Can engineers trust AI for railway infrastructure asset management?
Is AI worth it?

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Abstract:

This paper focuses on the application of AI for railway infrastructure asset management and the potential for AI to facilitate optimisation of the rail system. It is based on Cordel's own automated sensor data acquisition (covering 35,000 track miles of data service per month) and our processing and analytics outputs, with our growing range of railway-specific AI/ML training sets.

We begin by characterising three types of AI, including the Machine Learning AI that we are experienced in applying for railway engineers. We then work through our methodology with a case study of a specific implementation applied to LiDAR and other data captured from Cordel sensor sets installed in October 2022 (and still running) on Class 165 passenger trains (owned by Angel Trains). These trains are operated by Great Western Railways in normal passenger service on Network Rail infrastructure. We highlight one of the asset management applications that we delivered for Overhead Line Equipment (OLE) engineers, which focused on reliably and repeatedly measuring the Heights and Staggers of catenary wire along the electrified route.

The key aim for Heights and Staggers was to build local engineers' trust in the data and the AI; in order to show that it could efficiently assure standards compliance, and promptly detect change, enabling corrective action. Since this aim was demonstrated, we have embarked on the next stage: to embed the application of AI into NR's asset management systems. This stage will integrate our actionable insights into established NR enterprise IT architecture to enable the most cost-effective pro-active prevention of impact on operational train service delivery.

We also provide an overview of other asset management outputs, with AI applications on railways in Australia, the US and the UK. Case studies include AI solutions that propose interventions and provide decision-support tools for maintainers such as:

- Vegetation management within the rail corridor: measuring the volume of vegetation propagating into sensitive spaces such as the vehicle gauge or the Overhead Line Equipment (OLE); quantifying and trending the rate of growth to pinpoint intervention requirements; and/or to assess the effectiveness of interventions made.
- Structures, Platforms and Track Intervals: to produce standard gauging/ clearance files into Network Rail's Railway Gauging Data Solution (RGDS) that we provide, delivering the National Gauging Database for vehicle/ route clearance assessments. Amtrak also benefits from an analogous Amtrak Clearance Data Solution (ACDS) that we provide in the USA.
- The location, orientation, sightlines and condition of Level crossings, signalling and other assets in the rail corridor: to efficiently assure standards compliance and promptly detect change to enable corrective action, preventing impact on operational train service delivery.

We conclude by summarising key learning points from our experience on railways, such as:

- that explainable methodology and quality assurance (based on precision and accuracy, comparing with existing methods) builds confidence in the validity of AI outputs; alongside
- the power of AI to enable disparate datasets to be integrated for a bigger, better picture; and
- the size of the potential cost-effectiveness and performance prizes for infrastructure maintainers from applying AI to railway networks.

What is AI?

There is a huge range of material defining Artificial Intelligence, and this paper will not attempt to be definitive, merely to set the context. A Cordel colleague characterises AI as taking three forms:

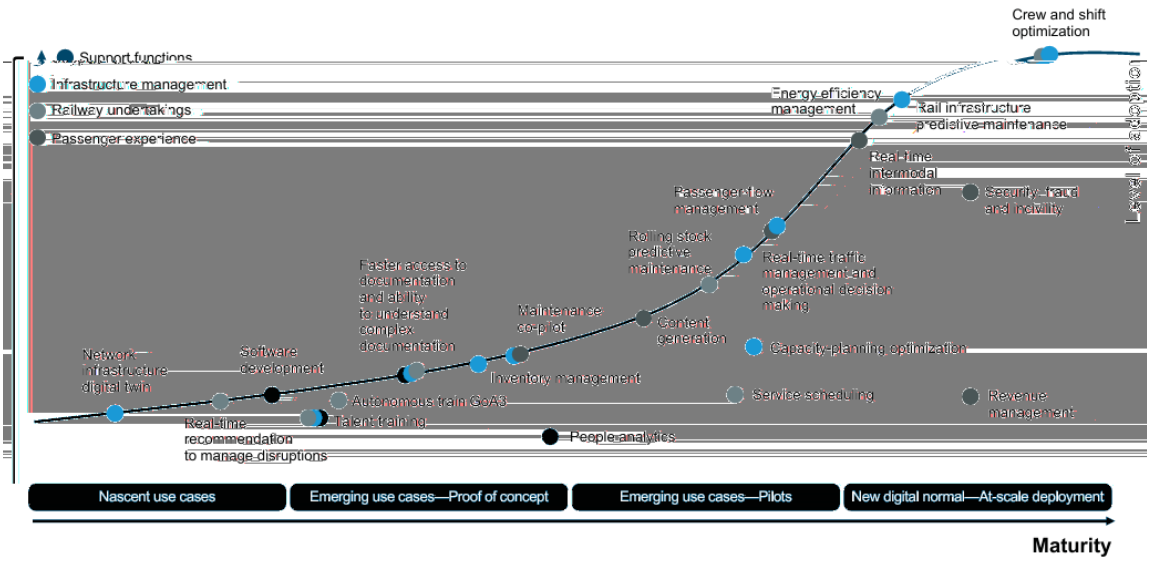
1. **Generative AI** – what Chatbots and virtual assistants do, large language models. Generative AI encodes a simplified model of the data they are trained on. When prompted by humans, the AI responds by generating statistically probable outputs, based on the data. The (increasingly) good models aspire to create new work that passes the Turing test, making us think we are engaging with a human being, encouraging their use in customer service applications. Current ethical concerns include: the risk of partial training datasets skewing outputs (perpetuating the dominance of the global north and/ or more local bias); intellectual property theft (human authors are challenging generative models trained on their works); and, particularly during the current election period, potentially damaging deep fakes generated by malicious actors.
2. **Analytical AI** – what Cordel does. We create Machine Learning (ML) models that use algorithms and statistical techniques. Once trained on a dataset, ML models recognise patterns and make inferences, rather than being specifically programmed. AI analytics provide supporting automation to human data analysts, typically delivering faster analysis, bigger scale and more granular data ingestion. Solutions created feed into railway decision-support tools, so human-AI collaboration can enable key criteria of responsibility, transparency and accountability - as set out in Route Services' Artificial Intelligence Policy (NR 2023) - to be met.
3. **Fake AI** – frankly, given that AI is fashionable, claims are sometimes made that AI is being deployed when conventional analysis is actually undertaken (and may well be perfectly sufficient to solve the problem posed). On a positive note, *fake* AI is much simpler (and less dangerous) than *flawed* AI (which might consist of a poor or unfair realisation, a particular risk with Generative AI, as mentioned above), but never-the-less worth identifying for clarity.

