Railway Infrastructure Monitoring Framework (RIMF) for Hudson Bay Railway

Final Report

Prepared For

Brett Young

General Manager

Hudson Bay Railway

Address

728 Bignell Avenue

The Pas, Manitoba

Prepared By

Oliver Wang

CEO

ApoSys Technologies Inc.

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1 Project review

1.1 Background

Railway networks are critical for northern communities' transportation and supply chains. Recently, extreme weather conditions have become more frequent and have impacted the safety and operation of HBRY railway infrastructure. The 2017 rail outage cut off Churchill by land for 18 months and caused a significant impact on employment, cost of living, business and tax. Transport Canada data shows the derailment rate on the HBRY was a few times higher than a few times higher than a decade earlier.

Traditional infrastructure assessments, often based on visual checks and scheduled Hi-Rail truck inspections, fall short in accurately monitoring track conditions. There needs to be more than just general thawing permafrost analysis for effective railway maintenance. A solution combining regular data collection, precise measurements, deformation detection, permafrost studies, and detailed climate models is essential. This approach is critical for regional railways to prevent costly, unanticipated events.

1.2 Proposed Project

The proposed project will test, implement and apply the innovative technology of the Railway Infrastructure Monitoring Framework (RIMF) developed collaboratively by ApoSys Technologies Inc. ("ApoSys") and the railway technology company – HBRY. RIMF is an Integral Transportation Analysis Model-based Artificial Intelligence algorithm for combining the Canadian climate model with InSAR and other satellite imagery for ground/infrastructure deformation, railway underground mapping, a loaded rail track geometry, and local track environmental data for rail-based transit monitoring as an innovative solution.

1.3 Scope

The following tasks are in the scope and completed:

- ApoSys has developed, tested and deployed the data sensing unit - Hardware Rail Track Monitoring Unit (ATMU)
    - Prototype – 2.0 collected 2000 miles data including LiDAR, camera, Ground Penetrating Radar, temperature, and vehicle motion in June 2023
    - Prototype – 3.0 deployed at HBRy locomotive to collect sensing data continuously in 2024 January;
- ApoSys conducted InSAR Satellite imagery analysis to detect the ground surface deformation at Herchmer, Churchill and Thompson;
- ApoSys also developed a customized climate model for above areas;
- ApoSys collaborated with universities to develop algorithm development for basic defect detection, parameter calculations, and parameters abnormally;
- ApoSys developed a RIMF prototype including a dashboard and reporting system.

1.4 Reporting

In this report, we provide the details we have achieved in the past year

- The general achievement;
- The variations from original proposal and schedules;
- Data indicators and performance indicators;
- Lessons to learn; and including
- The further development after the project.

2 Major activities and achievement

HBRY plans to address weather impacts and predictive risks with an advanced system combining rail track measurement, underground mapping, InSAR imagery, and local climate models for infrastructure monitoring. Utilizing AI/ML algorithms, the system will process data on track conditions and environmental trends, improving risk assessment and maintenance planning. This approach aims to reduce manual inspections, offering a cost-effective solution for climate adaptation in regional railways.

HBRY aims to test, evaluate and enhance RIMF technology with ApoSys and apply strategic implementations. The project's vision extends beyond HBRY, aiming for RIMF's adaptability across other railways and scalability to a Canada-wide network for global railways. In this project, we perform the following tasks:

1. TASK 1 – Rail track measuring unit data collection, field testing and validation
2. TASK 2 – Downscaling climate model to local in short time and long interval scale and coupling climate data into the infrastructure
3. TASK 3 – integrating track geometry data with InSAR and other processed satellite imagery for infrastructure monitoring and climate model
4. TASK 4 – Initial implementation of the proposed AI/ML algorithms into prototype prediction models to anticipate future anomalies in rail-based transit section considering the effects of climate change
5. TASK 5 – Platform development, including database, data network, application programs, and web portal

2.1 Autonomous Track Monitoring Unit (ATMU)

In the past year, we have developed two new versions of ATMU for HBRy to collect rail line data. The data include track geometry data, underground data and environmental data.

2.1.1 ATMU ver2.0 (ATMU-2.0)

In June 2023, we mounted the ATMU-2.0 to the HBRY GP38 locomotive to collect rail track geometry data, embankment data and environmental data. We also mount the ATMU to a rail track inspection truck to collect data. Data has been collected for diverse scenarios using different vehicles – locomotive and inspection truck, lighting conditions – darkness at night and daytime, environments – from The Pas to Churchill, and speeds up to 30mph. The primary sensors on the ATMU:

- Ground Penetrating Radar
- LiDARs
- Cameras
- Track Temperature Sensors
- Laser Distance Sensors
- Audio Sensors
- Temperature Sensors
- Accelerometers
- Humidity Sensors
- Gyro Sensors
- GPS.

