

Review Article:

Laser Scanning in Industry: A Review of LiDAR, Terrestrial and Handheld Systems and Their Industrial Applications

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Abstract

Laser scanning has evolved from a specialised surveying technique into a core reality-capture technology underpinning the digital transformation of industry. By emitting laser pulses and recording the coordinates of millions of surface points per second, LiDAR systems generate dense point clouds that describe complex objects rapidly and without contact. This review provides an integrated overview of the laser-scanning family, airborne, mobile, terrestrial (TLS) and handheld simultaneous-localisation-and-mapping (SLAM) scanners, and their industrial applications. The physical principles of laser ranging, the nature of point-cloud data, and the metrics governing accuracy are summarised, and the main platform classes are compared by range, accuracy, throughput and typical use. A generic processing pipeline is described, spanning scan planning, registration, filtering, segmentation and modelling for reverse engineering and CAD, together with the growing role of deep learning for automated point-cloud interpretation. Industrial applications are then reviewed in manufacturing metrology, process plants, automotive production, and asset management. The review shows that laser scanning is a key enabler of as-built documentation, quality control and digital-twin creation, while occlusion, data volume, registration error and the absence of standardised performance evaluation remain persistent challenges. Directions for future work, including tighter integration with artificial intelligence and Industry 4.0, are identified.

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Contribution to the field statement:

This review integrates the full laser-scanning family, airborne, mobile, terrestrial and handheld SLAM systems, with their industrial deployment, linking measurement principles and processing pipelines to manufacturing, process-plant and asset-management applications, and identifying persistent gaps in registration accuracy and standardised performance evaluation.

Highlights:

- Reviews airborne, mobile, terrestrial and handheld laser scanning.
- Compares platform classes by range, accuracy and throughput.
- Links the processing pipeline to industrial deployment and AI.
- Identifies gaps in registration accuracy and standardisation.

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1. INTRODUCTION

The ability to capture the geometry of physical objects and environments quickly, accurately and without contact has become central to modern industrial practice. Light detection and ranging (LiDAR), also referred to as laser scanning, meets this need by emitting laser pulses towards a surface and reconstructing the three-dimensional (3D) position (x, y, z) of each measured point from the travel time or phase of the returned signal. The result is a point cloud: a dense set of coordinates, often enriched with intensity or colour, that describes the scanned scene with millimetre-level detail. Because a single instrument can record hundreds of thousands to millions of points per second, laser scanning replaces the discrete, labour-intensive measurements of conventional metrology with a rapid and comprehensive digital record of reality [1].

Laser-scanning systems are now available on a range of platforms. Airborne laser scanning (ALS) captures terrain and large facilities from aircraft and unmanned aerial vehicles; mobile laser scanning (MLS) mounts sensors on vehicles for corridor mapping; terrestrial laser scanning (TLS) uses tripod-mounted instruments for high-accuracy static capture; and lightweight handheld scanners exploit simultaneous localisation and mapping (SLAM) to map spaces while the operator walks through them. Although these platforms share the same ranging physics [2], they differ substantially in range, accuracy, acquisition speed and cost. The airborne configuration, in particular, was among the first to be formalised for large-area measurement [3], and the same measurement chain has since been miniaturised down to hand-portable devices.

The industrial relevance of laser scanning has grown with the fourth industrial revolution. Concepts such as reality capture, as-built documentation and the digital twin, a continuously updated virtual replica of a physical asset, depend on accurate 3D data that technologies like laser scanning can provide at scale. In parallel, advances in the automated interpretation of point clouds, driven by deep learning, are transforming raw scans into structured, semantically labelled models with limited manual effort [4], and are a core enabler of autonomous perception in vehicles and robots [5]. Across manufacturing, energy and transport industries, laser scanning has consequently moved from a specialised surveying tool towards general-purpose industrial infrastructure [6].

Existing reviews tend to focus on a single platform, for example TLS or automotive LiDAR, or on a single application domain, which makes it difficult to appreciate how the different members of the laser-scanning family complement one another in industrial settings. This paper addresses that gap by providing an integrated, application-oriented review of LiDAR, terrestrial and handheld laser scanning in industry and production. The objectives are (i) to summarise the physical principles and data characteristics of laser scanning; (ii) to classify and compare the main platform types; (iii) to describe the processing pipeline that turns point clouds into usable industrial models; and (iv) to review the principal industrial application domains, together with their challenges and future directions. The remainder of the paper is organised accordingly.

2. METHOD

2.1. Review scope and approach

This review synthesises peer-reviewed journal articles, major conference proceedings, international standards and authoritative technical references on laser scanning published up to 2025, with an emphasis on sources from the last decade. The scope spans airborne, mobile, terrestrial and handheld laser-scanning systems and their application in manufacturing, process industries, automotive and robotics, and asset management; construction, mining and tunnelling applications were deliberately excluded to keep the review focused on discrete-manufacturing and process-industry contexts. Sources were identified through major scientific databases and cross-referencing of citations in key reviews, and were prioritised for relevance to industrial, rather than purely topographic or cultural-heritage, applications, methodological clarity and recency.