What is the potential for AI in railways?

Global railway industry adoption of 100 potential AI Use Cases was assessed with surveys of 11 railway companies in Europe and Asia, supplemented by interviews with 15 railway companies and OEM vendors worldwide (International Union of Railways (UIC), 2024). The report identified 20 different AI applications from 'nascent' (early-stage exploration) to proofs, pilots and a few deployments at-scale. These were mostly Generative AI applications, with Use Cases for railway undertakings, customer management and support functions; however, they also found a fourth group of business activities in infrastructure management, the focus of this paper.

But first, what is the potential value of AI for rail? McKinsey (UIC, 2024) estimates the size of the global AI prize in terms of annual impact for railway companies as $13 billion to $22 billion, suggesting a 14% uplift in the total value of the companies. This figure derives from increased revenue (eg enhanced sales from AI-driven marketing; greater network capacity from AI-driven planning and disruption support to better (re)schedule trains and people); and from reduced costs (eg tighter energy efficiency management; maintenance optimisation, of both rolling stock and infrastructure). Moreover, the biggest single potential lever to drive this railway company value uplift (25% of the total identified) was attributed to the deployment of AI for infrastructure maintenance, the subject of this paper.

Research identified roughly 20 AI use cases, at different maturity levels, being applied by railways



urce: UIC survey of 11 railway companies across Europe and Asia, and 15 interviews with railway companies and OEM vendors, worldwide, June to November 2023

The above graphic (from UIC, 2024) illustrates survey findings that some rail infrastructure predictive maintenance applications are moving from “Emerging use cases” towards the “New digital normal”.

In other words, AI in rail infrastructure is poised to deliver. Before diving into the AI itself, we start with an overview of the core ingredient: the extent and adequacy of data in railways.

What infrastructure asset management data do railways have?

To harness the power of AI we need to access relevant data, ‘big data’. But data itself presents three key challenges for railways:

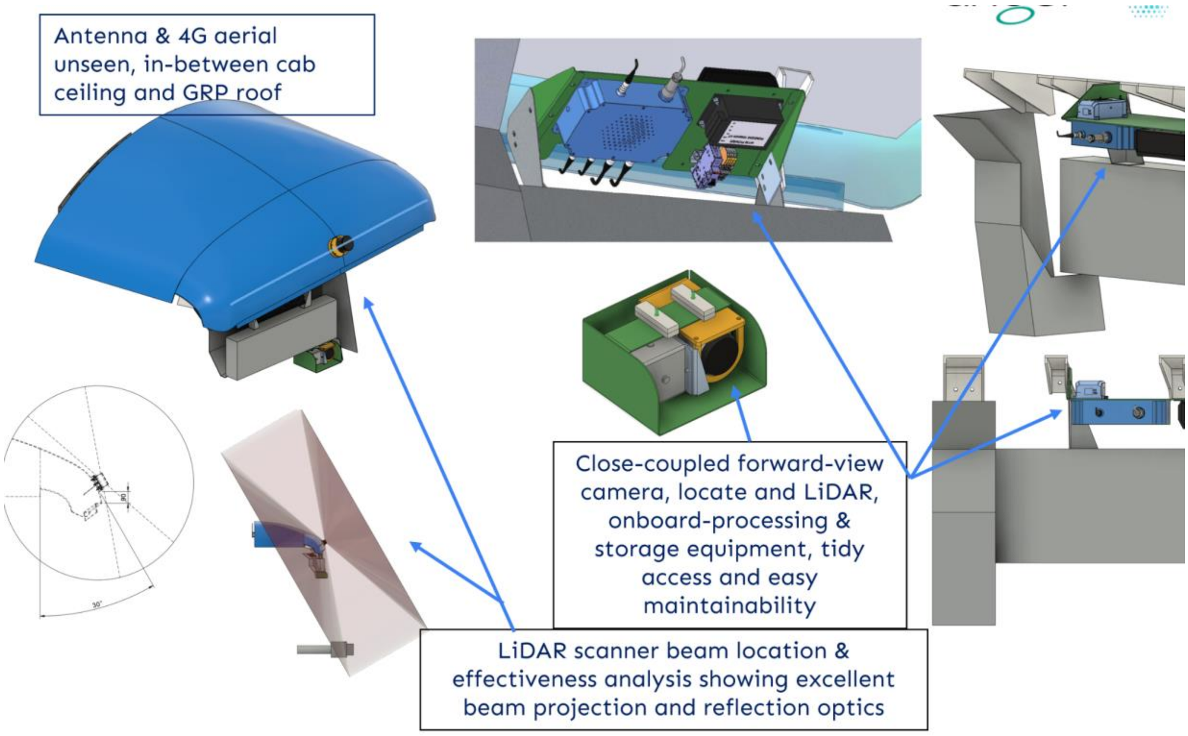
a. **Volume**: historically, railways have had insufficient data. More recently, with the advent of affordable data capture methods, the challenge is to manage the abundance of data. The sheer volume of data can overwhelm railways, especially if data cannot be efficiently transferred from capture to consumer. Siloed data storage often hinders effective data sharing and limits optimisation even within the same railway company, both geographically and across engineering disciplines.

b. **Variety**: even within the limited field of infrastructure asset management, railways have access to diverse data sources such as video, acoustic recordings, satellite imagery, and LiDAR data (both aerial and trainborne). It is challenging to derive quantitative data from some data sources, limiting their utility for measurement-based degradation modelling and hence their potential for asset management optimisation. Beyond quantification, it is difficult to assess how much weight to put on disparate sources individually, because the real value lies in effective integration to create holistic insight.

c. **Quality**: railway data is notoriously inaccurate, particularly with respect to geospatial location and alignment with the Linear Reference System of each rail network. Challenges arise from uneven length ‘miles’, incomplete asset registers, and post-processing inconsistencies. Regulatory bodies, like the Office of Rail and Road, have explicit requirements for Accuracy, Completeness and Currency of infrastructure gauging data, for example.