Figure 1: Inspection Truck installation at Gillam

Figure 2: ATMU locomotive installation

2.1.2 ATMU Ver3.0 (ATMU-3.0)

In Jan 2024, an ATMU-3.0 prototype installed HBRY GP38 locomotive, which mainly has:

- Ground Penetrating Radar for track underground mapping
- Temperature sensors for track temperature
- GPS
- Ambient temperature

Figure 3: ATMU Ver3.0 mounted onto locomotive

Figure 4: ATMU ver3.0 in HBRY workshop

2.1.3 Accomplishment

From ATMU-2.0, we collected 1000km of data between Gillam and Churchill by mounting it onto the inspection truck. The same unit was also installed onto the GP38 locomotive to collect data between Thompson and Churchill for about 1600km data. The data amount is around 2TB.

From ATMU-3.0, we installed the unit permanently onto a GP38 locomotive. The primary purpose of this version of the installation is to collect data starting from winter, mainly so that this continuous data collection will cover the transition period from frozen to thawing to summer. We would like to find out what changes occurred during the process.

2.1.4 Outcomes – we found

- The ATMU concept is feasible in any environment.
- An onboard processing module is a must if we want to have a full sensors set
- The modular design will improve the field installation.
- Real-time defect detection is not critical to railway operators

2.1.5 Lessons to learn

To install an inspection unit to a locomotive for run continuously, we have to put below factors into the consideration:

- In winter, snow will impact on camera, LiDAR performance
- In summer, sunshine will impact on camera image quality
- In spring, liquid from seeds and vegetation will spray over the sensors
- Heating system is critical at winter time, especially at Churchill area
- The sharp turn rail line has to be considered for unit mechanical design
- Data fusion mechanism has to be improved to save a large amount of in time
- stainless steel is not always good option

2.1.6 Future development

In future development, we will have to improve the ATMU in a few fields:

- Make it lighter and smaller
- Further modular design for convenient installation and maintenance
- Improving data fusion to make sure no data loss
- Integrating with GPU-based edge computing onboard processing component
- Improving heating system
- Considering the cleaning system for optical sensors

2.2 Downscaling climate model

Our team is actively engaged in the development of a cutting-edge Meteorological Analysis Tool that aims to revolutionize how we perceive and utilize climate data for both long-term climate analysis and short-term operational decision-making. This tool integrates the CanLEAD climate model to provide comprehensive insights into climate patterns and trends over extended periods while also employing machine learning algorithms to offer real-time recommendations for daily operational planning. Users can select a coordinate on the map and specify a date range of interest, receiving graphical and numerical representations of relevant climate data.

2.2.1 Long-Term Climate Analysis:

The CanLEAD climate model is the cornerstone for our long-term climate analysis. This sophisticated model incorporates a wide array of meteorological variables and historical data, allowing users to understand climate trends over specific regions and timeframes deeply. Users can select a coordinate on the map and specify a date range of interest, receiving graphical and numerical representations of relevant climate data.

Features

- **Spatial Analysis:** The tool lets users choose specific coordinates on the map, facilitating localized climate analysis tailored to user-defined regions.
- **Temporal Analysis:** Users can set precise date ranges for analysis, allowing for observing seasonal, annual, or even decadal climate trends.
- **Graphical Representation:** Climate data is presented graphically, aiding in the visualization of temperature, precipitation, wind patterns, and other crucial variables. Graphs provide an intuitive way to comprehend complex climate information.
- **Numerical Insights:** For users preferring a quantitative approach, numerical data allows for in-depth statistical analysis and data-driven decision-making.
- User-Friendly Interface: **The tool boasts an intuitive interface, ensuring accessibility for users with varying levels of technical expertise.**