2.2. Principles of laser ranging

All laser scanners derive distance from the interaction of a laser beam with a target, and three measurement principles dominate industrial practice [2] (Figure 1). Time-of-flight (pulsed) ranging measures the round-trip travel time of a short laser pulse; because the speed of light is known, a picosecond-level timing resolution translates into millimetre-level distances, and long unambiguous ranges of hundreds of metres are achievable. Phase-shift ranging emits a continuously modulated beam and infers distance from the phase difference between the emitted and returned signals; it offers very high acquisition rates and excellent short-to-medium-range precision, at the cost of a limited ambiguity interval. Frequency-modulated continuous-wave (FMCW) ranging, a coherent variant, provides simultaneous range and velocity and is increasingly used in automotive sensors.

For close-range, high-precision work (typical of manufacturing metrology), optical triangulation is also used: a laser stripe or spot is projected onto the surface and its image position on a calibrated detector yields depth. Triangulation delivers micrometre-level accuracy over short stand-off distances but does not scale to the tens or hundreds of metres reached by time-of-flight instruments. The choice of principle therefore fixes the fundamental trade-off between range, precision and speed that characterises each scanner class [2].

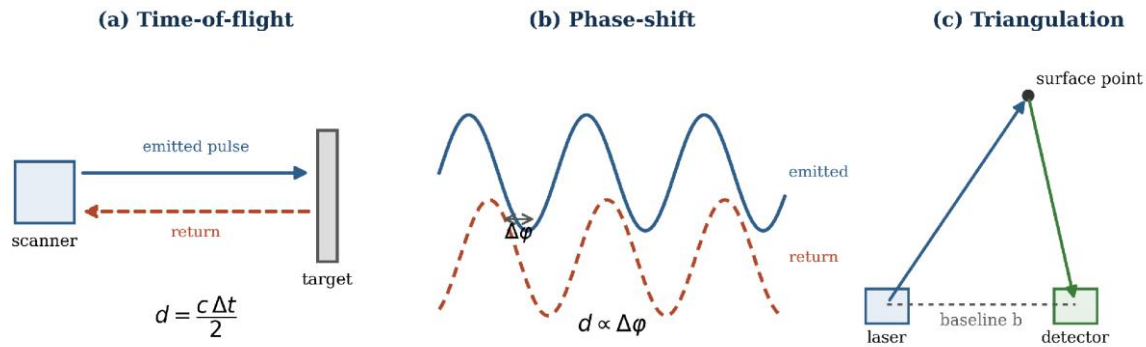


Figure 1. Principles of laser ranging used in industrial scanners: (a) time-of-flight, (b) phase-shift and (c) optical triangulation.

2.3. Wavelength and beam-steering architecture

Two design choices at the sensor level shape a scanner's suitability for industrial use: the laser wavelength and the beam-steering architecture. Most terrestrial and automotive systems operate at either 905 nm or 1550 nm. The 905 nm band uses inexpensive silicon detectors but limits the emitted power that remains safe for the human eye, which constrains range and makes the sensor more susceptible to solar background noise; the 1550 nm band is absorbed by the eye's cornea rather than reaching the retina, so higher powers and longer ranges are permissible, at the cost of more expensive indium-gallium-arsenide detectors and greater attenuation in humid or foggy air [7], [8]. The wavelength therefore trades range, eye-safety, cost and robustness to ambient conditions against one another.

Beam steering has evolved along a parallel path. Traditional opto-mechanical and electro-mechanical scanners sweep the beam with rotating mirrors or by turning the whole sensor head, offering a wide field of view and mature performance but with moving parts that add bulk and wear. Micro-electro-mechanical-system (MEMS) mirrors miniaturise this steering, and fully solid-state approaches (optical phased arrays and flash LiDAR) remove moving parts altogether, promising greater robustness and lower cost as they mature [9]. For static industrial metrology, mechanical survey-grade instruments still dominate; for embedded perception on vehicles and robots, MEMS and solid-state designs are increasingly preferred.

2.4. Point clouds and data attributes

A laser scanner behaves, in effect, as a motorised angular measurement system that couples a distance meter with a beam-deflection unit, systematically sweeping the beam across the scene and converting each return into an (x, y, z) coordinate. The dense set of such coordinates is the point cloud. Beyond geometry, each point usually carries a reflected-intensity value, and many instruments co-register calibrated colour (RGB) imagery, so that the cloud conveys both metric information (object geometry and spatial relationships) and thematic information (surface radiometric properties). From this common representation, plans, sections, meshes and parametric models can be derived for whichever engineering task is required [1].

2.5. Accuracy, resolution and performance

The industrial value of a scan depends on well-characterised performance. Key metrics include ranging accuracy and precision, angular accuracy, point spacing (resolution), and the noise induced by surface reflectance, beam incidence angle and atmospheric conditions. Tolerances demanded by industry span several orders of magnitude, from tens of millimetres for site documentation down to tens of micrometres for high-precision assembly. Because manufacturers report specifications under different conventions, comparing instruments and establishing metrological traceability is non-trivial; national metrology institutes have therefore proposed dedicated test procedures and stitching-based range-error evaluations to place laser-scanner measurements on a documented, traceable footing [10]. A fully standardised, universally adopted evaluation framework nevertheless remains an open issue.

