

# Planning for Terrestrial Laser Scanning in Construction: A Review

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## **Abstract**

Terrestrial Laser Scanning (TLS) is an efficient and reliable method for collecting point clouds which have a range of applications in the Architecture, Engineering and Construction (AEC) domain. To ensure that the acquired point clouds are suitable to any given application, data collection must guarantee that all scanning targets are acquired with the specified data quality, and within time limits. Efficiency of data collection is important to reduce jobsite activity disruptions. Effective and efficient laser scanning data collection can be achieved through a prior planning optimisation process, which can be called Planning for Scanning (P4S). In the construction domain, the P4S problem has attracted increasing interest from the research community and a number of approaches have been proposed.

This manuscript presents a systematic review of prior P4S works in the AEC domain and presents a categorisation of point cloud data quality criteria. The review starts with the identification and grouping in three categories of the point cloud data quality criteria that are commonly considered as constraints to the P4S problem. The three categories of data quality criteria include 1) completeness, 2) accuracy and spatial resolution, and 3) ‘registrability’. The prior P4S works are then reviewed in a structured way by contrasting them in the way they formulate the P4S optimisation problem: the type of inputs they assume (model and possible scanning locations), the constraints they consider, and the algorithm they utilise to solve the optimi-

sation problem. This work makes two contributions: (1) it identifies gaps in knowledge that require further research such as the need to establish a fully automated scan plan which provides the optimum coverage in construction domain specifically for indoor construction; and (2) it provides a framework — principally a set of criteria — for others to compare new P4S methods against the existing state of the art in the field. This will not only be valuable for young researchers who want to start research in solving the P4S problem, but also for the ones already working in the domain to rethink the problem from different perspectives.

*Keywords:* Laser Scanning, Network design, Planning for Scanning, Data Quality, Level of Accuracy (LOA), Level of Detail (LOD), Level of Completeness (LOC), Computer-Aided Design (CAD), Building Information Modelling (BIM), Point Cloud, Optimisation

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## 1. Introduction

### 1.1. Reality Capture in Construction

Different reality capture technologies have been proposed for application in the construction domain, especially with the upsurge in the application of Building Information Modelling (BIM) in recent years. These applications vary from monitoring and managing construction projects to preparing as-built/as-is documentations, and more. Akinici et al. [1] are among the pioneers who suggested application of sensor systems in construction projects for active quality control and defect detection. They linked inefficiency of quality controls on construction sites to late detection of construction defects, and discussed the importance of efficient inspection of construction sites. They also proposed three-dimensional (3D) laser scanning as an essential data collection technology to perform active project control through frequent, complete, and accurate dimensional and visual assessment of as-built conditions at construction sites [1].

3D laser scanner is one of the technologies used to create detailed and accurate indoor and outdoor building models. Terrestrial Laser Scanning (TLS) is a ground-based 3D reality capture technology that produces dense 3D point clouds of its surrounding by utilising time-of-flight or phase-based distance measurement principles. Point clouds come with additional data like colour or intensity information per point or support images, which helps the user to better visualise the raw point cloud. TLS' single-point accuracy is at

23 the *mm* level and below, and the technology can measure millions of points in  
24 a matter of minutes. This makes TLS suitable for a wide range of applications  
25 in the Architectural Engineering Construction and Facilities Management  
26 (AEC/FM) sector, such as creating as-built/as-is documentation, monitoring  
27 construction activities, dimensional quality control, asset monitoring, reverse  
28 engineering, cultural heritage recording, and urban planning [1, 2, 3, 4, 5,  
29 6, 7, 8, 9]. Although mobile laser scanning (MLS) is also now relatively  
30 common for outdoor point cloud acquisition for construction purposes, there  
31 are still some challenges (e.g. GPS limitations) that make it less practical for  
32 indoor applications [5]. Application of Simultaneous Location and Mapping  
33 (SLAM) is investigated as a substitute to GNSS (Global Navigation Satellite  
34 System) for indoor MLS, but the result remains inadequate for obtaining high  
35 scanning accuracy [10]. While these technologies and their performances are  
36 improving rapidly, this review only focuses on ground-based TLS.

37 Photogrammetry is an alternative approach to the production of 3D point  
38 clouds for some similar applications [11, 12, 13, 14, 15]. It has advantages  
39 over TLS in terms of portability and price; but it also presents a number of  
40 limitations in terms of accuracy, data completeness, scaling, robustness to  
41 various material textures, etc.

42 The network of data acquisition for any reality capture device (TLS, pho-  
43 togrammetry, etc.) can be optimally arranged to best capture the scanning  
44 targets given constraints (requirements) in quality, time, cost, etc. This is  
45 generally called network design and in the case of scanning, we refer to it  
46 as Planning for Scanning (P4S). In Geodesy, geodetic network design com-  
47 bines general concepts of mathematical optimisation to the design concept.  
48 The design of geodetic networks is dated back to 1974 [16]. The network  
49 design problem in photogrammetry is also relatively well-addressed in the  
50 literature [17, 18]. This review paper focuses on 3D point clouds acquired  
51 by terrestrial laser scanners only, and investigates the works that have been  
52 published on P4S to date. Although the main focus has been given to TLS  
53 alone, the findings and the framework will benefit other types of point cloud  
54 generating devices, as the problem statement is broad and can be adjusted  
55 to different hardware associated limits. The comparison approach presented  
56 for TLS would also be useful in any other novel application of scanners (e.g  
57 aerial scan or scanner on robots, mobile laser scanning (MLS)), however the  
58 corresponding criteria for evaluation and the device limitations need to be  
59 identified for any device first.

## 60 1.2. Planning for Scanning (P4S)

61 Some domain experts formalised the P4S problem as the problem of find-  
62 ing the minimum number of predefined view points that give a full coverage  
63 of the scanning targets while satisfying the data quality requirements. This  
64 problem is similar to Art Gallery problem for monitoring with minimum cam-  
65 eras [19, 20], and the Next Best View (NBV) problem for robotic navigation  
66 in unknown environments [21, 22].

67 The algorithms to solve Art Gallery and robotic navigation problems  
68 focus on the line-of-sight factor that influences the coverage of the collected  
69 3D point clouds, with limited consideration for other factors [22]. In contrast,  
70 in the context of P4S, other parameters that affect data quality must be  
71 taken into account in addition to visibility, such as single point incident angle  
72 and range [23, 24]. Interestingly, only González-Baños and Latombe [25]  
73 applied these constraints as well as visibility in their randomized Art-Gallery  
74 approach to find the best locations for (robot- mounted) sensor placement.

75 Current practice of laser scanning data acquisition relies on human intu-  
76 ition for planning the scanning locations and acquisition parameter settings  
77 at each selected location. Yet, construction sites are complex and constantly  
78 changing environments, which makes it impossible, even for experienced sur-  
79 veyors, to guarantee that the acquired point clouds fully cover all scanning  
80 targets with the specified levels of quality [5, 26, 27, 28]. The complexity  
81 is further increased by the fact that scanners present varying technical per-  
82 formances, and all scanning targets (e.g. objects) across a site may have  
83 differing data quality requirements.

84 Naturally, the risk of incomplete and insufficiently accurate data can be  
85 reduced by increasing the amount of scanning done on site (i.e. increasing  
86 the number of scanning locations, and/or changing the scanner settings);  
87 But increasing the number of scans and/or scanner settings can introduce  
88 redundancies in the data and result in inefficiencies. Point cloud data are no-  
89 toriously large and redundancies make data storage and management a chal-  
90 lenge. Moreover, collecting more data always needs more time and labour,  
91 and thus can be costly [27, 28] and result in further site disruptions. There  
92 is, therefore, a need to optimise scanning operations to achieve the required  
93 data completeness and quality while minimising site interferences and data  
94 quantity. Figure 1 graphically represents the P4S optimisation elements.

95 P4S is commonly done manually, before site visit using 2D sketches of  
96 the environment or 2D CAD models when available. On-site visual investi-  
97 gation can be used to complement this process. However, it has been shown

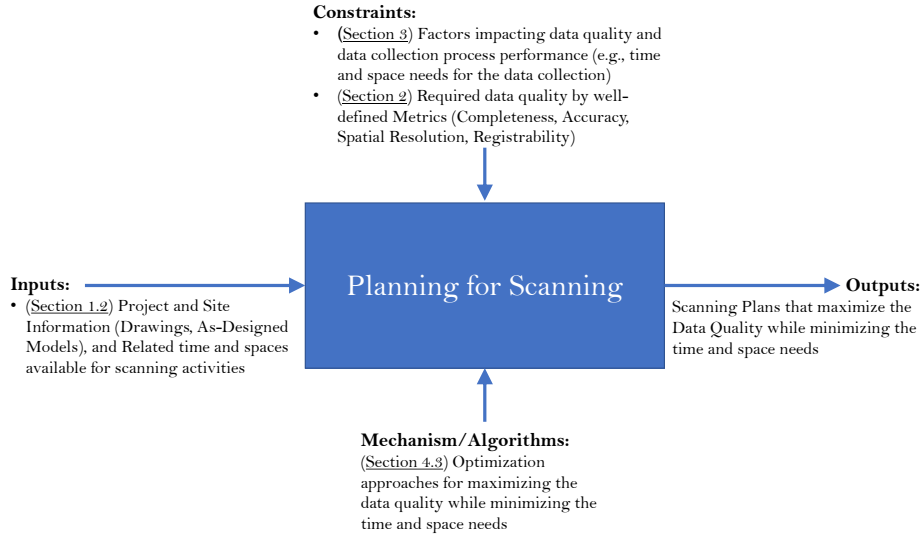


Figure 1: P4S Optimisation Elements.

