffolding, and shoring) of steel-reinforced concrete
518 structures. Such advancements demonstrate the feasibility of using automated modeling to track
519 the accuracy of progress on a construction site.

520 In addition, several methods have been proposed for automated layout of built assets. Most
521 of these efforts have targeted as-built pipelines in MEP systems in industrial facilities and
522 buildings [12–16] and in indoor structures in low-rise buildings [38]. These research efforts have
523 improved the level of automation that can be applied in the layout of certain parts of an entire
524 facility and have expanded the types of parts that can be modeled in an automated manner.

525 The reviews in Sections 2 and 3 show the extent and emergence of survey technologies that
526 aim to improve and enhance the accuracy and ease of acquiring and communicating as-built
527 information. While these technologies have already been widely studied by architecture,
528 engineering, construction, and facility management (AEC/FM) researchers and practitioners,
529 further developments in the performance of such technologies are needed—particularly in regard
530 to their robustness across different kinds of environments—for them to become widely accepted
531 and used in the civil engineering field. Some of the existing challenges and the likelihood that
532 future research and development will succeed in meeting them are discussed in what follows.

533 First, combinations of different surveying technologies are expected to overcome the
534 drawbacks of individual methods. The so-called hybrid approach combines data acquired from
535 photo/video-grammetry and terrestrial laser-scan surveys, which has the potential for enhancing
536 the fidelity of the measurements and hence the overall accuracy of the 3D reconstruction. Few
537 research studies have used the hybrid approach for acquisition of as-built data on civil
538 infrastructure (e.g., [49–52]). However, the feasibility of this approach in applications such as
539 production monitoring and automated layout merits investigation.

540 Second, the data acquired by photogrammetry and terrestrial laser-scan surveys can be
541 combined with data obtained by other identification and localization technologies, including
542 radio frequency identification (RFID) [53–55], ultra-wide band [56,57], near-field
543 communication [58,59], wireless local/personal area network [60], and information and
544 communication technologies such as building information modeling and mobile technologies
545 [61–63]. For example, Valero et al. [63] proposed combining terrestrial laser scanning with RFID
546 for the purpose of constructing basic 3D semantic models of inhabited interiors. As is well
547 known, the segmentation and identification of objects from a 3D point cloud acquired by

548 terrestrial laser scanning is a challenging task. In their study, Valero et al. [63] applied RFID tags
549 to various objects and found that they served as a valuable aid in the identification and
550 positioning of those items. Therefore, the fusion of photogrammetry and terrestrial laser-scan
551 surveys with data acquired by other identification and localization technologies holds promise as
552 a source of improvements in the applications discussed above.

553 Third, the structural components of buildings that have been targeted for automation of
554 production monitoring thus far are frames of buildings, brick façades, and MEP systems, but
555 automation of production monitoring of other components (substructure, foundation, external
556 envelope, roof, internal complementary elements, finishes, and so on) needs to be demonstrated
557 as well. In addition, despite the fact that significant progress has been made in the automation of
558 data acquisition and processing, further progress is needed, particularly for the complete
559 automated layout of built assets. Advancements in this area should be extended to even larger
560 classes of structures and their constituent parts, and may benefit from further development of as-
561 built data acquisition methods.

562 Fourth, in order for production monitoring and automated layout methods and technologies
563 to become established practice in the civil engineering field, there must be significant
564 improvements in the methods used for processing of the huge amounts of 3D as-built data
565 acquired from civil infrastructure. Most civil infrastructure is large scale and complex, hence
566 data must be acquired at dozens or hundreds of locations, and the data are usually vast, noisy,
567 and unstructured. Thus research is needed in order to realize advancements in the speed of data
568 acquisition, the accuracy of the models generated, and the degree of detail provided in the
569 models.

570 Fifth, recent work has shown that recognition techniques based on scan-versus-BIM
571 frameworks indeed enable the recognition of 3D objects in 3D as-built data acquired by
572 terrestrial laser scanning, leading to progress in areas such as dimensional quality control
573 [2,19,4,6–8,20]. Similar approaches use 3D as-built data reconstructed through photogrammetry-
574 based surveys [3,27,5]. However, the authors argue that methods based on scan-versus-BIM
575 frameworks have not yet achieved a high level of effectiveness, and that the use of scan-to-BIM
576 frameworks for generation of as-built 3D BIM models from 3D point clouds could contribute to
577 overcoming this limitation.

578 Finally, the practicality of the methods and technologies used in the generation of models of
579 3D as-built data should be ensured. As-built data acquired from different types of civil
580 infrastructure may have different characteristics in terms of complexity, noise level, and
581 completeness. Hence, it is imperative that such differences in characteristics be taken into
582 account—and that, if need be, the methods and technologies used for specific civil engineering
583 projects be tailored to those projects.

584

585 4.2. Concluding Remarks and Future Directions

586 Academic research and industrial efforts in automation of analyzing of 3D as-built data have
587 laid the cornerstone for future research and development, especially in terms of advancements in
588 the efficiency of construction tasks such as production monitoring and automated layout. It is
589 expected that such tasks can be more fully automated through academia–industry collaboration.
590 It is also expected that future efforts will contribute to the realization of the automation of
591 additional construction tasks, such as dismantling, renovation, and revision of existing civil
592 infrastructure.

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