2.6. Error sources and environmental effects

Nominal specifications describe performance under ideal conditions; real industrial environments introduce additional error sources that the analyst must anticipate. Surface properties are foremost: highly reflective



machined-metal, polished or glass surfaces produce specular returns that either saturate the detector or scatter away from it, leaving data voids and spurious points, whereas dark, absorptive surfaces weaken the return and raise range noise. The scanning geometry matters just as strongly: as the incidence angle between the beam and the surface normal grows and the range increases, the laser footprint elongates and the individual-point precision degrades, so that grazing-angle measurements are markedly noisier than near-perpendicular ones [11]. Redundant scanning from several well-distributed stations mitigates both effects.

Environmental conditions add further uncertainty. Temperature gradients near furnaces, boilers and hot piping change the refractive index of the air and bend the beam, introducing millimetre-scale range bias, while dust, humidity, vibration and strong ambient light raise noise or cause dropouts. For kinematic and handheld systems a distinct failure mode arises in long, smooth, geometrically repetitive industrial corridors, where the scarcity of distinctive features starves the SLAM estimator and lets the trajectory drift; fusing inertial and camera data, placing occasional control targets, and exploiting loop closure when the platform revisits a location are the standard remedies [12]. Anticipating these effects at the planning stage is what separates a metrologically reliable survey from a merely complete-looking one.

3. RESULTS

3.1. Classification of laser-scanning systems

The laser-scanning family is conventionally organised by platform. Figure 2 summarises the four classes considered here (airborne, mobile, terrestrial and handheld) together with their mounting, typical accuracy and their common basis in laser ranging; each is described in turn below.

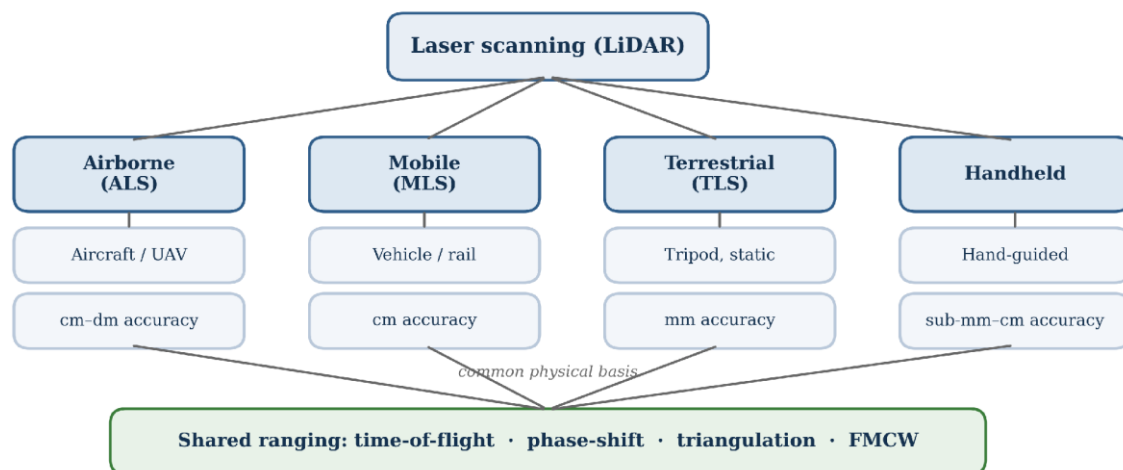


Figure 2. Taxonomy of the laser-scanning family by platform, with mounting, typical accuracy and the common ranging basis shared by all classes.

3.1.1. Airborne laser scanning

Airborne laser scanning mounts a LiDAR sensor, together with a global navigation satellite system (GNSS) receiver and an inertial measurement unit (IMU), on a crewed aircraft or an unmanned aerial vehicle [3]. The system records the position and attitude of the platform continuously, so that each range measurement is georeferenced directly into a mapping frame. ALS covers large areas rapidly and is well suited to site-scale industrial mapping, such as plant-site, stockpile and tank-farm survey, albeit at coarser point spacing and centimetre-to-decimetres accuracy relative to ground-based systems.

3.1.2. Mobile laser scanning

Mobile laser scanning integrates one or more scanners with a GNSS/IMU navigation suite on a moving vehicle, boat or rail trolley. Trajectory estimation fuses satellite positioning, inertial data and, where satellite visibility is poor, odometry and scan matching. MLS captures long linear corridors (pipelines, conveyor lines and process-plant racks) far faster than static methods, and the same sensing principle underlies the perception stacks of autonomous vehicles, where real-time LiDAR feeds object detection and navigation [5].

3.1.3. Terrestrial laser scanning

Terrestrial laser scanning uses a tripod-mounted instrument that scans from a fixed station. A TLS system comprises the scanning unit, a power supply, a tripod and reference targets (spheres or checkerboards) used to link successive stations. Static operation and long integration times yield the highest accuracy of the ground-based family, with millimetre-level ranging over distances from a fraction of a metre to several hundred metres, making TLS the reference technology for high-fidelity as-built capture, dimensional control and deformation monitoring [1], [13].