98 that such manual approaches based on intuition and experience often lead  
 99 to sub-optimal plans. For example, Zhang et al. [27] asked two experienced  
 100 surveyors to generate plans to scan target points on the facades of a build-  
 101 ing with specified point accuracy and detail. The results showed that (1)  
 102 the plans were only able to capture 60% to 75% of all target points with  
 103 the specified quality, and (2) the additional scans subsequently required to  
 104 capture all remaining target points with the specified quality increased the  
 105 overall scanning time by 60 to 80%. Such findings motivate the development  
 106 of (semi-)automated P4S approaches, and recent years have indeed seen a  
 107 growing number of research publications in this area. These can be cate-  
 108 gorised as:

- 109 • *model-based* approaches where existing information about the environ-  
 110 ment to be scanned is provided, e.g. 2D (CAD) floor plans [29, 30, 31,  
 111 32]. These approaches are typically employed for offline P4S; or
- 112 • *non-model-based* approaches, generally used for online planning. These  
 113 approaches are commonly considered within the robotics field of Sim-  
 114 ultaneous Localisation And Mapping (SLAM). In that context, the  
 115 terms *view planning* or *next best view (NBV)* are commonly employed  
 116 [22, 33, 34, 35, 36, 37, 38, 39].

117 Within the construction context, the focus has been primarily on developing  
118 offline model-based solutions. This is motivated by the wide use of CAD, or  
119 even the ease of rapidly creating 2D floor plan sketches of sites to be scanned.  
120 However, the recent decade has seen Building Information Modelling (BIM)  
121 becoming increasingly employed in the AEC/FM sector to integrate design,  
122 construction and management processes of building projects [40]. Some gov-  
123 ernments, such as the UK government, are even mandating BIM on public  
124 projects [41]. BIM processes are typically based upon the production of  
125 (semantically-rich) 3D models, and has been shown that the integration of  
126 TLS and BIM can hugely improve the delivery of as-built documentation,  
127 construction quality control, progress control, etc. [42, 1]. These applica-  
128 tions can be categorised as ‘Scan-to-BIM’ (generating a 3D BIM model from  
129 a reality point cloud) [43, 44, 42, 45] or ‘Scan-vs-BIM’ (comparing a reality  
130 point cloud with a 3D BIM model) [6, 46, 47]. For example, Turkan et al.  
131 [3] suggested a 4D progress tracking system by combining point cloud -based  
132 3D object recognition with schedule information. Note that they also high-  
133 lighted the need for an effective P4S, because the results of their case study  
134 showed that incomplete scan data has a negative impact on the proposed 4D  
135 progress tracking system.

136 The advent of 3D modelling and BIM indicates that the availability of  
137 such digital models can help generate 2D (CAD) floor plans that could be  
138 used to support P4S. More interestingly, such digital models could replace  
139 2D (CAD) plans, so that complete 3D geometric and semantic information  
140 contained in those models could be leveraged to achieve more efficient and  
141 effective P4S.

142 In fact, a number of works have already been conducted to solve the P4S  
143 problem given 3D models of the target scene [27, 48, 49, 50, 51].

144 Given the progress made in the last decade in the area of P4S, this paper  
145 aims to conduct a systematic review of prior P4S works in the construction  
146 domain with the aim to synthesis the progress made to date and identify  
147 areas requiring further research. Section 2 first reviews the criteria that are  
148 commonly considered to assess point cloud data quality, and that should  
149 thus be taken into account by P4S algorithms. It is proposed to group the  
150 criteria in three categories reflecting their general importance in the P4S  
151 problem. Section 3 subsequently explores the various parameters impacting  
152 those criteria, such as time and space constraints, and various data collection  
153 parameters (e.g., incidental angle, range). Section 4 reviews prior P4S works

154 in construction, analysing them in the light of their capacity to account for  
155 the identified data quality performance criteria. Section 5 complements this  
156 analysis with a short discussion of P4S works in the manufacturing sector.  
157 Section 6 summarises the review with a discussion of the main challenges and  
158 gaps to be addressed moving forward.

159 This work makes two contributions: (1) it identifies knowledge gaps that  
160 needs further research, such as the lack of systematic investigation into geode-  
161 tic network setup in the construction domain, and the lack of compre-  
162 hensive characterisation of scan planning algorithms to reveal trade-offs among  
163 data quality, time, and space constraints; and (2) it provides a criteria-based  
164 comparison framework for others to compare new P4S methods against the  
165 existing state of the art in the field, giving them an overview of what needs  
166 to be sought in order to optimise P4S process.

## 167 2. Point Cloud Data Quality Criteria

168 Point clouds are increasingly acquired to generate semantically-rich 3D  
169 model of sites (i.e. BIM models) or to compare the as-is state they capture  
170 against some prior “as-design” state represented by a 3D (BIM) model or  
171 even prior point clouds. In all cases, the quality of the obtained data is  
172 important; hence the need to define point cloud data quality criteria. This  
173 paper proposes to group data quality metrics into *primary*, *secondary* and *ter-*  
174 *tiary* categories based on the priority of certain metrics in field applications.  
175 Normally, surveyors first emphasise the need for *coverage* or *completeness* of  
176 scanning targets in the field, and then consider the *accuracy* and *spatial res-*  
177 *olution* of data points covering those targets. Adequate *overlapping* between  
178 adjacent scans must also be achieved to enable reliable alignment of all scans  
179 into a global coordinate system. We refer to this *tertiary* criterion as ‘*regis-*  
180 *trability*’. The following sub-sections will present firstly the *primary* category  
181 related to the completeness of 3D data collected (Section 2.1), then the *sec-*  
182 *ondary* category about the accuracy and spatial resolution of the collected  
183 data (Section 2.2), and finally the *tertiary* category related to registrability  
184 of multiple scans collected (Section 2.3).

### 185 2.1. Primary Criteria - Completeness

186 The most critical, and therefore *primary* point cloud data quality criterion  
187 is arguably that all scanning targets are captured in the final point cloud. In  
188 other words, each scanning target should be scanned, or be ‘*visible*’, in at least

189 one of the scans making up the final point cloud. These *targets* can be points  
190 (e.g. corners of walls and windows), lines (e.g. slab or window boundary),  
191 or surfaces (e.g. a wall face, or the entire surface of an object). Most prior  
192 model-based P4S works implicitly consider such completeness criterion as a  
193 ‘hard’ constraint that all such features be fully captured [51, 52, 53].

194 However, it can be observed that it is often challenging to acquire en-  
195 tire lines or surfaces that are part of an object. Yet, acquiring a certain  
196 minimum portion or percentage of target surfaces may be sufficient for the  
197 intended purpose. For example, Son et al. [54] showed that the diameter of  
198 a cylindrical pipe can be accurately modelled as long as the points cover at  
199 least a third of its cross-section. Covering the whole cross-section is usually  
200 not necessary for deriving the radius of a cylinder. Rabbani et al. [55] also  
201 demonstrated that complete coverage is not required for modelling through  
202 their algorithm. Based on this observation, Biswas et al. [50] introduced a  
203 softer *Level of Completeness (LOC)* (or *Level of Coverage*) criterion, defined  
204 as: “the amount of surface of a scanned object of interest which is covered  
205 in the overall scan” [50]. Rebolj et al. [46], in their work on establishing  
206 point cloud quality specifications to successfully perform scan-vs-BIM pro-  
207 cesses (for object recognition), also mentioned the need for a surface coverage  
208 criterion that does not have to be set to 100%. Similarly, Heidari Mozaffar  
209 and Varshosaz [51] introduced the surface-based criterion ‘Lack of Coverage’,  
210 for which they also used the acronym ‘LoC’. ‘Lack of Coverage’ is defined  
211 as the ratio of surface (descretised as points) in the scan that are not visi-  
212 ble from the selected scanning locations over the total surfaces needed to be  
213 captured. With this description, a lower ‘Lack of Coverage’ figure close to  
214 %0 is desirable. Heidari Mozaffar and Varshosaz [51] employed this metric  
215 at a scene level only, while Biswas et al. [50] and Rebolj et al. [46] defined  
216 and applied LOC for each individual object of interest.

217 While LOC has been defined with focus on surfaces [50] we note that it  
218 is also applicable to lines, although this has never been considered in the  
219 literature.

## 220 2.2. Secondary Criteria - Accuracy and Spatial Resolution

221 According to scan data quality specifications developed by the U.S. Gen-  
222 eral Service Administration (GSA), there are currently two major criteria  
223 that a point cloud can be evaluated against [41, 56]:

- 224 • LOA (Level of Accuracy): tolerance of positioning accuracy of each  
225 individual point in 3D point cloud data. LOA is typically defined in



226 millimetre.

- 227 • LOD (Level of Detail or Level of Density): Minimum object size that  
228 can be extracted from the point clouds. LOD relates to *surface sam-*  
229 *pling*, i.e. how dense the scanned points are. LOD is thus typically  
230 defined as a distance (in millimetres) between neighbouring scanned  
231 points.

232 LOA and LOD are meaningful, only once targets have been acquired, i.e.  
233 if target completeness is achieved. For this reason, LOA and LOD can be  
234 categorised as *secondary* performance criteria.

235 Table 1 shows the four specification levels for LOA and LOD that the  
236 GSA has developed and that are selected depending on the intended use  
237 of the point clouds or the 3-D models derived from them [41]. Typically,  
238 for indoor applications (e.g. indoor layouts, HVAC systems), where smaller  
239 dimensions are involved, higher LOA/LOD is required. For outdoor appli-  
240 cations (e.g. outdoor building components, building facade), that deal with  
241 larger dimensions, lower LOA/LOD is desired [28].