What data was collected for the OLE Heights and Staggers Case Study?

The Class 165 analytical AI case study ingested LiDAR data captured using Cordel Wave 32 systems installed onto railway vehicles operating in normal passenger service.



Key modules in the Cordel Wave 32 system

Class 165 with Cordel Wave 32 installed

The exterior-mounted LiDAR sensor can be seen: it is closely coupled with an Inertial Navigation System (INS), approved as accurate to ±50mm under NR/L2/TRK/3100 (NR 2019). Accuracy is further enhanced using the Network Rail GeoRINM network model. Co-located Video imagery is also captured.

When vehicle movement is detected, the sensors automatically start capturing data which is stored on a trainborne server. Up to 110 GB of data per day are captured in normal passenger service: all this data is successfully retrieved entirely autonomously. Once we have collated and curated disparate datasets, as captured by ourselves and others, we use AI to address the problems that railways have.

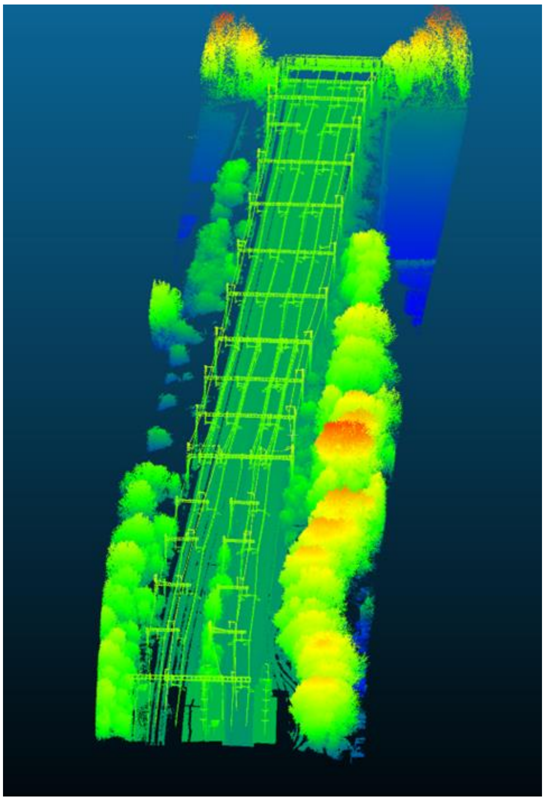
Specifically in our specialist field of automating infrastructure asset monitoring, next we will share how we apply artificial intelligence with modern enterprise IT architecture to provide actionable insights.

How is analytical AI applied to railway infrastructure asset data to create insight?

Here we set out how Cordel analytical AI is applied to produce Height and Stagger measurements for overhead line electrification (OLE) engineers, detailing a specific case study (later we outline other use cases, with analogous deployments).

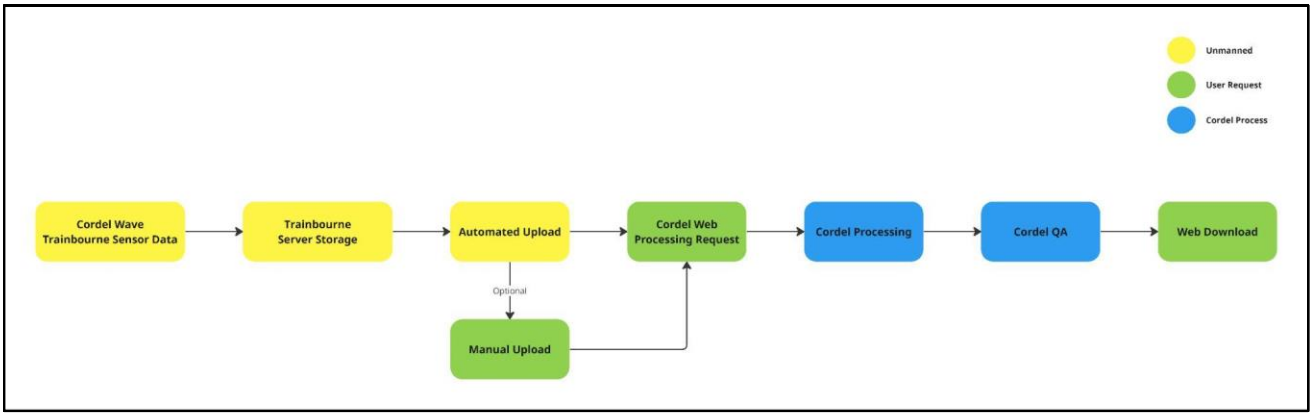
The first stage in AI application is to create a Digital Twin. There are notoriously many different definitions of Digital Twin, but in this case, we refer to the pictured model, which is a full 3D representation of the railway corridor. Cordel provides this from the LiDAR point cloud data collected by the Cordel Wave 32 system. It is hosted on a web viewer, where authorised users can access the data and make manual measurements within it.

This Digital Twin is also the base input into the Cordel contact wire extraction process, so the subsequent accuracy of the OLE detection module correlates directly with the accuracy of the point cloud input. We can utilise other LiDAR point clouds to feed our AI pipeline, but the outputs can then become less accurate.