3.1.4. Handheld and SLAM-based scanners

Handheld and backpack scanners remove the tripod altogether. They rely on SLAM, which simultaneously builds a map and estimates the sensor trajectory from the LiDAR data themselves, often aided by an IMU and cameras. This allows an operator to capture a space simply by walking through it, and is particularly valuable in GNSS-denied environments such as building interiors and dense industrial plant [14], [15], [16]. The trade-off is accuracy: comparative studies against static reference clouds report handheld-SLAM deviations at the centimetre level, typically one to five centimetres depending on the device and environment, versus the millimetre level of static scanners [17], [18]. For rapid, first-pass documentation where centimetre accuracy suffices, this is an attractive compromise; for tight-tolerance metrology it is not. Distinct from these SLAM mapping devices, close-range handheld metrology scanners based on structured light or laser triangulation digitise individual parts at sub-millimetre accuracy, albeit over much smaller working volumes.

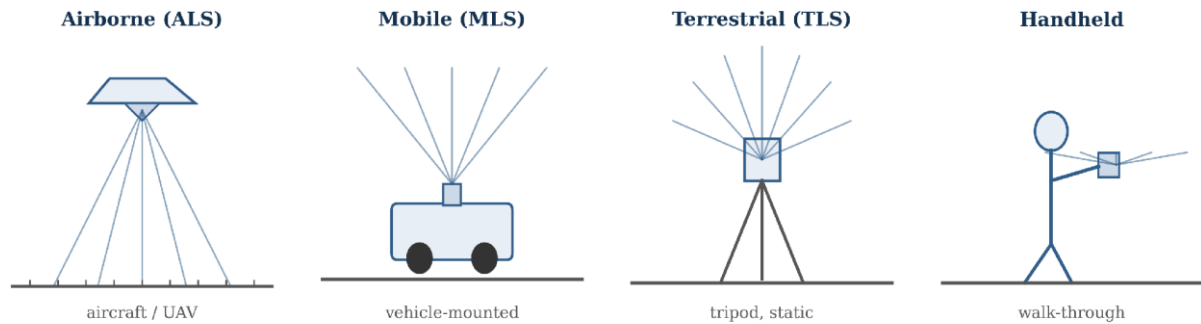


Figure 3. The four laser-scanning platform classes: airborne (ALS), mobile (MLS), terrestrial (TLS) and handheld systems.

3.1.5. Comparative overview

The four platform classes (Figure 3) are complementary rather than competing. Airborne and mobile systems prioritise coverage and speed over absolute accuracy; terrestrial systems prioritise accuracy over coverage; and handheld systems prioritise accessibility and throughput in confined spaces, a trade-off confirmed by direct field comparisons between mobile and terrestrial systems in indoor environments [19]. Table 1 summarises indicative ranges, accuracies, acquisition modes and typical industrial uses, and Table 2 lists indicative technical specifications (angular accuracy, point rate, weight and ingress protection); the values are representative rather than absolute, since performance depends strongly on the specific instrument and operating conditions. In practice, industrial projects increasingly combine several platforms, for example TLS for accurate detail and handheld SLAM for rapid coverage within a single deliverable.

Table 1. Indicative characteristics of the main laser-scanning platform classes. Values are representative and depend on the specific instrument and operating conditions.

Platform	Typical range	Ranging accuracy	Acquisition mode	Main industrial uses
Airborne (ALS)	100 m – several km	0.05 – 0.30 m	Kinematic (GNSS/IMU)	Site-scale plant and terrain survey, stockpile and tank-farm volumes
Mobile (MLS)	up to ~100–200 m	0.02 – 0.10 m	Kinematic (vehicle)	Pipeline and facility corridors, plant mapping, autonomous perception



Platform	Typical range	Ranging accuracy	Acquisition mode	Main industrial uses
Terrestrial (TLS)	0.5 – 350 m (long-range >1 km)	1 – 6 mm	Static (tripod)	High-accuracy as-built capture, metrology, deformation monitoring
Handheld	~0.5 – 100 m	sub-mm – cm	Kinematic (walk-through)	Rapid indoor and confined-space capture, first-pass documentation

Table 2. Indicative technical specifications of typical instruments in each platform class; exact values vary by model

Platform	Angular accuracy	Max point rate	Range	Weight	Ingress protection
Airborne (ALS)	N/A (GNSS/IMU)	0.1–1.5 M pts/s	100 m – several km	1–5 kg (sensor)	IP5x–IP6x
Mobile (MLS)	N/A (GNSS/IMU)	0.5–2 M pts/s	up to ~100–200 m	5–20 kg (system)	IP5x–IP6x
Terrestrial (TLS)	8–19" (≈ 0.002 – 0.005°)	up to ~2 M pts/s	0.5 – 350 m	4–6 kg	IP54
Handheld	N/A	0.3–0.7 M pts/s	~0.5 – 100 m	1–2 kg	IP54–IP64

3.2. From point clouds to industrial models

Raw scans are seldom the final product. A sequence of processing steps, summarised in Figure 4, converts overlapping point clouds into structured models that engineering workflows can consume. The pipeline is broadly common across platforms, although the emphasis of each step varies with the instrument and the intended deliverable.

3.2.1. Scan planning and acquisition

Effective capture begins with planning the number and placement of scan stations (or the trajectory, for mobile systems) so that the object is covered with sufficient overlap and point density while occlusions are minimised. Poor geometry inflates noise and leaves gaps that are expensive to revisit. Formal optimisation of scan-station layout (balancing coverage, redundancy and effort) improves completeness for complex scenes and is increasingly automated.