<b>GSA Level</b>	<b>LOA (Tolerance) mm/inch</b>	<b>LOD (Data Density) (mm mm)/(inch inch)</b>
1	51/ 2	(152 152)/(6 6)
2	13/ 1/2	(25 25)/(1 1)
3	6/ 1/4	(13 13)/(1/2 1/2)
4	3/ 1/8	(13 13)/(1/2 1/2)

Table 1: Data quality requirements standardised by GSA.

242 While LOD can be assessed using the acquired survey data only, assess-  
243 ing LOA demands extra data obtained for a control network using another  
244 sensor with accuracy that should be an order of magnitude higher (e.g. to-  
245 tal station). This makes LOA a dependent measure that requires additional  
246 surveying work. Also, LOA will be calculated for only a limited number of  
247 points (the control network), thus it only provides a partial assessment of ac-  
248 curacy. These considerations make LOA a quality measure that is difficult to  
249 predetermine during P4S. LOA and LOD are applicable in both model-based  
250 and non-model-based P4S contexts.

251 Precision is another metric of data quality that is often considered in the  
252 literature, often instead of LOA. This is discussed in more detail in Section  
253 3.2.1.

254 Finally, in the case of model-based P4S to support scan-vs-BIM applica-  
255 tions, Rebolj et al. [46] proposed to use another point cloud quality measure,  
256 *Level of Scatter (LOS)*. LOS estimates the percentage of points that are likely  
257 to be mistakenly matched with other objects in close proximity to the object  
258 they are actually acquired from. However, as the authors acknowledge, LOS  
259 is not an independent parameter as it depends on: (1) the matching distance  
260 threshold employed in the Scan-vs-BIM process; and (2) point accuracy (i.e.  
261 LOA). Arguably, the latter relation makes LOS redundant with LOA.

### 262 2.3. Tertiary Criteria - 'Registrability'

263 TLS is limited to capture only the points with a clear line of sight, there-  
264 fore capturing all scanning targets requires performing multiple scans from  
265 different view points. The acquired scans are then aligned into a unified  
266 point cloud, through a process called registration. The number of scans and  
267 the quality of the scanned data play a significant role in the registration out-  
268 come. Insufficient data (quantity and quality wise) will not provide enough  
269 overlap and make registration impossible. In contrast, too many scans cost a  
270 significant, yet unnecessary amount of time. So, there is a trade-off between  
271 the number of scans and the computational efforts [23].

272 Point cloud registration can be conducted in one or two stages: coarse  
273 registration, possibly followed by fine registration [57]. In coarse registration,  
274 matching 3D features of the two scans are aligned. The most common method  
275 is using artificial targets inserted in the scene in such ways that they can  
276 be scanned from two or more scanning locations [58]. However, having to  
277 insert such targets increases the scanning time. Robust algorithms have also  
278 been produced that can extract and match discriminatory features (visual  
279 or geometric) that are naturally present in scenes, and therefore present in  
280 scans. This removes the need for manually placing artificial targets in the  
281 scene, which can significantly shorten data acquisition time on site. However,  
282 such feature-based registration also requires ensuring that matching features  
283 do exist among two or more scans (at least three targets need to be matched  
284 between two scans so they can be co-registered) [58].

285 Fine registration follows a coarse registration and results in finding a more  
286 optimal solution by using more data from the scans than the few features  
287 commonly used for coarse registration. Solutions for fine registration are  
288 commonly based on the Iterative Closest Point (ICP) algorithm [59, 60, 61]  
289 that iteratively estimates the rigid transformation that aligns point from

290 one point cloud with the nearest points in the second point cloud. Fine  
291 registration is not commonly employed in the construction domain.

292 In the context of P4S, the main challenge in terms of registrability is  
293 ensuring that matching, discriminatory features (ideally natural features e.g.  
294 wall's or ceiling's corners) are present in pairs of scans. This ensures all scans  
295 can be collectively and robustly aligned in the same coordinate system. But,  
296 it can also be argued that, given the fact that modern laser scanners can  
297 produce individual scans that cover large FOV ( $360^0$   $290^0$ ) [62, 63], and  
298 assuming that successive scanning locations are not excessively far from each  
299 other (which is commonly the case), then scan overlap is in fact highly likely  
300 to be present between the two respective scans, as illustrated in Figure 5.

301 For construction site progress monitoring, frequently acquired point clouds  
302 need to be compared against each other [64]. The point clouds are co-  
303 registered with the BIM. Any co-registration error results in wrong deviation  
304 detection (i.e. false progress monitoring). A model-based strategy, where the  
305 point clouds are co-registered against an existing as-planned model, could re-  
306 sult in misalignment because of the potential deviations between as-planned  
307 and as-built models. To avoid inaccuracy direct georeferencing is proposed  
308 in the literature [65, 64].

309 Another issue which makes registration a critical step in P4S is the fact  
310 that registration error contributes to final point cloud accuracy (controlled  
311 by the LOA specification). Registration error is commonly of the order of a  
312 few millimetres. This is similar even often higher than single point scanning  
313 accuracy, which implies that registration error can impact LOA performance  
314 just as much as, if not more than, single point accuracy.

### 315 **3. Parameters Impacting Data Quality Criteria**

316 We now investigate the parameters that influence the point cloud quality  
317 criteria presented above. Section 3.1 below reviews parameters that influ-  
318 ence point visibility, or 'scannability', as well as LOC. Section 3.2 introduces  
319 parameters influencing point accuracy (LOA), precision, and density (LOD)  
320 for objects captured in point clouds. Parameters impacting 'registrability'  
321 are discussed in Section 3.3.

#### 322 *3.1. Parameters Impacting Target Visibility and LOC*

323 A point in the scene is considered visible (or 'scannable') if it is within  
324 scanning distance and without occlusion from at least one selected scanning

325 location. There are three parameters that influence point visibility (see also  
326 Figure 2):

- 327 • Line of Sight: Only points with direct line of sight from the scanning  
328 location can be acquired.
- 329 • Depth of Field (DOF): Only points within the minimum and maximum  
330 scanning distances of the scanner can be acquired. DOF varies for  
331 different types of scanners.
- 332 • Field of View (FOV): Only points within the vertical and horizontal  
333 angle ranges of the scanner can be acquired. These ranges result from  
334 each scanner's physical and mechanical characteristics. Typical modern  
335 laser scanners (e.g. Leica ScanStation P30/P40 and FARO<sup>3D</sup> Focus  
336 X330) can cover  $360^{\circ}$  horizontally and around  $290^{\circ}$  vertically, i.e. close  
337 to an entire sphere with only a small invisibility cone right below the  
338 scanner [28, 62, 63].

339 If a point complies with the three constraints above, it is visible from the  
340 given scanning location. The LOC criterion generalises the visibility criterion  
341 and is thus affected by the same parameters.

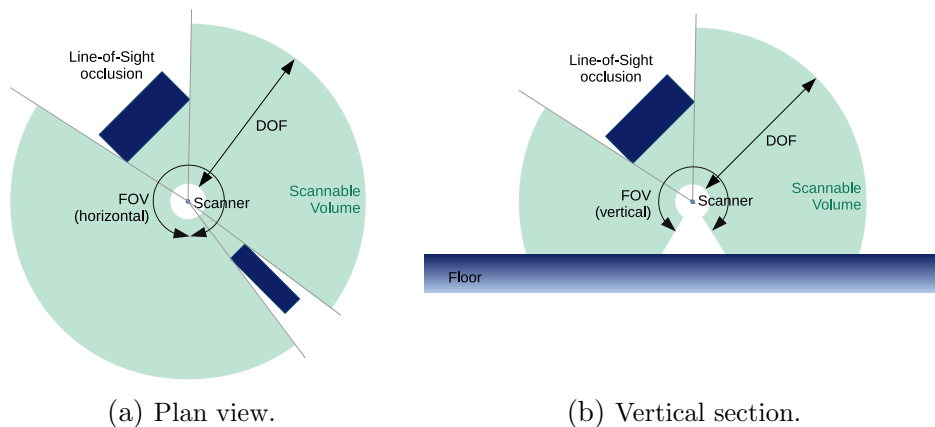


Figure 2: Parameters impacting target visibility: line of sight; depth of field (DOF) and field of view (FOV).

### 342 3.2. Parameters Impacting Point Data Quality

343 Scanning accuracy (LOA), precision, and detail (LOD) are affected by  
344 parameters such as: instrument technical capability and calibration, en-  
345 vironmental conditions, object properties (e.g. surface roughness, surface  
346 reflectance, surface colour), edge effect, scanner settings (i.e. angular reso-  
347 lution and number of measurements per point) and scanning geometry (i.e.  
348 scanning location) [66, 67, 68, 69].

#### 349 3.2.1. LOA and Precision

350 LOA is affected by instrument technical capability and calibration, at-  
351 mospheric conditions, object properties, scanning geometry and registration  
352 quality [70, 66, 71, 72, 73, 74]. Among those, scanning geometry relates  
353 to the location of the scanner, which is possibly the parameter most easily  
354 controllable by the surveyor after instrument calibration. Scanner location  
355 impacts the incidence angle ( $\alpha$ ) and range ( $\rho$ ) at which each individual point  
356 is scanned, that both have been found to have significant impact on single  
357 point scanning accuracy and precision [75].