Cordel LiDAR Point Cloud – from one trainborne pass

What is the overall pipeline from sensors to AI outputs?



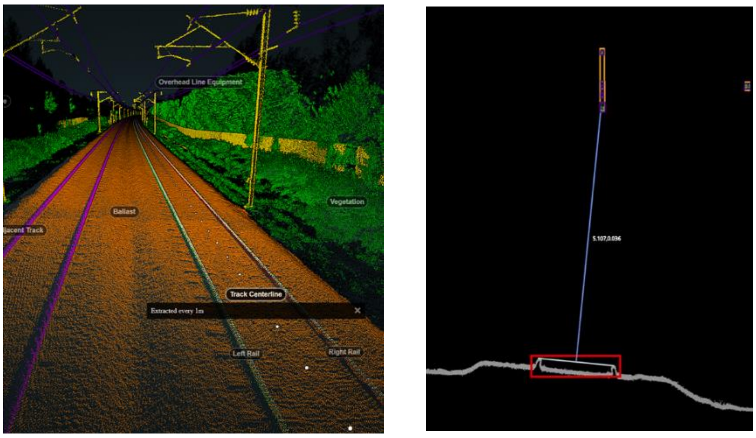
The Cordel data pipeline (see above process flow) is normally operated virtually, with sensor data automatically uploading to cloud storage. Data from a particular capture is selected for processing into, for example, OLE Heights and Staggers or gauging files. The data is then processed through the Cordel workflow into the requested output datatype, prior to internal Quality Assurance.

Once the data is processed and assured, it becomes available on the Cordel Platform for user download and review; Cordel outputs can also be fed into other systems to facilitate consistent visualisations and effective implementation (eg for onward processing into familiar formats, and to align with historical datasets, particularly important for legacy IT interfaces).

Typical Cordel Service Level Agreements deliver turnarounds from capture to outputs within 2 weeks: the high level of automation means that large data volumes and long-term requirements unlock economies of scale, but users can also make ad hoc additional requests.

What is the OLE Measurement Extraction AI Methodology?

Robust railway-compliant, repeatable outputs are most readily achieved using accurately geo-located LiDAR point cloud, providing very big but highly granular and quantifiable datasets into AI processing engines. The Cordel point cloud data undergoes classification using an AI model to identify and categorise different assets. Specifically for OLE extraction, this automated classification process accurately detects the contact wires and rail heads present in the point cloud. By isolating these specific elements, we effectively eliminate interference from other point sources, optimising OLE extraction:



The data is segmented into cross-sections based on the direction of travel, each cross-section being 1 metre deep and representing a 2D snapshot of all points within that depth in 3D space. This depth provides a standardised container for the AI classification algorithm to analyse LiDAR points across different speeds while maintaining accurate point classification.

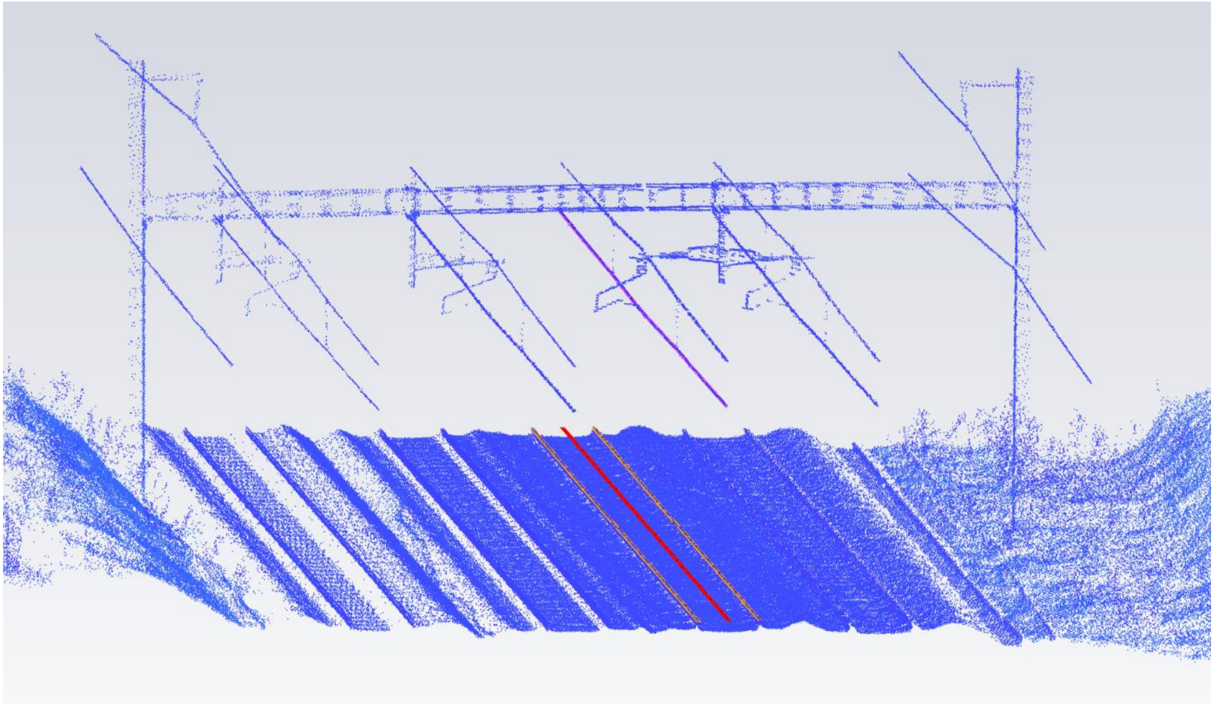
Cordel AI-Classification of 3D Point Cloud (left) and extracted 2D OLE Height and Stagger Cross-Section (right)

From these classified points and knowledge of expected asset geometry, measurements for height from the contact wire centreline and horizontal offset (stagger) to the rail centreline are extracted. Reducing the cross-section depth decreases the available points, thereby impacting the accuracy of automated classification. To address this, an extended Kalman filter is utilised to report data at the desired 0.2-metre intervals. The Kalman filter serves a dual purpose, statistically inferring OLE properties from noisy OLE detection data and acting as a statistical interpolant between the 1-metre cross-sections.