3.2.2. Registration and georeferencing

Individual scans, each in its own local frame, must be aligned into a single coordinate system. Registration is achieved through common targets, through cloud-to-cloud matching using variants of the iterative closest point algorithm, or through direct georeferencing in which the instrument position and orientation are measured externally. Direct georeferencing and self-calibration reduce dependence on artificial targets and are essential where control is scarce or the object is inaccessible [20]. Registration quality, typically reported as a residual alignment error, propagates into every downstream product and is therefore a primary quality metric.

3.2.3. Filtering, segmentation and feature extraction

Registered clouds contain noise, moving objects and irrelevant background that must be filtered out. The cleaned cloud is then segmented into meaningful units (planes, cylinders, edges and complete components) using geometric primitives (for example RANSAC plane and cylinder fitting), region growing or, increasingly, learned models [21]. Reliable segmentation of pipes, structural members and equipment is the step that most directly determines how much manual effort the subsequent modelling requires.

3.2.4. Modelling, reverse engineering and CAD integration

Segmented data are converted into the representation the application demands: triangulated meshes for visualisation and inspection, parametric solids for computer-aided design, or object-based models for plant-information systems. In reverse engineering, the cloud is fitted to surfaces and solids so that a physical part or installation without drawings can be reconstructed as an editable model [1]. The quality of this step depends



heavily on the preceding data-capture and conditioning: consistent acquisition practice determines how reliable and reusable the resulting models are.

3.2.5. Artificial-intelligence-based processing

Manual segmentation and modelling remain the principal bottleneck in laser-scanning workflows. Deep learning has consequently become central to point-cloud processing, with architectures for shape classification, object detection and semantic and instance segmentation now able to label large clouds with limited supervision [4]. The same methods drive real-time perception in autonomous driving, where networks must detect and track objects from sparse, unstructured LiDAR data at speed [5]. Automating interpretation is widely regarded as the key to scaling laser scanning from bespoke surveys to routine industrial monitoring.

Architecturally, the field has moved from voxel- and projection-based methods to networks that consume raw points directly. PointNet first showed that a permutation-invariant network can learn per-point and global features without voxelisation [22], and its hierarchical successor PointNet++ added multi-scale local aggregation [23]. Point-convolution designs such as KPConv then introduced flexible, deformable kernels that improved segmentation of complex scenes [24], while efficiency-oriented models made semantic labelling of very large clouds tractable. Progress is measured on public benchmarks (Table 3): ModelNet40 [25] for shape classification and S3DIS [26], Semantic3D [27] and KITTI [28] for segmentation and detection, using metrics such as overall accuracy, the mean intersection-over-union (mIoU) and, for surface reconstruction, the Chamfer distance, which let the industrial practitioner gauge how far automated interpretation can be trusted before manual checking is required [4].

Table 3. Representative public benchmarks used to evaluate deep-learning methods on point clouds, with their domain, primary task and common evaluation metrics.

Benchmark [ref]	Domain / data	Primary task	Common metric(s)
ModelNet40 [25]	CAD models, 40 categories	Shape classification	Overall accuracy
S3DIS [26]	Indoor building scans, 6 areas	Semantic segmentation	mIoU, overall accuracy
Semantic3D [27]	Outdoor terrestrial LiDAR scenes	Semantic segmentation	mIoU, overall accuracy
KITTI [28]	Automotive LiDAR (road)	3D object detection	Average precision (AP)

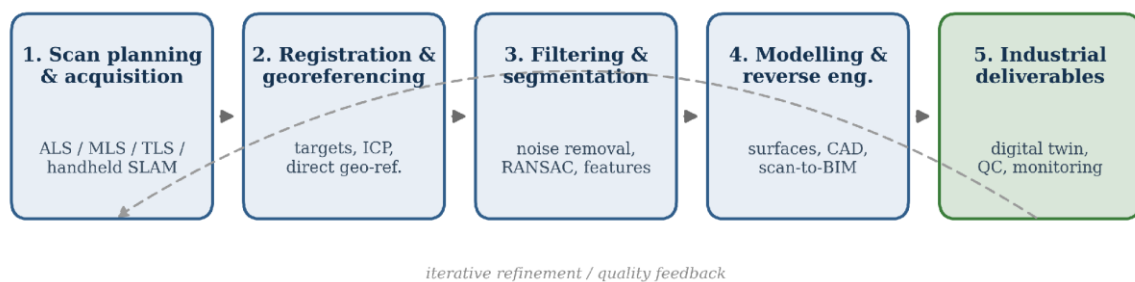


Figure 4. Generic laser-scanning data-processing pipeline, from acquisition through registration, filtering and modelling to industrial deliverables, with iterative quality feedback.