358 There are two components for error in laser scanner instrument measure-  
359 ments: systematic error and random error. Single point scanning accuracy,  
360 as specified by manufacturers, identifies the systematic error specific to each  
361 laser scanner and is typically reported without regard to any changing con-  
362 dition either in scanners hardware [76], geometry, atmospheric condition, or  
363 object properties. In addition to systematic error the other error component,  
364 measurements random error (i.e. precision), also impacts the final 3D point  
365 cloud quality depending on scanning geometry. To model how the scanning  
366 geometry affects the scanning measurements, Soudarissanane et al. [24] pre-  
367 sented an approach mainly focused on incidence angle ( $\alpha$ ) and range ( $\rho$ ), as  
368 the main parameters affecting the signal to noise ratio (SNR) of the measure-  
369 ments. Soudarissanane et al. [24] shows that higher incident angles ( $\alpha > 70^\circ$ )  
370 and longer ranges to the surface result in less precise measurements. The re-  
371 sult of Soudarissanane et al.'s work has been applied in most subsequent  
372 researches and conditions on incident angle and range are commonly con-  
373 sidered as principal criteria for achieving specified single point accuracy and  
374 precision.

375 The relationship between precision, incidence angle ( $\alpha$ ) and range ( $\rho$ ), as  
376 well as the wider set of parameters impacting precision are often investigated  
377 individually [77, 78, 23]. Nonetheless, some researchers have attempted to  
378 provide some different insight into this matter. There are studies that focus

379 on random error component of TLS to predict the precision of TLS by estab-  
380 lishing the functional relation between the precision of TLS and its intensity  
381 values considering the effect of range, incidence angle, and surface properties  
382 [73, 79, 80, 81, 82]. Wujanz et al. [73] stated that, since most of the effects  
383 on precision imposed by different parameters cannot be explicitly modelled,  
384 those approaches that consider various effects separately are not practical.  
385 Soudarissanane and Lindenbergh [23] related the precision of the laser scan-  
386 ner measurements to the quality of the received signal. Zámečníková et al.  
387 [78] also took the same approach and considered signal strength in laser scan-  
388 ner error modelling. Kavulya et al. [83] investigated the effect of object colour  
389 and texture on point cloud quality. Although Kavulya et al.’s experiment is  
390 limited in scope, their results suggest that for objects with low laser return  
391 intensity surfaces (e.g. red-painted steel) quality rapidly deteriorates with  
392 range. On the other hand, the incidence angle (up to  $70^0$ ) does not seem to  
393 significantly influence point cloud precision. This latter conclusion is similar  
394 to that in [66] (see Figure 3). Finally, Shen et al. [75] studied how modelling  
395 accuracy of cylinders is impacted by range, resolution, surface reflectance,  
396 shape curvature (i.e. cylinder radius, temperature, time of day (i.e. night-  
397 time or daytime), dew point’ and relative humidity. Their results show that  
398 the top five variables impacting modelling accuracy are distance, resolution,  
399 colour, intensity, and surface curvature. Their comparison of different error  
400 models as well as their limited (albeit interesting) experimental setup also  
401 confirm the difficulty to develop reliable general error models.

402 Among all of the studies mentioned above, most of the reviewed studies in  
403 table 2 referred to Soudarissanane et al.’s approach and considered a threshold  
404 on incident angle in order to assure the LOA they seek to achieve.

405 Soudarissanane et al. [66] studied the influences of  $\alpha$  and  $\rho$  on single point  
406 precision (for a given scanner while keeping the other parameters constant),  
407 presenting the result in two separate graphs reproduced in Figure 3. These  
408 graphs can serve as baseline for estimating scanning quality results for a  
409 given plan. Although the results cannot be fully generalised (because they  
410 are obtained with a specific scanner and a limited experimental setup), they  
411 have been used to justify rejecting any scanning point for which  $\alpha > 70^0$ , as  
412 precision rapidly deteriorates beyond that angle.

413 The effects of incident angle, range, as well as object colour on point  
414 cloud quality have also been investigated in the manufacturing context for  
415 part inspection [84]. However, such scanning activities employ different types  
416 of scanners (e.g. line scanners mounted on robotic arm) and are conducted in

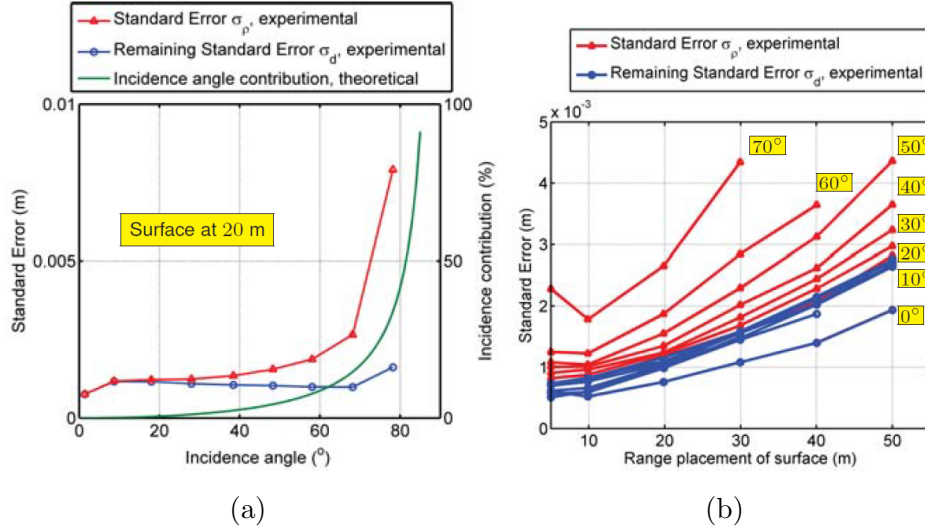


Figure 3: Measurement precision with respect to (a) the incidence angle of the surface and (b) the range placement of the surface. In both figure, the remaining standard error  $\sigma_d$  is obtained after removal of the incidence angle effect. (Reproduced with permission from [66]).

417 controlled environments and at much shorter distances (e.g. 1m) than those  
 418 experienced in the construction domain. Consequently, those results cannot  
 419 be realistically applied nor extrapolated to the construction domain.

### 420 3.2.2. LOD

421 LOD can be specified by a measure called surface sampling distance ( $s$ )  
 422 [28], which is mainly affected by range ( $\rho$ ), angular resolution of the scanner  
 423 ( $\Delta$ ) and incidence angle ( $\alpha$ ), with the following formula [28] (see also Figure  
 424 4):

$$s = \frac{\rho \Delta}{\cos \rho \alpha} \quad (1)$$

425 If necessary, Equation (1) can be applied independently to obtain separate  
 426 vertical and horizontal sampling distances, using the decomposition of the  
 427 incidence angle into its corresponding horizontal and vertical components  
 428 (and the horizontal and vertical scanner resolutions, if they are not identical).

429 Lichti et al. [85, 86] showed that surface sampling is also effectively im-  
 430 pacted by the beamwidth, when the selected angular resolution is high, near-  
 431 ing the beam divergence angle. As a result, they introduced an alternative

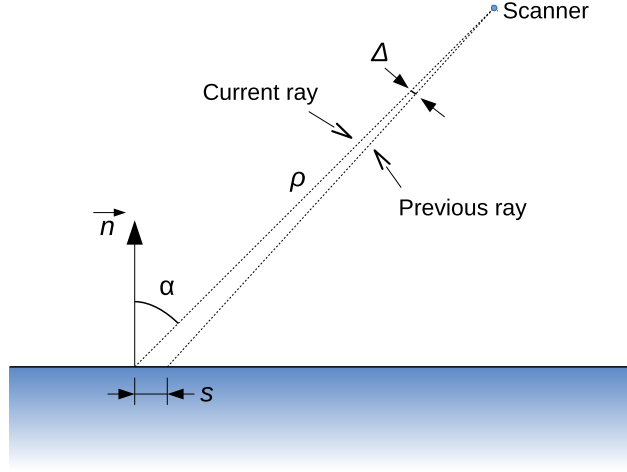


Figure 4: Parameters impacting surface sampling ( $s$ ), as captured in Equation (1): range ( $\rho$ ), angular resolution of the scanner ( $\Delta$ ) and incidence angle ( $\alpha$ ).

432 measure, the *E active Instantaneous Field of View (EIFOV)*, that considers  
 433 not only the scanner’s angular resolution but also the laser beamwidth.

### 434 3.3. Parameters Impacting ‘Registrability’

435 ‘Registrability’ requires that a sufficient number of artificial or natural  
 436 targets be visible in adjacent scans and be distributed as widely as possible  
 437 avoiding linear configurations [52].

438 Researchers have suggested that this requirement is essentially impacted  
 439 by the level of *overlap* between the scans — i.e. the percentage of data  
 440 in one scan that is also captured in another scan acquired from another  
 441 location [87, 88]. Ahn and Wohn [87] suggest to set such *Level of Overlap*  
 442 (*LOO*) specification to 20%, and Equation 2 shows a typical LOO constraint  
 443 formula presented by Chen et al. [88]. This equation guarantees that the line  
 444 segments  $LP_i$  (which represent target vertical building facades on a 2D CAD  
 445 model of the building to be scanned) acquired in each selected scan overlap  
 446 at least  $Overlap\%$  (e.g. 20%) with the line segments acquired in another scan  
 447 [88].

$$\min_i \max_j \frac{LP_i \times LP_j}{LP_i} \geq Overlap\% \quad (2)$$

448 It is important to highlight that these previous studies only consider  
 449 the overlap between the data acquired of the scanning *targets* (points, lines



450 or surfaces). This certainly guarantees a minimum *Overlap%* but it can  
 451 also be argued that, given the fact that modern laser scanners can produce  
 452 individual scans that cover large FOV ( $360^{\circ}$   $290^{\circ}$ ) [62, 63] with large DOF  
 453 ( $\geq 50m$ ), scan overlap is highly likely to be present between scans acquired  
 454 from successive scanning locations (as discussed earlier). Scan overlap is  
 455 thus not necessarily a critical performance criterion, and could in fact be  
 456 discarded. For this reason, ‘registrability’ can be categorised as a *tertiary*  
 457 criterion to assess P4S techniques. Notwithstanding, the error associated  
 458 with registration is a source of systematic error impacting overall point cloud  
 459 accuracy (as opposed to single point scanning accuracy), and it should be  
 460 considered when assessing LOA.