In addition to the height and stagger, the 3D position is calculated to determine the location of the contact wire. The 3D positions are stored using the same datum scheme as the input point cloud, specifically the OSGB36 datum, as approved for geospatial accuracy by Cordel Wave 32 according to Network Rail survey standard NR/L2/TRK/3100 (NR 2019). CSV outputs include metadata of ELR, TrackID, Capture Date and GPS positioning information at whatever granularity Height and Stagger are required (traditionally every 0.2m on NR).

Building trust in the AI outputs

The beauty of this explainable AI approach means that data can then be shown back on the point cloud by using the Cordel Contact Wire CSV as an input to create line segments. An example of this is shown below where the magenta line represents the contact wire, the red line represents the track centreline and the orange lines represent the gauge face of the rail heads.



Cordel LiDAR Point Cloud with overlaid extracted contact wires and rail geometry

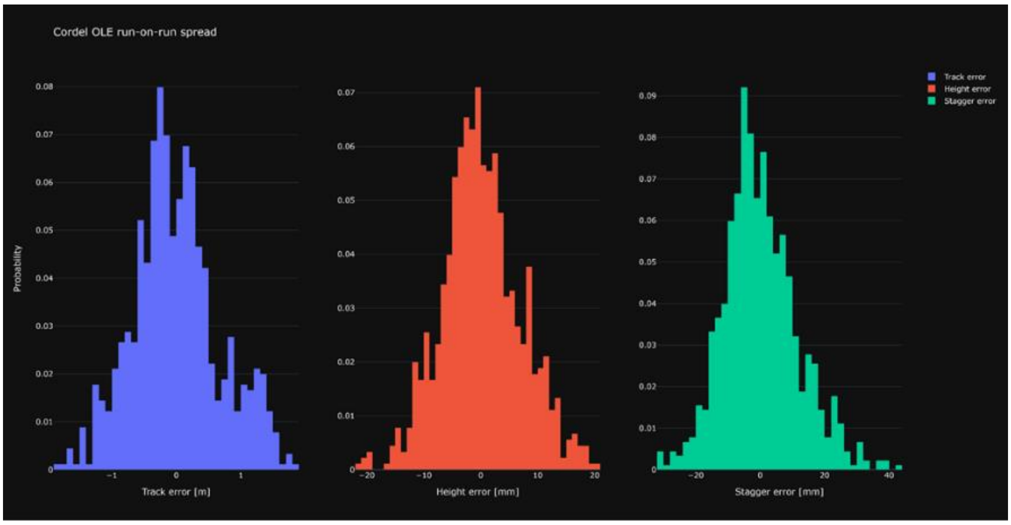
Thus, it can be seen that the extracted OLE measurements match the physicality of the point cloud, classified as shown, giving confidence that the AI outputs are correct. This discipline-specific confidence of engineers is consolidated into trust with in-depth statistical analysis, particularly to confirm standards compliance and to ascertain accuracy and precision.

Standards Compliance, Accuracy and Precision

Standards compliance (to NR/L2/ELP/27325 for OLE Heights and Staggers, NR 2016) was proved out across a variety of railway features such as track curve and cant, tunnels and overbridges; and different asset types and attributes (eg masts/ portals/ anchor fixings, neutral sections, insulators). Requirements can be very granular and specific, for example (from Table 3 in the standard):

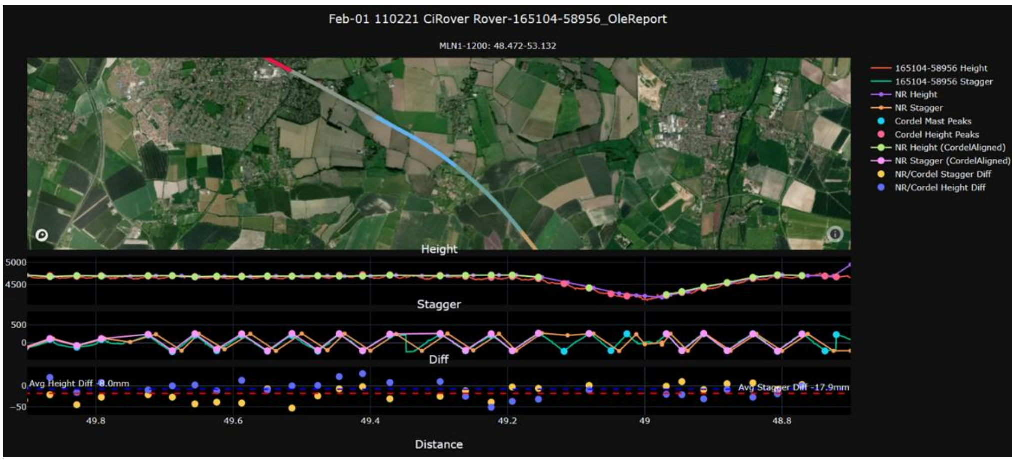
Parameter	Unit of measure	Accuracy measurement	Sampling rate	Measure of exceedance
Static contact wire stagger / deviation	mm	+/- 25mm	> 1kHz	Two levels to be reported: • ≥ 400mm** • ≥ 460mm**
Static contact wire height	mm	+/- 25mm	> 1kHz	Low: ≤ 4165mm** High: ≥ 5940mm**

The AI was found to deliver compliant results with run-on-run spread over multiple datasets giving averaged standard deviations for track, height and stagger (see below distributions):



Accuracy was also checked out by comparing AI outputs with existing non-AI methodologies eg manual measurement, other automated technologies, with repeat runs across the same track section.