3.2.6. Data standards and interoperability

A practical obstacle to industrial adoption, largely independent of sensor performance, is data interoperability. Point clouds are exchanged in a mix of open and proprietary formats: the vendor-neutral ASTM E57 standard (E2807) stores points, intensity, colour, imagery and scan metadata in a single archive and is the de-facto choice for exchange between different scanners and software [29]; the ASPRS LAS format and its compressed LAZ variant dominate airborne and mobile LiDAR; and lightweight formats such as PCD, used by the Point Cloud Library, and PLY are common in processing and research pipelines [30]. These formats differ in how they encode attributes, whether they support gridded structure and how efficiently they compress, so the choice affects file size, transfer cost and the risk of attribute loss during conversion.



Beyond raw exchange, integrating scans into engineering and operational systems requires semantic and protocol standards. In the built-asset domain the Industry Foundation Classes (IFC, standardised as ISO 16739) provide the object schema into which scan-to-BIM workflows map recognised components (Figure 5), turning geometry into queryable building- and plant-information models. For living digital twins, the geometric state derived from periodic scans must be exchanged with control and monitoring systems through industrial protocols such as OPC UA, so that the reality-captured model stays synchronised with real-time process data [31]. Weak support for these standards is a recurring bottleneck in scaling facility digital twins across mixed hardware fleets [6].

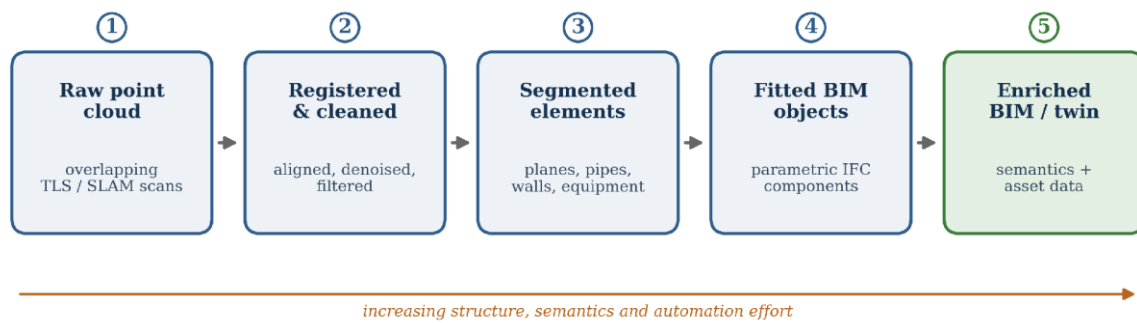


Figure 5. Scan-to-BIM workflow: from a raw point cloud to a semantically enriched building- or plant-information model, with effort and structure increasing at each stage.

3.3. Industrial applications

3.3.1. Automotive, robotics and autonomous production systems

Automotive and robotic systems consume LiDAR in real time rather than as archived surveys. Mounted on vehicles, mobile robots and production cells, scanners feed perception pipelines that detect obstacles, segment the scene and localise the platform (Figure 6). Here the challenge is not archival accuracy but latency and robustness: networks must interpret sparse, noisy, high-rate point streams reliably enough for safety-critical decisions [5]. Progress in this domain feeds back into industrial scanning through shared advances in solid-state sensors and learned point-cloud processing.

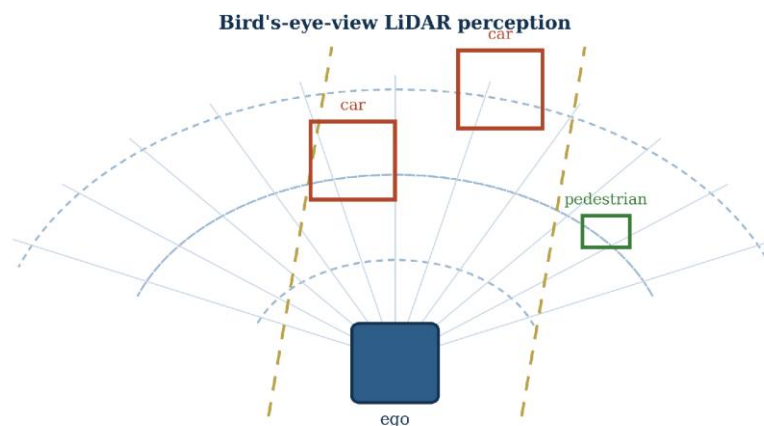


Figure 6. Bird's-eye-view LiDAR perception: the ego vehicle senses its surroundings and detects objects (cars, pedestrian) and lane markings in real time.



3.3.2. Process plants, oil and gas, and as-built documentation

Process plants and oil-and-gas facilities are among the most established industrial users of laser scanning. Dense TLS and handheld-SLAM capture record congested piping, structural steel and equipment as millimetre-to-centimetre-accurate as-built point clouds without interrupting operations, providing reliable geometry for retrofit and revamp design, clash detection and fabrication. These clouds are the geometric foundation of facility digital twins (Figure 7), which increasingly link the as-built model with real-time process data for monitoring, simulation and optimisation across the asset lifecycle [6].



Figure 7. Process-plant workflow: a congested as-built point cloud is fitted to a parametric plant model that forms the geometric basis of a facility digital twin.