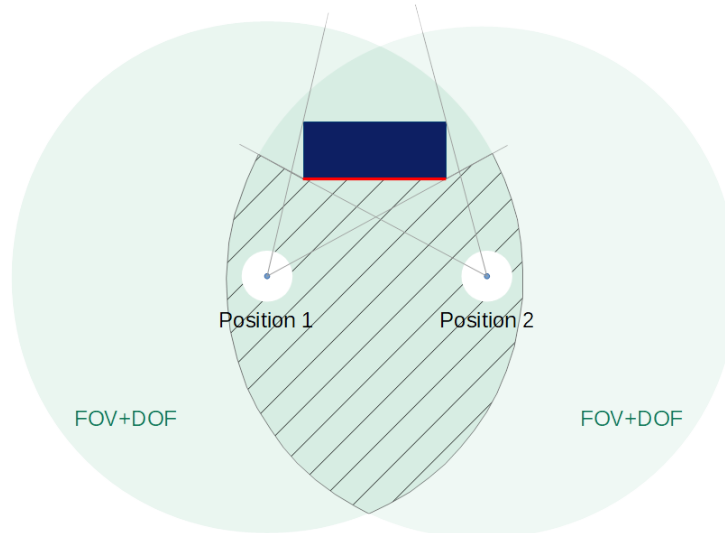


Figure 5: The overlap between the data acquired of the scanning targets (red line) typically constitutes only a part of the total overlap between two scans (hatched area).

#### 461 4. P4S in Construction

462 P4S methods are all formulated as optimisation problems, but with dif-  
 463 ferent characteristics of the three main elements of optimisation problems:  
 464 input, constraints, and optimisation model. This section reviews significant  
 465 prior P4S methods along these three dimensions with a focus on discussing  
 466 their strengths and limitations for application in the domain of construction

467 and built environment management. Section 5 then briefly reflects on works  
468 published in the manufacturing domain.

469 Table 2 lists those prior works and summarises the key characteristics of  
470 prior model-based P4S approaches for application in the built environment.  
471 The characteristics of P4S methods are synthesised along three dimensions,  
472 as mentioned above:

- 473 • **Input:**
  - 474 – **Model:** whether the approach uses an existing 2D or 3D model  
475 of the facility as input to the process.
  - 476 – **Target:** whether the scanning target are points, lines or surfaces.
  - 477 – **Locations:** the set of possible scanning locations.
- 478 • **Constraints:**
  - 479 – **Primary:** whether the approach considers primary parameters,  
480 *Visibility*, or more generally *LOC*.
  - 481 – **Secondary:** whether the approach considers secondary parame-  
482 ters, *LOA*, *Precision* and *LOD*.
  - 483 – **Tertiary:** whether the approach considers tertiary parameters,  
484 here *Registrability*.
- 485 • **Optimisation:**
  - 486 – **Objective:** the objective function being optimised.
  - 487 – **Technique:** the optimisation techniques or algorithms employed  
488 to solve the scan planning optimisation problem.

489 Sections 4.1, 4.2 and 4.3 review generic P4S methods along the three  
490 dimensions mentioned above. Section 4.4 covers some P4S methods designed  
491 for specific application contexts, such as tunnel construction , inspection and  
492 as-built modelling of piping systems..

#### 493 4.1. *Input: Model, Target and Locations*

494 *Model.* Model-based P4S techniques assume that some existing *model* of the  
495 asset or environment to be scanned is available as input. That model can be  
496 in various forms. As shown in Table 2, a number of previous works assume  
497 that the model is a 2D plan view of the asset to be scanned. This assumption  
498 is generally justified by the fact that such models are widely available [33] or  
499 they can easily be generated from sources like aerial imagery [88].

500 While 2D plan views of buildings are commonly available, they can lack  
501 spatial details of the scanned asset or environment for properly guiding the  
502 P4S process. In comparison, 3D (BIM) models contain more details of the

503 scene to be scanned, and are increasingly available for applications where  
504 P4S can be model-based (e.g. dimensional quality control).

505 As shown in Table 2, five of the previous works assume a 3D model of  
506 the facility is available. The authors all justify this assumption based on  
507 the rapid development of 3D (BIM) models in that construction domain and  
508 their increasing availability for construction-related applications.

509 *Targets.* We observe that all reviewed methods that assume 2D (CAD) input  
510 model consider line targets. These methods attempt to plan the scanning  
511 of 3D surfaces in the built environment, but they only focus on walls, that  
512 they assume to be vertical 3D surfaces with limited height. While such  
513 assumptions limit the range of application, they enable reducing the 3D  
514 P4S problem to a 2D P4S problem where walls appear as line segments. In  
515 contrast, prior works that assume 3D input models consider targets as either  
516 points or surfaces. Only two of the studies [50, 51] have proposed a P4S  
517 method for surface targets within a 3D model. They however do this using  
518 two different approaches. Heidari Mozaffar and Varshosaz [51] discretised  
519 surfaces with homogeneously distributed point sets, reducing the problem of  
520 surface coverage to point coverage. In contrast, Biswas et al. [50] attempted  
521 to measure actual surface coverage. But, as will be shown later in section  
522 4.3, their optimisation approach in fact presents a significant flaw.

523 *Locations.* In all reviewed works scanning locations are generated on a 2D  
524 map, typically in the form of a regular 2D grid. Instead of regular 2D grids,  
525 two other studies [33, 88] employed methods that generate locations randomly  
526 in the 2D map and one study [52] presented a hierarchical planning strategy  
527 with an improved greedy method to produce an optimal 2D grid of scanning  
528 locations.

529 Notably, Latimer et al. [49] took a different approach. Instead of specific  
530 scanning locations, they solve the P4S problem by considering as input only  
531 the space of 2D *intersection sets* between the *con guration spaces* calculated  
532 for all scanning targets — a configuration space is the 2D space within which  
533 the target is visible and can be acquired with the desired data quality. If an  
534 intersection set is selected in the final scanning plan, then the optimal scan-  
535 ning location within that intersection set is calculated (see [49] for details).  
536 The number of intersection sets is likely to be smaller than the number of  
537 scanning locations in 2D grids typically employed by other works. There-  
538 fore, using intersection sets helps reduce the complexity of the optimisation  
539 problem.

540 Interestingly, no existing work has yet investigated scanning locations  
541 defined in 3D, including those studies that assume 3D models as inputs.

#### 542 4.2. Constraints: Primary, Secondary and Tertiary Data Quality Criteria

543 *Primary constraints.* First of all, it must be highlighted that point targets  
544 can only be acquired fully or not at all. While the visibility criterion applies  
545 to point targets, the more general LOC criterion is not applicable to them.

546 Looking at the works that consider line targets (in a 2D input model),  
547 they all define their optimisation frameworks with constraints demanding  
548 that all line segments be fully covered by the output scan plans (%100 line  
549 coverage), not just the end points or a portion of those lines. Although  
550 none of these works explicitly makes such suggestion, we note that their  
551 frameworks could easily be adapted to LOC constraints that require only a  
552 portion of lines to be covered.

553 Among all other reviewed model-based scan planning methods that use  
554 3D models as inputs [51, 50] considered surface targets and are thus the  
555 only ones that can meaningfully apply the LOC criterion. Heidari Mozaffar  
556 and Varshosaz [51] applied LOC at scene level, meaning their optimisation  
557 algorithm (Greedy algorithm; see Section 4.3) attempts to optimise surface  
558 coverage irrespective of which object the covered surface comes from. In  
559 contrast, Biswas et al. [50] set LOC requirements per object, which steers  
560 the algorithm to more rapidly ensure all objects get sufficient coverage.

561 *Secondary constraints.* Two main accuracy measures, i.e. single point scan-  
562 ning accuracy and registration accuracy, impact LOA. [27, 48, 49] and [51]  
563 all discarded the LOA criterion in their framework. A number of other scan  
564 planning approaches [18, 23, 33, 50, 52, 53, 87], and [89] took the LOA cri-  
565 terion into account indirectly using a simple model based on incidence angle  
566  $\alpha$  and/or range thresholding (e.g. discard any portion of a line segment for  
567 which  $\alpha \geq 70^\circ$ ). However, incidence angle is only one of the many factors that  
568 can significantly impact accuracy. Therefore these scan planning approaches  
569 only consider basic metrics for LOA (i.e. incident angle that indirectly affects  
570 measurement accuracy) which is referred by in Table 2. On the other hand  
571 some other studies consider more complete metrics for assessing LOA (where  
572 both measurement accuracy and registration accuracy are considered) and  
573 this can be identified through an (big) in Table 2.

574 Regarding LOD, [48] and [27] automatically defined ‘feasible spaces’ (i.e.  
575 constraints) within which each given feature can be acquired with the re-

576 quired LOD level. These feasible spaces are then fed into the optimisation  
577 engine to generate an optimal scanning plan. Chen et al. [88] utilised sweep-  
578 ray algorithm to satisfy LOD along with LOA as part of the visibility check on  
579 line targets. Notably, while [27, 48, 87] and [88] considered both range and in-  
580 cidence angle to indirectly assess LOD (which is shown by a (big) in LOD  
581 column in Table 2), the other studies follow a less robust approach by not  
582 explicitly considering LOD but by only considering either one [49, 51, 18, 50]  
583 or both of the range and the incidence angle [23, 88, 89, 52, 33, 53] as part  
584 of their visibility check. [49, 51] only considered range, while [18, 50] con-  
585 sidered incident angle only. This is recorded in the LOD column of Table 2  
586 with: an (small) when  $\alpha$  and  $\rho$  are both considered; an when only  $\alpha$  is  
587 considered; and an when only  $\rho$  is considered.