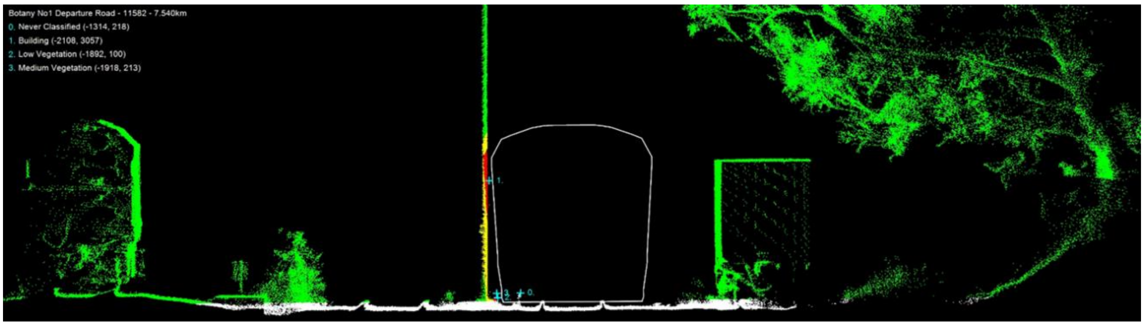
Precision (AI self-consistency comparisons) were also undertaken, overlaying AI-generated measurements, as shown below:



Capture once, use many times

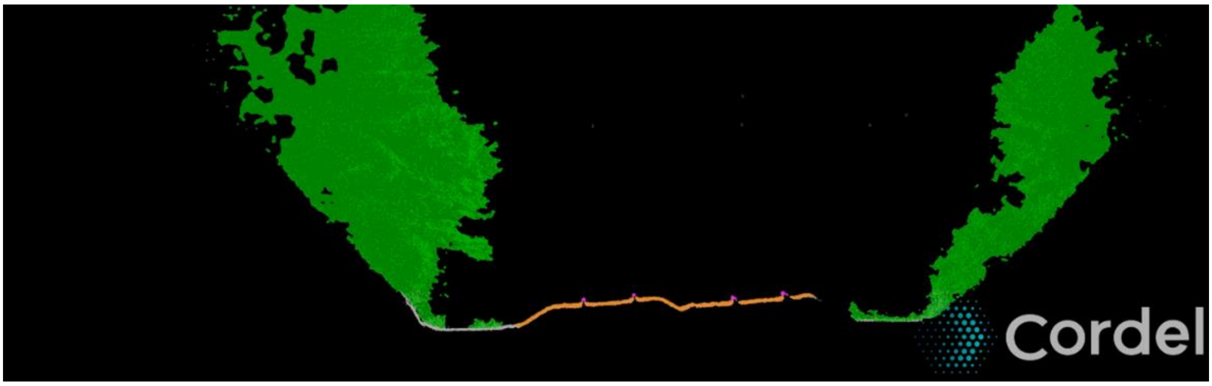
Once railway engineers find that they can trust AI to deliver standards-compliant, repeatable measurements that are accurate and precise in one domain, such as OLE, applications can be extended to other specialisms. We can use the same captured LiDAR dataset to train the AI to identify additional outputs, and satisfy the requirements of other infrastructure disciplines.

International use cases that are currently delivering trusted AI applications '**commercially at scale**' include **Vegetation management** for ARTC (the Australian Rail Track Corporation) see below:

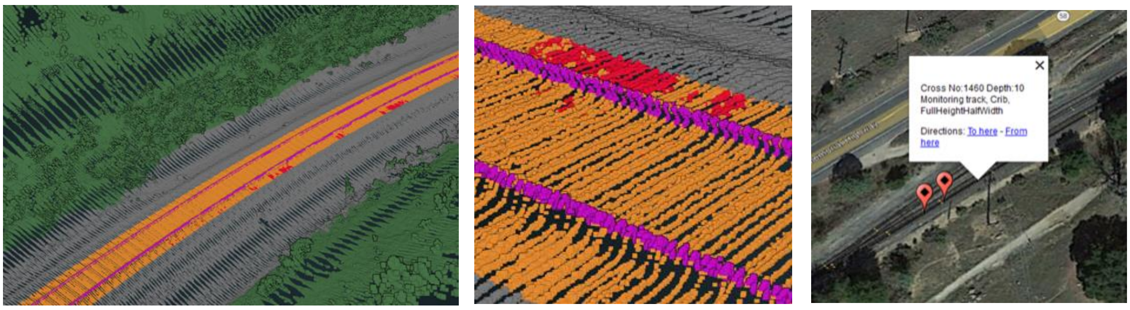


For ARTC, Cordel AI delivers decision-support triaging by analysing vegetation growth according to location (hence risk). Staff time is saved by the AI detecting and pinpointing exceedances for engineering review to prioritise and target physical interventions on site.

After significant rainfall following a dry spell, AI-based vegetation detection has proven invaluable to determine and triage worst cases of rapid growth into spaces that are critical for the unobstructed passage of trains, and/ or the integrity of sightlines, etc.