3.3.3. Manufacturing, metrology and reverse engineering

In manufacturing, laser scanning supports dimensional inspection, tolerance verification and reverse engineering. A scanned part is compared against its nominal computer-aided-design model to reveal form errors, misplaced or missing features and deviations that accumulate across production stages, while parts lacking drawings can be digitised and rebuilt as editable models [1]. Terrestrial and handheld scanners can reach the accuracies demanded by high-value assembly; for example, terrestrial scanners have been shown to recover aerospace-fastener surface normals to better than half a degree for wing-assembly conformance [32]. Reverse-engineering workflows continue to advance through scanning methods that reduce reliance on external reference targets and repositioning, streamlining part digitisation on the shop floor (Figure 8) [33]. Establishing the metrological traceability of such measurements, which feed the spatial layer of a manufacturing digital twin, remains an active field of standards development [10].

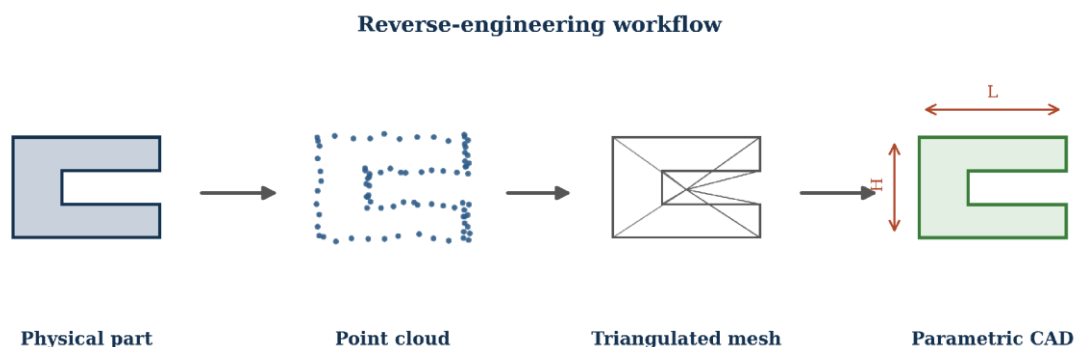


Figure 8. Reverse-engineering workflow in manufacturing: a physical part is digitised into a point cloud, converted to a triangulated mesh and finally reconstructed as a parametric CAD model.

3.3.4. Energy, utilities and asset management

In the energy and utilities sector, laser scanning documents power stations, substations, transmission corridors and tank farms, and supports clash-free upgrade planning in space-constrained plants. Beyond one-off surveys, periodic scans underpin asset-management programmes (Figure 9): linked to a digital twin, they let operators track change, plan maintenance and manage multiple facilities remotely from a single reality-based



model [6]. Table 4 maps the principal industrial application domains reviewed here to their typical platforms and representative studies.

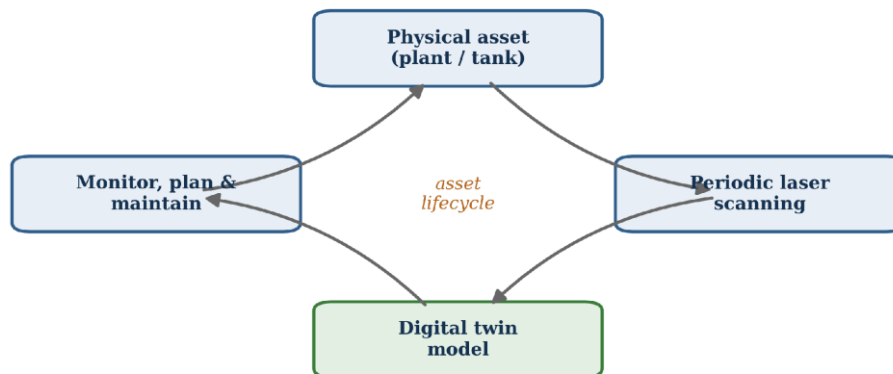


Figure 9. Asset-management lifecycle: periodic scans keep a digital twin of a facility up to date, supporting monitoring, planning and maintenance.

Table 4. Principal industrial application domains of laser scanning, with representative tasks, typical platforms and cited studies.

Application domain	Representative tasks	Typical platforms and references
Automotive and robotics	Real-time perception, navigation, object detection	MLS / automotive LiDAR; [5]
Process plants, oil and gas	As-built piping capture, retrofit design, digital twins	TLS, handheld SLAM; [6]
Manufacturing and metrology	Dimensional inspection, CAD comparison, reverse engineering	TLS, handheld, laser trackers; [1], [10], [32], [33]
Energy and utilities	Asset management, plant documentation, monitoring	TLS, handheld SLAM; [6]

4. DISCUSSION

To position the present work, Table 5 compares it with five representative laser-scanning reviews spanning deep-learning methods for point clouds [4], automotive LiDAR [5], mobile-laser-scanning data processing [34], laser scanning for transport infrastructure [35], and digital twins for oil-and-gas plants [6]. The comparison uses five coverage dimensions: breadth of platform coverage, the treatment of ranging fundamentals and data, the processing pipeline, industrial and production applications, and artificial-intelligence-based processing.

Table 5. Comparison of this review with representative laser-scanning reviews across five coverage dimensions (Yes = covered; ~ = partial; No = not covered).