588 Surprisingly, Blaer and Allen [33] and Biswas et al. [50] do not seem to  
589 explicitly consider LOD. Yet, this could have easily been done using the same  
590 approach as [87, 88], since they already assessed incidence angles for the LOA  
591 criterion.

592 In a different approach, although not explicitly mentioned as LOD, Giorgini  
593 et al. [89] defined a 2D cell grid that includes a set of line segments represent-  
594 ing elements only above the scanner height, considered as the ground. They  
595 then estimate the number of horizontal scan lines in each cell and propose  
596 a new function so called ‘ground coverage function’ for every scan station  
597 (location). Ground coverage is calculated as the ratio between the difference  
598 of the vertical angles of the outer beams that hit the cell, and the vertical an-  
599 gular resolution (refer to [89] for the formula). Although the approach does  
600 not assess explicitly LOD, the coverage function addresses LOD in some way.

601 *Tertiary Constraints.* Table 2 shows that only one of the approaches designed  
602 for a 3D input model takes into account overlap [49]. All the other approaches  
603 that account for registrability in their constraints are those designed for a  
604 2D (CAD) input model and line targets [87, 88, 33, 52, 89]. In [88] and  
605 [33], the authors’ proposed algorithm embeds the overlap constraint as a  
606 constraint within the optimisation algorithm. This approach differs from the  
607 cases in other studies [49, 89, 52, 87] in which that condition is satisfied only  
608 a posteriori, after the optimised set of locations is found. [87] and [88] used  
609 the same approach to address the registrability constraint, i.e. overlap of  
610 target line segments. In a different approach, Giorgini et al. [89] defined the  
611 overlap constraint as a function of cell coverage and calculate the ratio of  
612 the ground coverage common between each scan and all previous scans and

613 compares it against a threshold value (33%).

614 In contrast, in [48] and [27], the authors did not attempt to ensure that at  
615 least three or more target points acquired in one scan have also been acquired  
616 in at least one other scan. Similarly, [50] and [51] did not attempt to ensure  
617 that a minimum surface acquired in one scan has also been acquired in at  
618 least one other scan. This lack of consideration for overlap seems to be the  
619 result of the observation made in Section 3.3 that laser scanners with large  
620 panoramic field of views have better chances of generating sufficient over-  
621 lapping between successive scans. Nowadays, software packages provided by  
622 scanner manufacturers make registration of point cloud very straightforward  
623 [51]. As a result, ensuring successful registration is less critical.

624 Jia and Lichti [52] considered artificial targets for the purpose of point  
625 cloud registration. The authors' propose a hierarchical design system to  
626 provide a near-optimal solution for scanner network configuration as well as  
627 target placement. Their target placement algorithm updates the preliminary  
628 near-optimal target arrangement to minimise the number of required targets.  
629 The algorithm begins with creating a target-point grid in the area of scanning.  
630 Then for every potential scanning location (selected view-points obtained in  
631 the first stage) the target-points alternatives are saved as potential target-  
632 points only if they are visible from the corresponding scanning location. From  
633 the potential scanner locations (i.e. first part of the study) the ones that  
634 observe the minimum number of target points (set as four) are saved as  
635 benchmark geometry. A (near)-optimal target-point selection algorithm for  
636 every scanning location of the benchmark geometry picks four randomly-  
637 selected potential target-points within the area of that scanning location in  
638 every iteration. Near-optimal target point set (i.e 4 target points in this case)  
639 are the first ones that satisfy the predefined criterion of not being distributed  
640 collinearly or near-collinearly.

641 Then, the algorithm moves to the next potential scanning location and  
642 generates the target point set for that location. Finally, some trimming  
643 happens in order to remove redundant target points from the final pool of  
644 all selected sets for all scanning locations.

#### 645 4.3. Optimisation Approaches

646 *Objective Function.* As can be seen in Table 2, most of the prior P4S works  
647 set their optimisation objective function to minimise scanning time. All  
648 approaches except one [27] assumed fixed scanner settings (e.g., spatial res-  
649 olution, noise level parameters at any give scanning locations), which means

Approach		Input		Constraints		Objective		Optimisation Method		
Publication	Year	Model	Target	Locations	Primary LOC	Secondary LOA	Tertiary LOD	Overlap	Objective	Optimisation Method
Zhang et al. [27]	2016	3D	Points	Grid 2D	,	,	,	,	Min. time	D&C + Relaxed Greedy
Song et al. [48]	2014	3D	Points	Grid 2D	,				Min. scans	Greedy
Latimer et al. [49]	2004	3D	Points	Sets 2D	,	x <sup>†</sup>	,	,	Min. sets/scans	Greedy / SA
Soudarissanane et al. [23]	2011	2D	Lines	Grid 2D	,	x	,	,	Min. scans	Greedy
Gorgini et al. [89]	2019	2D	Lines	Grid 2D	,	,	,	,	Min. scans	Greedy
Jia and Lichti [52]	2019	2D	Lines	Grid 2D	,	,	,	,	Min. scans	Weighted Greedy
Chen et al. [88]	2018	2D	Lines	Random 2D	,	,	,	,	Min. scans	Greedy+ / SA
Ahn and Wohn [87]	2016	2D	Lines	Grid 2D	,	,	,	,	Min. scans	Greedy (interactive)
Blaer and Allen [33]	2009	2D	Lines	Random 2D	,	,	,	,	Min. scans	Greedy
Jia and Lichti [18]	2017	2D	Lines	Grid 2D	,	x	x*	,	Min. scans/Min. $\alpha$	SA/PSO/GA
Kim et al. [53]	2014	2D	Lines	Grid 2D	,	x	,	,	Min. scans	GA
Heidari et al. [51]	2016	3D	Surfaces	Grid 2D	,		x <sup>†</sup>		Min. sets/scans	Greedy
Biswas et al. [50]	2015	3D	Surfaces	Grid 2D	,	x	x*		Min. scans	Integer Programming

Table 2: Scanning criteria and optimisation approaches considered in published model-based P4S works.  $\star$ : incidence angle only.  $\dagger$ : range only.

650 that scanning time is the same at all locations. As a result, these scan plan-  
651 ning approaches simply minimise the number of scans. One of the exceptions  
652 to this approach is [27], in which the authors set the scanning resolution set-  
653 ting as an additional parameter to be optimised for each selected scan. This  
654 means that their algorithm must maintain the objective function as min-  
655 imising scanning time, but it also has consequences on the complexity of the  
656 problem.

657 *Optimisation Method.* The P4S problem is normally defined as a constrained  
658 non-linear optimisation problem, for which the objective function is gener-  
659 ally linear (with the number of locations) but the constraints are non-linear.  
660 Solving such optimisation problem is complex. Such complexity is mainly  
661 due to the large number of variables and exponentially large number of pos-  
662 sible value combinations among them (e.g., combinations of possible spatial  
663 resolution values of the scanner and large number of possible scanning loca-  
664 tions).

665 As summarised in Table 2, almost all existing P4S works, except [50,  
666 53, 18] employed a *greedy algorithm* to find a solution in their optimisation  
667 model. Greedy algorithms do not normally produce an optimal solution, but  
668 have shown in practice to efficiently yield reasonable local optimal solutions.  
669 Greedy algorithms are based on iterative processes that employ the heuristic  
670 of making a locally optimal choice at each stage. In the case of P4S, the  
671 greedy algorithms employed by prior studies usually select the first scanning  
672 location by choosing the location that covers the most targets with the re-  
673 quired data quality. Then, at each iteration, they select the next scanning  
674 location by choosing the one that provides the best improvement towards  
675 the fulfilment of the goal, e.g. the coverage of the scanning targets with the  
676 specified data, or minimising occluded spaces. The process normally ends  
677 once the scanning targets are all visible with the specified data quality, in  
678 at least one of the scans. A second termination criterion is normally added  
679 that stops the algorithm in cases when the problem is in fact infeasible —  
680 i.e. when one or more targets are not visible with the specified quality from  
681 any location. A third termination criterion is also sometimes employed to  
682 stop the algorithm when the improvement after each iteration is too small.

683 Song et al. [48], and Blaer and Allen [33] considered a standard greedy  
684 algorithm; the other studies proposed some variants or enhanced approaches.  
685 Latimer et al. [49] first employ a greedy approach implemented using a depth-  
686 first traversal of an intersection set tree, which appears equivalent to the



687 greedy approaches employed in the other, more recent studies. This process  
688 is then followed by a *Simulated Annealing (SA)* algorithm. The *SA* algorithm  
689 iteratively alters the initial solution based on their coverage of the scanning  
690 targets (to be maximised as the objective function). Sets of locations that  
691 collectively cover all the targets of interest are selected as the initial solution  
692 candidates. Through the *SA* process, at each iteration, if the randomly  
693 selected initial solution shares the same targets covered by another alternative  
694 location set, then the algorithm reduces the number of potential solutions to  
695 choose from and reflects the change in the next round of location set selection.