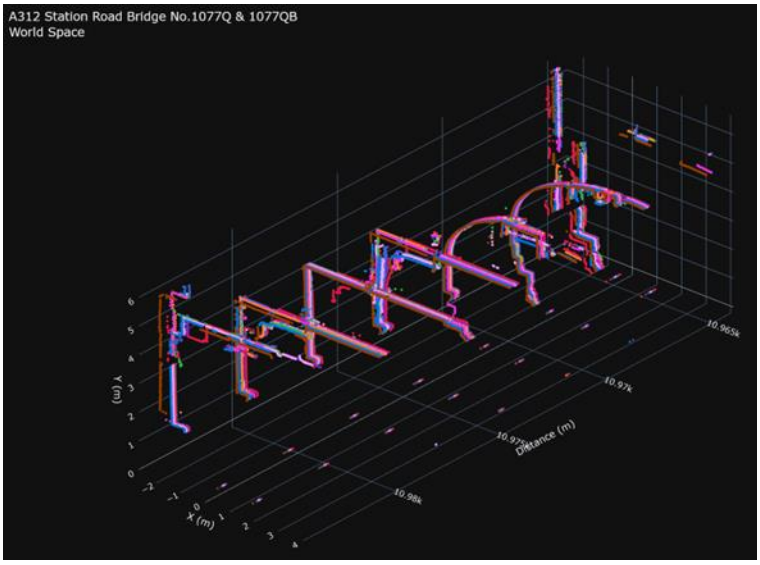
Many more railways have reached the emerging use case stage with '**pilot deployments**' for example AI for **ballast profiling** in the USA:



Km	Depth(m)	Desc	Longitude	Latitude	Altitude	Easting	Northing	MaxWidth	Volume	Track	Sector
1.2	10	Automatically Found	-121.6591323	35.33901164	228.12689	712743.05	3913153.77	0.945	0.357	Monitoring track	Crib
1.8	5	Automatically Found	-121.6780106	35.33014424	182.21938	711050.11	3912129.67	0.581	0.332	Monitoring track	LeftShoulder
2.4	10	Automatically Found	-121.8591323	35.34901164	228.12689	712943.05	3913153.77	0.945	0.57	Left track	Crib
3.9	25	Automatically Found	-121.8780106	35.34014424	182.21938	711150.11	3912129.67	0.581	5.6	Monitoring track	LeftShoulder Crib

For ballast, we compare with profile requirements in standards to detect and identify exceedances and deficiencies (in red), pinpointing their locations on our viewer to build engineering trust. The quantified volumetric data can then prioritise intervention, drive improvement and verify outcomes.

AI for **Gauging clearances** on Network Rail:



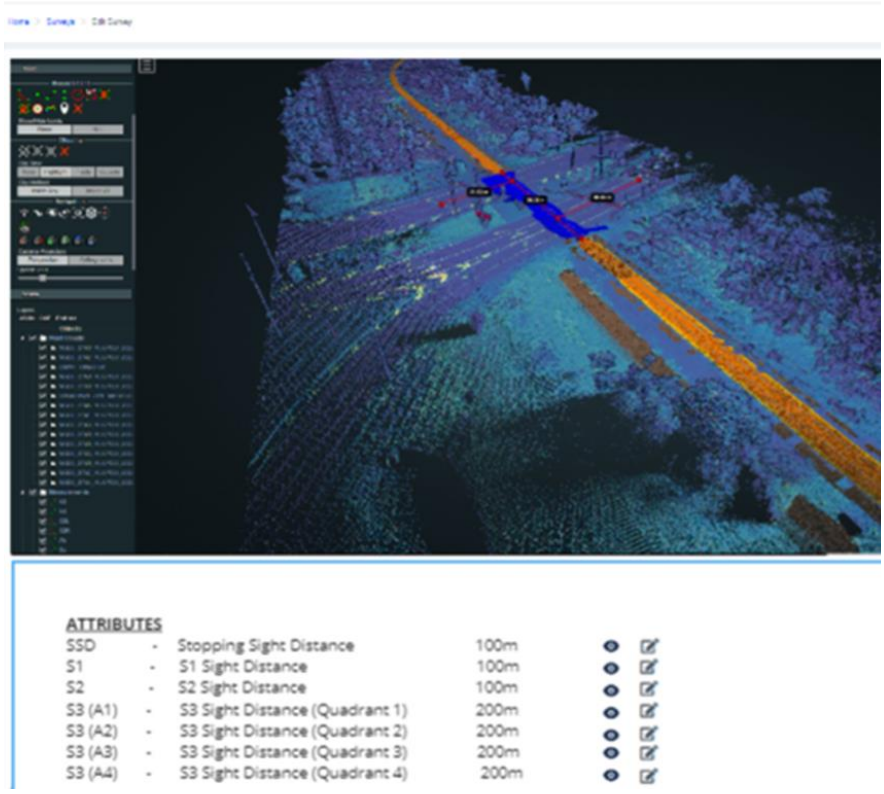
Here we show 8 different overlaid runs, where the AI cut 2D cross-sections at precisely the same 1m locations through a complicated tunnel-bridge structure that changes shape as it progresses.

This was part of our submission to the NR Technical Authority for approval to NR/L2/TRK/3204/01 Gauging survey, equipment, editing and outputs for Structures, Platforms and Track intervals (NR 2024), even in 3rd rail areas.

Other use cases are being developed from R&D into proof of concept, such as AI for **Level Crossings** in Australia where Cordel won R&D funding to develop a National Level Crossing Data Management Platform. We will use automation and AI to provide low-cost purpose-built tools that improve the resilience and efficiency of data analysis, drawing on our own LiDAR data for the railway-facing measurements, and integrating different datasets including manual inspections

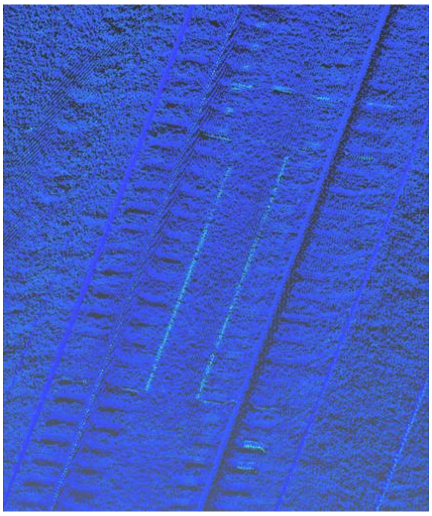
Building on our Railway Gauging Data Solution (RGDS), where we provide the National Gauging Database for NR in a 6.5-year contract, our Level Crossing AI integration in Australia will:

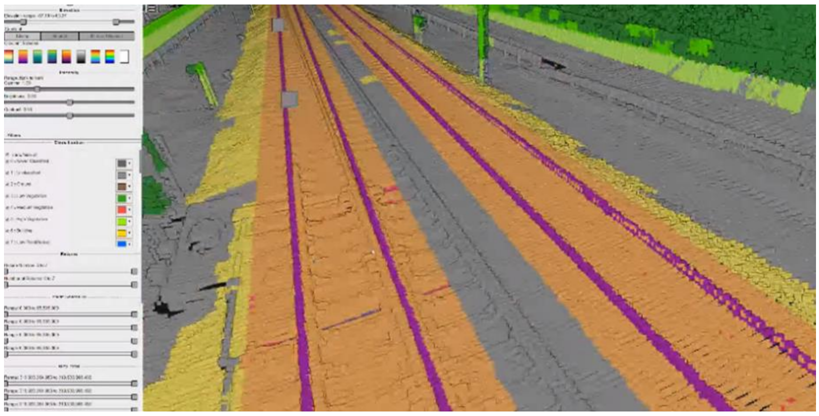
- Store large multi-modal datasets, searchable in Time, Space and by asset class condition
- Provide asset-specific visualisations (eg Map views, LiDAR visualiser, Camera footage, etc…)
- Deploy automated attribute extraction using AI and ML
- Create managed workflows of Quality Assurance processes
- Include inspection attribute editing tools (Manual or AI-operated)
- Maintain Asset Audit Logs
- Provide historical context
- Deliver robust security through well-defined user access controls.



Capture again to detect any delta

On HS1, Network Rail (High Speed) have taken the run-on-run accuracy a stage further, turning it around to identify small run-on-run changes, particularly to detect emerging potential obstructions such as bird's nests being constructed in the vicinity of OLE. Our AI can also identify cm-level changes in Signalling and Telecommunications assets eg orientation of transponders in the 4-foot (below left), integrity of cable trunking in the cess, lineside equipment boxes (below right):

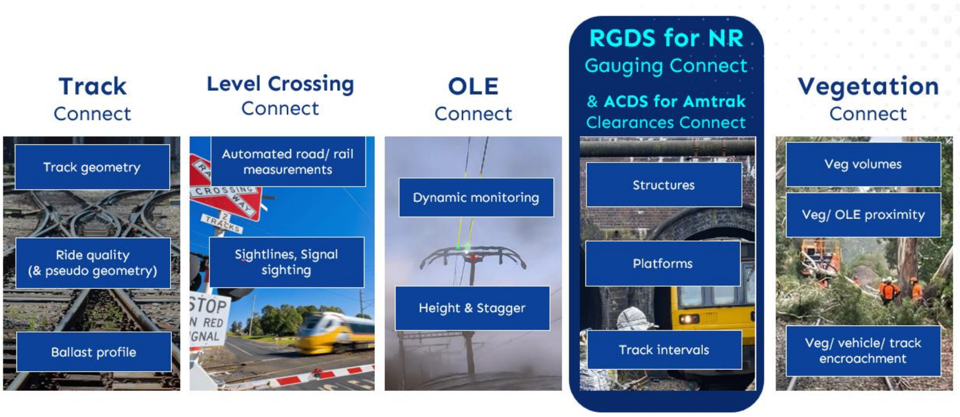




Apply AI to different datasets to enable holistic management

The concept of combining multiple datasets for a holistic picture is challenging, given the traditional challenges of different infrastructure disciplines having different linear refence systems and different data silos (see figure below). However, if datasets are tagged with accurate time/date/location metadata, AI analysis can combine them unlock latent potential. This enables questions such as "Why is my height/ stagger drifting outside limits?" to be traced to an underlying lineside drainage root cause, relating to the movement of the OLE mast foundation, and thereby to the fix.

Similarly, mature AI applications in continental Europe include using photogrammetry data to spot potential rail defects. Whilst this data is useful of itself to trigger interventions, there is potential for holistic risk analysis:



such as taking weather patterns and tree species failure data; combined with up-to-date trainborne LiDAR (to detect standing water or small earth movements under vegetation); and with other condition monitoring datasets to prioritise lineside trees for attention, in order to prevent incursions onto the track (and hence potentially preventing incidents as well as reducing delays).

Conclusion

The case study we have presented indicates the robust processes undertaken to enable railway engineers to trust AI for infrastructure management, by configuring proven AI outputs to meet each railway company's standards compliance requirements, and then successfully demonstrating accuracy with respect to existing measurement systems, as well as self-consistent precision and repeatability.

Mirroring Cordel's experience in the UK, USA and Australia, European-based researchers (UIC 2024) found that all the major infrastructure managers they interviewed are using AI to prioritise and schedule maintenance work for assets with the highest criticality and highest probability of failure. Infrastructure managers want to minimise boots-on-ballast safety exposure for people undertaking routine inspection, so they increasingly rely on trainborne sensors measuring the railway corridor to identify emerging issues. AI enables risks to be more cost-effectively identified and managed, and has demonstrated potential to prevent failures, connecting disparate datasets to target true root causes.

We have set out how Cordel's experience supports the finding of UIC (2024) that there is scope for wider application of AI for rail infrastructure maintenance, utilising primarily trainborne LiDAR sensors. The UIC report quantified the potential benefits of AI applications for infrastructure asset management, based on the shared top customer-facing KPI of on-time railway system performance, as AI could enable:

- 15-30% lower maintenance costs
- 15-25% less unplanned downtime
- 20% reduction in delays per service.

The UIC authors suggest that railway companies do not need to drive AI implementation from scratch on their own; instead they could tap into the robust ecosystem of expert partners and vendors for support. Cordel aims to facilitate their journey to AI-enabled railway asset management, drawing on our AI expertise and extensive experience in railway deployment, some of which is shared in this paper.

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