Study [ref]	Primary focus	Multi-platform	Fundamentals	Pipeline	Industry apps	AI / DL
Guo et al. (2021) [4]	Deep learning for 3D point clouds	~	No	~	No	Yes
Li et al. (2021) [5]	Deep learning for automotive LiDAR	No	No	~	~	Yes
Che et al. (2019) [34]	Mobile-laser-scanning data processing	No	~	Yes	No	~
Soilán et al. (2019) [35]	Laser scanning for road/rail infrastructure	~	~	Yes	~	No



Study [ref]	Primary focus	Multi-platform	Fundamentals	Pipeline	Industry apps	AI / DL
Hamidishad et al. (2025) [6]	Digital twins for oil and gas plants	No	No	No	Yes	~
This review	Integrated LiDAR/TLS/handheld for industry and production	Yes	Yes	Yes	Yes	Yes

As Figure 10 summarises, the existing reviews are each strong within a narrow scope, typically one platform class or one application domain, but none spans the full breadth addressed here. Method-oriented surveys emphasise algorithms over platforms and industrial context, whereas domain-oriented reviews concentrate on a single sector. By integrating the LiDAR, terrestrial and handheld families with an explicit industry-and-production focus, the present review addresses all five dimensions, complementing rather than duplicating the earlier work.

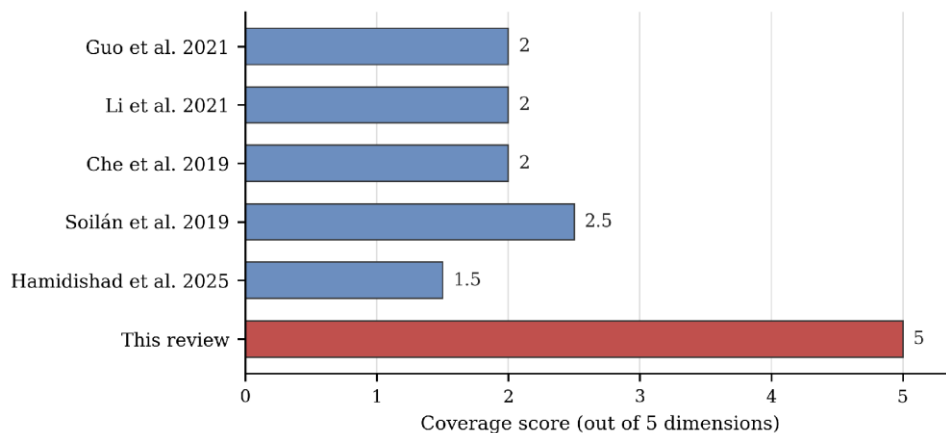


Figure 10. Coverage score (out of the five dimensions in Table 5) for each review; this review addresses all five.

The evidence surveyed above shows that laser scanning has matured into a versatile, accurate and increasingly indispensable industrial measurement technology. Its defining strength, acquiring millions of accurate 3D points rapidly and without contact, addresses limitations of conventional point-by-point methods and enables deliverables, from as-built models to digital twins, that discrete measurement cannot support at comparable speed [1], [6]. The complementary nature of the platform classes means that the practical question is rarely which technology to use, but how to combine airborne, mobile, terrestrial and handheld data to meet a given accuracy and coverage requirement.

Several challenges nonetheless persist. Occlusion and limited line of sight leave gaps in congested industrial scenes; beam incidence angle, surface reflectance and atmospheric effects degrade accuracy; and the sheer volume of point-cloud data strains storage, transfer and processing. Registration error accumulates through the workflow and remains a primary source of uncertainty, while the absence of a fully standardised, universally adopted performance-evaluation procedure complicates instrument comparison and metrological traceability [10]. Handheld-SLAM systems, although transformative for accessibility and speed, still trade centimetre-level accuracy for their convenience [17], [18].

The clearest trend is the convergence of laser scanning with artificial intelligence and Industry 4.0 platforms. Deep-learning methods are steadily removing the manual segmentation and modelling bottleneck [4], [5], while digital-twin frameworks integrate reality-captured geometry with real-time operational data for monitoring, simulation and control [6]. Future work is likely to centre on faster and more robust automated interpretation, tighter multi-sensor and multi-platform fusion, continuous or permanent scanning for change detection, and the standardisation needed to make laser-scanning products reliably interoperable across the industrial data ecosystem.



5. CONCLUSION

This paper has reviewed the laser-scanning family (airborne, mobile, terrestrial and handheld SLAM systems) and its applications in industry and production. From a common basis in laser ranging and point-cloud representation, the platform classes offer distinct and complementary balances of range, accuracy, speed and accessibility, and a shared processing pipeline turns their point clouds into models for reverse engineering and computer-aided design. Reviewed across manufacturing metrology, process plants and oil and gas, automotive and autonomous production systems, and industrial asset management, laser scanning emerges as a key enabler of as-built documentation, quality control and digital-twin creation. Realising its full potential will depend on overcoming persistent challenges of occlusion, data volume, registration error and standardisation, and on the continuing integration of laser scanning with artificial intelligence and Industry 4.0 workflows.

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Conflicts of Interest

The authors report no conflicts of interest.

Data Availability Statement

No new data were created in this review study. All sources analysed are cited in the reference list and are available from their respective publishers.

Institutional Review Board Statement

Not applicable. This study did not involve humans or animals.

CRedit Author Statement

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