696 Chen et al. [88] investigated two ways to improve the standard greedy  
697 algorithm. First, they suggest a *greedy algorithm with backtracking (GS-BT)*  
698 which, after the addition of each new scanning location, searches and removes  
699 any now-redundant scanning location. Secondly, similarly to Latimer et al.  
700 [49], the authors suggest to follow the GS-BT process with a SA algorithm.  
701 The SA algorithm randomly removes a scanning location from the GS-BT  
702 solution and then assesses whether small changes in this reduced set of scan-  
703 ning locations can yield solutions to the P4S problem. Their experiments  
704 show that the GS-BT found a better solution in 50% of the 64 cases con-  
705 sidered in their study. Regarding the application of SA, it found a better  
706 solution in 15% of the cases, albeit at the cost of almost 10 times longer  
707 computing time. From an optimal solution viewpoint, SA thus also seems  
708 valuable, although its additional computational time could become a concern  
709 for large-scale facilities and workspaces.

710 Ahn and Wohn [87] employed a human-in-the-loop *interactive* approach  
711 to enable the user to contribute additional knowledge to the optimisation. In  
712 their approach, the algorithm ranks the best possible next scanning locations,  
713 but the user is responsible for selecting the next scanning location. The  
714 location selected by the users might not necessarily be the one ranked the  
715 highest by the algorithm. Arguably, this makes the approach only semi-  
716 automated.

717 Jia and Lichti [52] proposed a hierarchical strategy along with an im-  
718 proved greedy algorithm (so called *weighted greedy*) to optimally select the  
719 scanning view points. In their proposed weighted greedy algorithm each  
720 scanning view point is assigned a visibility score, calculated as the weighted  
721 sum of objects of interests that are visible from that view point. For each  
722 object, the weight is set as one divided by the the total number of locations  
723 (view points) that have a clear line of sight to that object. For instance, if  
724 one object is visible from three different locations then the visibility score for

725 each of those three locations is  $1/3$ . As any other greedy algorithm, the view  
726 point with the highest visibility score is selected and the visibility scores are  
727 updated for the next iteration.

728 While most of the works assumed a fixed angular resolution ( $\Delta$ ) setting for  
729 all scans, Zhang et al. [27] and Chen et al. [88] did not make that assumption.  
730 Zhang et al. [27] relaxed that constraint and instead set  $\Delta$  as an optimisation  
731 parameter. This relaxation makes the optimisation problem significantly  
732 more complicated, minimising data collection time now depends not just on  
733 the set of possible scanning locations but also on the set of possible scanning  
734 resolutions to be selected for each candidate location. The authors solve this  
735 new problem by wrapping the greedy algorithm within a *Divide-and-Conquer*  
736 ( $D+Q$ ) strategy that splits the overall problem into independent, smaller  
737 problems that can be solved faster. In the ‘Divide’ stage, targets (points) with  
738 the same data LOD specifications are grouped in clusters according to some  
739 visibility analysis. In the ‘Conquer’ stage, within each cluster, the greedy  
740 algorithm is employed to find the optimal set of locations. The minimum  $\Delta$   
741 required to acquire all point targets with their specified LOD is then found,  
742 with the same  $\Delta$  set for all scanning locations within each cluster.

743 Notably, Zhang et al. [27] also relaxed the local optimisation problem  
744 by not requiring that the greedy algorithm finds a solution that covers all  
745 targets. Instead, they employ a stronger termination criterion on the minimal  
746 improvement in the coverage of targets that each additional location must  
747 make to the solution. This leads to targets (points) being discarded from  
748 clusters. An additional ‘garbage collection’ process collects the discarded  
749 point targets and initiate a search for scans to cover those discarded ‘garbage  
750 targets’. That search uses the same local optimisation (greedy) algorithm.  
751 This relaxation of the local optimisation problem may in some cases yield  
752 better scanning plans (fewer scanning locations), although the authors of  
753 that study do not experimentally demonstrate the level of improvement this  
754 yields. Besides, it must be highlighted that the  $D+Q$  strategy enables the  
755 approach to scale well to much larger problems, and is independent of the  
756 method used for solving each local optimisation problem.

757 Chen et al. [88] started with an initial constant angular resolution for all  
758 scanning locations. Based on this initial value an initial scan plan is gener-  
759 erated. Then that initial angular resolution in the generated scan plan is  
760 refined for every scanning location through a greedy search algorithm. The  
761 conditions on LOD, visibility, and overlap are satisfied with every refined  
762 angular resolution. Although this greedy approach provides flexibility for

763 surveyors in refining the angular resolutions for all scanning positions, the  
764 final scan plan would not be optimal. To address this issue it is suggested, for  
765 the future work, to consider different angular resolutions while running visi-  
766 bility check; This approach would embed angular resolution into the problem  
767 formulation [88].

768 *Genetic algorithm (GA)* has been investigated as another optimisation  
769 method in [53, 18]. In [18], the authors compared three heuristic optimisation  
770 methods for their performance in a small-volume indoor network design of  
771 TLS: SA, GA and Particle Swarm Optimisation (PSO) The optimisation  
772 goal is set to find the minimum scanning locations that provides complete  
773 coverage for the objects of interest with a minimal sum of incident angles. For  
774 the problem they defined, SA performs the worst, while GA is the preferred  
775 optimisation method as it could provide an optimal solution requiring fewer  
776 parameters to tune.

777 In contrast to all other works, Biswas et al. [50] and Giorgini et al. [89]  
778 employed a different optimisation algorithm, *Integer Programming (IP)*. The  
779 main issue with IP is that it is NP-complete, which means that it does not  
780 scale well to large problems. However, Giorgini et al. [89] successfully applied  
781 their IP-based model in large scale environments capturing internal struc-  
782 tures. Through their experimental evaluation they claim their algorithm,  
783 which is purposefully implemented taking advantage of GPU, can achieve  
784 the required coverage in reasonable times.

785 Regarding [50], the way the authors formulated their optimisation prob-  
786 lem means that IP in fact leads to incorrect solutions. This is because their  
787 optimisation model fails to take into account the coverage overlaps between  
788 surfaces from the selected scanning locations. Notably, were those coverage  
789 overlaps taken into account, the problem would then not be solvable using  
790 IP.

#### 791 4.4. Context-specific Approach

792 The above methods aim to solve generic P4S problems. In contrast, Cabo  
793 et al. [90] proposed an approach to optimise P4S of tunnels with circular or  
794 elliptical sections and straight or curved axis. Their fully automatic method  
795 identifies the optimal scanning locations throughout a tunnel while ensuring  
796 the satisfaction of LOD and Precision criteria over the entire surface of the  
797 tunnel. This approach is specifically designed for tunnels application and  
798 does not generalise to other environments (e.g. as buildings). For this reason,  
799 we do not include this method in Table 2.

## 800 5. P4S in Manufacturing

801 P4S approaches have also been proposed for application in manufactur-  
802 ing, typically for defining scanning plans for part inspection [22, 91]. Scott  
803 et al. addressed some of the early works on sensor-based view planning tech-  
804 niques for specified inspection goals [22]. Although the P4S problem in the  
805 manufacturing domain outdates that in the construction domain, the solu-  
806 tions are not really transferable. In manufacturing, scanners are mounted on  
807 a robotic frame or arm and have narrow FOVs — they can only scan indi-  
808 vidual points, small lines or small surface areas at a time [92]. Furthermore,  
809 the cost (in terms of time) of moving the scanner to any new position and  
810 scan from it is small. This implies that the number of scanning locations is  
811 not critical, and an optimal scanning location could be defined for distinct  
812 target areas of the object. As a result, the P4S problem for part inspection is  
813 more about optimising the scanner’s path from one location to the next until  
814 all locations have been visited (travelling salesman problem). In contrast, in  
815 the context of construction TLS, the (time) cost of moving the scanner and  
816 conducting a scan is high, but each scan is 360-degree and can capture data  
817 at long distances, so that multiple scanning targets can be acquired from one  
818 location at once. This means that, in the construction context, the problem  
819 of minimising the number of scanning locations is more meaningful.

820 Despite these significant differences, approaches employed in the manu-  
821 facturing domain might still give valuable ideas on how to approach the P4S  
822 problem in the construction domain, since they normally work with 3D in-  
823 put models. For example, Son et al. [92] propose a laser scanning system for  
824 part inspection that assumes a 3D CAD model of the part as input. Their  
825 proposed automated system generates a scan plan including the number of  
826 scans, the scanning directions, and the scan path. To generate a scanning  
827 plan, a ‘Divide and Conquer’ approach is employed where each complex part  
828 is initially divided into functional surfaces, and individual scan plans are then  
829 generated for each functional surface. Each functional surface is represented  
830 by a point set sampled from that surface, and the system aims to minimise  
831 the number of scans necessary to capture all those sampled points. After  
832 generating the initial scan plan, the algorithm checks DOF (i.e. distance  
833 from the laser source to the surface) and occlusion constraints, and modifies  
834 the scan plan to assure all the points will be acquired and measured with  
835 the expected precision. This ‘Divide and Conquer’ strategy is similar to that  
836 employed by Zhang et al. [27].

## 837 6. Discussion

838 Section 4 reviewed prior approaches to develop automated P4S algorithms  
839 for the usage of TLS in construction. In this section, we review these holis-  
840 tically to identify gaps in knowledge.

### 841 6.1. Input:

842 While a number of works assume a 2D input model, which is justified  
843 by the general availability of such models, recent works have increasingly  
844 considered 3D input models. However, while the approaches developed for  
845 2D input models are all focused on line targets (which are the 2D represen-  
846 tations of vertical surfaces), that line targets have not been considered by  
847 any prior work that used 3D input models. Heidari Mozaffar and Varshosaz  
848 [51] and Biswas et al. [50] considered surface targets within 3D input models.  
849 However, since the optimisation method of [50] gives incorrect solutions, the  
850 approach of Heidari Mozaffar and Varshosaz [51] is the only one that fills the  
851 gap for solutions to the P4S problem for surface targets in 3D input models.

852 For approaches that consider 2D input model, it is logical that potential  
853 scanning locations be also defined in 2D (plan view) only. However, we  
854 observe that no work that considers 3D input model has yet attempted to  
855 consider scanning locations defined in a 3D space. Although none of the  
856 prior authors specifically discuss this decision, it is arguably justified by two  
857 observations. First, TLS is a ground-based technology operated on a tripod  
858 that can only be extended a few metres, which limits the range of locations  
859 the scanner can be positioned at along the vertical axis. Secondly, those prior  
860 studies assume only contexts where the environment to be scanned is large  
861 with little geometric variation along the vertical axis (e.g. building exteriors),  
862 which implies that sampling locations along the Z axis (within the limited  
863 extension capability of typical tripods) would unlikely provide any significant  
864 benefit. However, these assumptions are arguably inadequate in a number  
865 of other contexts, such as when scanning interiors with MEP components or  
866 in industrial environments. In such contexts, considering potential locations  
867 in 3D may in fact be necessary to ensure that the optimisation problems are  
868 feasible.

### 869 6.2. Constraints:

870 *LOA*. The first observation is that there is not yet any general parametric  
871 formula relating single point accuracy (*LOA*) to all factors — or at least the

872 main factors — that can impact it. This means that the claim from most  
873 prior works that their frameworks can account for accuracy is somewhat  
874 misleading. In practice, only approximate metrics are used, the main ones  
875 being to reject points with incidence angle  $\alpha \geq 70^\circ$  ( $60^\circ$  is also suggested)  
876 and range higher than a scanner-specific value (e.g.  $\rho \geq 50m$ ). Shen et al.  
877 [75] showed that important factors impacting accuracy also include surface  
878 reflectance. Some other studies [73, 80, 81] also included the effects of range  
879 and surface properties as well as incidence angle on range precision of TLS.

880 Therefore, developing more robust single point accuracy models is nec-  
881 essary. Since accuracy can vary widely among scanner, such models should  
882 ideally be developed by scanner manufacturers. But, researchers could also  
883 contribute by developing more general (albeit maybe still somewhat approxi-  
884 mate) models for typical groups of scanners. Furthermore, in contexts where  
885 P4S input models are BIM models, information about surface materials could  
886 be obtained from the model and factored in the optimisation framework to  
887 ensure that objects with challenging materials are scanned accordingly.

888 *LOD*. In contrast to accuracy, most prior works are able to account for  
889 LOD more robustly. Interestingly, these studies all use an LOD metric that  
890 depends solely on the scanner’s angular resolution, with no work having  
891 used the Effective Instantaneous Field of View (EIFOV) introduced in [85].  
892 Nonetheless, it seems that employing EIFOV would only be critical in cases  
893 of high LOD, where the specified surface sampling distance can be smaller  
894 than the beamwidth.

895 *LOC*. Although LOC, in particular surface LOC, has been shown to be crit-  
896 ical to ensure scanned data can support successful Scan-vs-BIM applications  
897 [50, 46], Biswas et al. [50] and Heidari Mozaffar and Varshosaz [51] are the  
898 only ones that have attempted to develop a P4S framework that takes surface  
899 LOC into account.

900 However, as mentioned earlier and further discussed below, there remains  
901 a significant research gap in P4S solutions that can consider 3D surface tar-  
902 gets and corresponding surface LOC specifications.

### 903 *6.3. Optimisation*

904 *Objective Function*. All prior works are in agreement that the main P4S  
905 objective is to minimise the time necessary to scan all necessary targets with  
906 the specified quality (LOA, LOD, LOC). Minimising scanning time is critical

907 to minimise interruptions of other activities on site. In the majority of cases,  
908 minimising the number of scans is used as a proxy objective function.

909 The use of such objective functions assumes that all activities on site  
910 will be stopped for all scans in the scanning plan to be performed before  
911 all activities can resume. This is however likely sub-optimal. Instead, it  
912 would be preferable to come up with scanning plans and programmes (order  
913 of scans) that can fully utilise the gaps between other on-site tasks (e.g.  
914 construction activities) so that those activities do not have to be halted  
915 to allow for data collection. This would first require conducting studies  
916 to understand how data collection can influence construction productivity  
917 (e.g. see [2]). These studies would then inform how the P4S optimisation  
918 problem could be revised with additional constraints so that the scanning  
919 plans are optimally interwoven with field workflows, fully utilising the idling  
920 time gaps and spaces between tasks to achieve an effective balance between  
921 data quality, data timeliness, and overall field productivity. Such problem  
922 may be approached using some temporal Divide-and-Conquer strategies (as  
923 opposed to spatial ‘Divide-and-Conquer’ strategies like the one in [27]).

924 *Optimisation Method.* As reported earlier, the greedy algorithm is commonly  
925 used to solve P4S problems in the built environment domain. While it does  
926 not guarantee optimal solutions, it does commonly achieve reasonable ones.  
927 Enhancements to the greedy algorithm, e.g. using weighted greedy, back-  
928 tracking or SA, have also shown to be able to effectively find more optimal  
929 solutions. We note that other methods for solving constrained non-linear  
930 optimisation problems, such as evolutionary algorithms (genetic algorithm,  
931 etc.), have hardly been investigated, except for the comparison study of Jia  
932 and Lichti [18] and a minimal case study in [53]. They could be employed  
933 either on their own or possibly in combination with other methods, such as  
934 the greedy algorithm or the Divide-and-Conquer strategy [27].

935 Most existing works have looked at medium-scale and generally reason-  
936 ably simple P4S problems (i.e. few P4S inputs, and somewhat simple input  
937 3D models). While the greedy algorithm they employ does help maintain  
938 P4S problem to tractable levels, the Divide-and-Conquer approach of Zhang  
939 et al. [27] offered a solution that better scales up to larger P4S problems. Such  
940 approach could be considered more systematically, and possibly alternative  
941 Divide-and-Conquer strategies could also be considered.

#### 942 6.4. Other Consideration - Progressive P4S

943 Model-based P4S approaches can only work when the input model matches  
944 the real environment well. However, often this may not be the case in prac-  
945 tice, due to: (1) *discrepancies*, e.g. due to construction having not progressed  
946 as planned or suffered some changes or errors; (2) *clutter* that prevents tar-  
947 gets to be scanned from certain locations as expected, or (3) *uncertainties*  
948 due to approximations in actual scanner placement on site. This implies  
949 that there is a need for solutions to the *Progressive P4S* problem, where the  
950 plan is reassessed and potentially altered after the acquisition of each new  
951 scan on site. Such problem is in effect an *online* model-based *view planning*  
952 (or *NBV*) problem. While the non-model-based view planning problem has  
953 received significant interest in the literature (e.g. [93, 94, 95, 96, 97]), solu-  
954 tions to the proposed new problem of *Progressive P4S* may require specific  
955 adjustments and dedicated research.

## 956 7. Conclusion

957 In this paper, we first have motivated the need for automated P4S meth-  
958 ods for application in the built environment domain. We have then conducted  
959 a detailed review of the types of performance criteria that such method should  
960 meet (Precision, LOD, LOC and registrability) and of the parameters im-  
961 pacting those criteria. This was followed by a review of significant prior  
962 P4S methods, with focus on thirteen particular studies published in the last  
963 decade (eight of which in the last five years). The types of input, constraints  
964 and optimisation problem formulations they consider were detailed, and this  
965 led to a final extended discussion on the achievements of those methods and  
966 identifications of the remaining key areas where further research is required.  
967 The following main conclusions (including areas for further research) are  
968 drawn.

969 **3D input models and targets:** While the problem of 2D model-based P4S  
970 has been well developed with mature solutions, there is a need for meth-  
971 ods to be developed that are able to handle 3D input models, in partic-  
972 ular BIM models, and that can provide plans for 3D targets that can  
973 be points, but also lines and surfaces. The need for methods that can  
974 work with 3D input models is particularly important for complex envi-  
975 ronments both indoors (e.g. scanning MEP systems located in ceilings)  
976 and outdoors (industrial sites).



977 **Accuracy mathematical models:** Mathematical models for calculating LOD  
978 and LOC are robust, but there is also a need to develop better accu-  
979 racy models. While such models may still trade robustness for gener-  
980 alisability, this would be preferable to the overly simplistic approach of  
981 rejecting points on the basis of incidence angle alone. There are also  
982 some studies which modelled random error of TLS based on intensity  
983 values of laser [73, 80, 81], but they can't be applied to estimate LOA  
984 as they deal with precision.

985 **Robust and scalable optimisation methods:** Regarding optimisation meth-  
986 ods, the work of Zhang et al. [27] has shown that it is possible to de-  
987 velop better methods than the basic greedy algorithm, using additional  
988 heuristics or well-designed Divide-and-Conquer strategies. Other opti-  
989 misation algorithms, for example evolutionary algorithms, should also  
990 be investigated more closely.

991 **Temporal constraints:** We noted that the current P4S problem tends to  
992 be approached as a temporally static one. It would however be ben-  
993 efiticial to extend it with additional temporal constraints to minimise  
994 interferences between data collection and other site activities.

995 **Progressive P4S:** Finally, while useful to prepare for site scanning activ-  
996 ities, current scanning plans can arguably often be inadequate due to  
997 unforeseeable circumstances (discrepancies, clutter) and various uncer-  
998 tainties. As a result, there is a need to conduct research developing  
999 Progressive P4S methods that are able to reassess and potentially alter  
1000 the plans in real time after the acquisition of each new scan on site.

1001 The authors expect that the identification of these gaps in knowledge will mo-  
1002 tivate individuals and groups around the world to research them and propose  
1003 P4S methods that are better than the current state of the art.

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