2.2.2 Climate analysis example

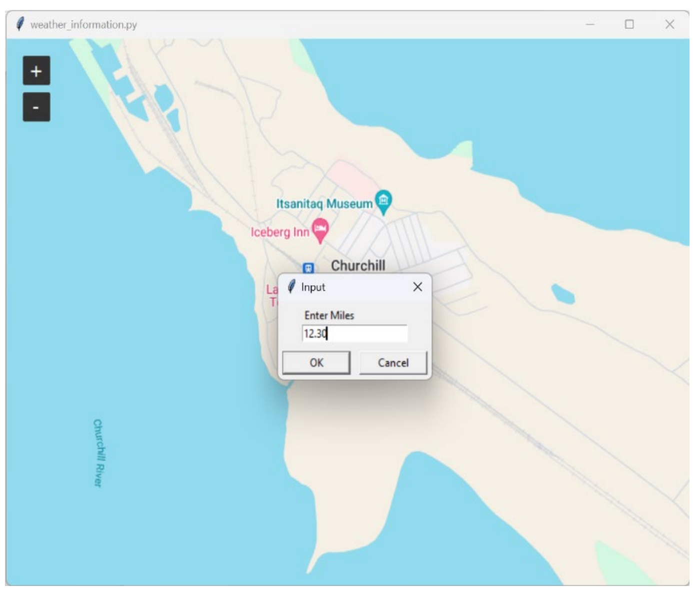


Figure 5: Location to be applied

	Dates	Surface Temperature	Air Temperature
0	2020-01-01	281.785217	280.270721
1	2020-01-02	281.797485	281.076965
2	2020-01-03	281.810669	281.869385
3	2020-01-04	281.806671	281.375214
4	2020-01-05	281.799042	281.724365
5	2020-01-06	281.798798	280.995422
6	2020-01-07	281.796417	280.645325
7	2020-01-08	281.789490	279.976929
8	2020-01-09	281.781830	282.028351
9	2020-01-10	281.769897	282.044586
10	2020-01-11	281.757874	280.567780
11	2020-01-12	281.768829	281.358276
12	2020-01-13	281.787964	280.996796
13	2020-01-14	281.793823	280.163544
14	2020-01-15	281.804535	280.174927
15	2020-01-16	281.816071	280.344513
16	2020-01-17	281.814240	281.153290
17	2020-01-18	281.804657	280.707489
18	2020-01-19	281.796173	280.172882
19	2020-01-20	281.793488	280.581665
20	2020-01-21	281.791077	280.700104
21	2020-01-22	281.777710	280.440979
22	2020-01-23	281.758850	280.202026
23	2020-01-24	281.750885	281.337738
24	2020-01-25	281.744385	281.136749
25	2020-01-26	281.744537	281.064240
26	2020-01-27	281.760620	281.461609
27	2020-01-28	281.786072	280.938202
28	2020-01-29	281.816254	281.287384
29	2020-01-30	281.841675	280.340607

Figure 6: predicted temperature numbers

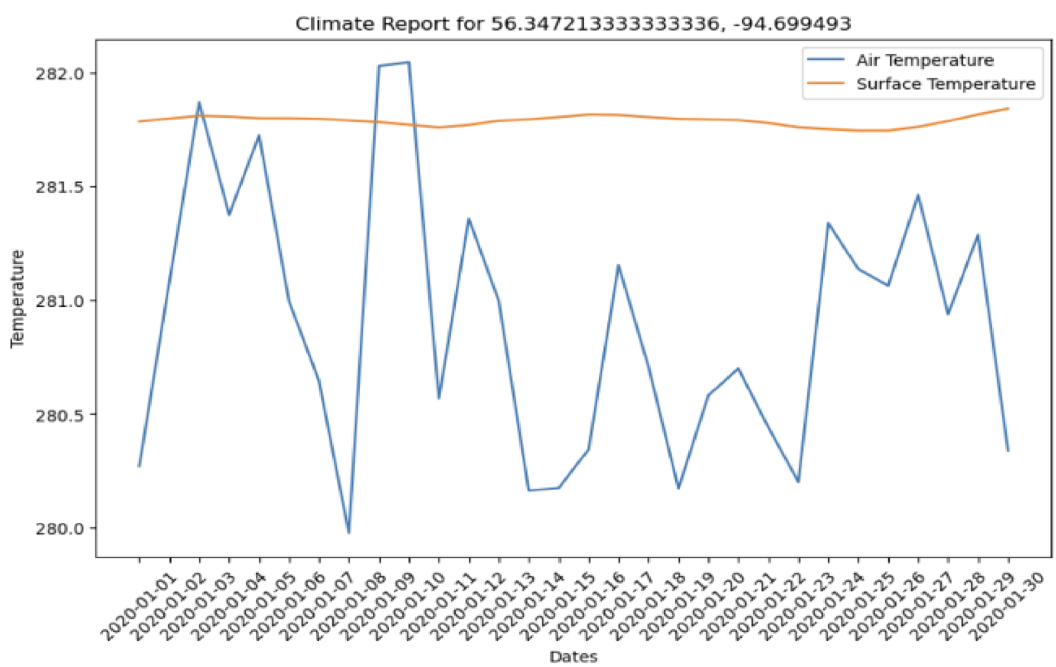


Figure 7: predicted temperature graphic

2.2.3 Short-Term Meteorological Analysis and Machine Learning Integration:

Beyond long-term climate analysis, our tool employs machine learning models to provide actionable insights for short-term operational planning. Specifically tailored for railway operators, the machine learning component utilizes real-time meteorological data to generate suggestions on load management for a given location.

Fundamental Components:

1. Real-Time Data Integration: The tool continuously updates live meteorological data, ensuring that short-term analyses are based on the latest and most accurate information.

2. Machine Learning Algorithms: Leveraging advanced machine learning algorithms, it analyzes real-time meteorological data and historical operational patterns to make predictions and recommendations.

3. Operational Suggestions: Railway operators receive tailored suggestions on load management, considering weather conditions, potential disruptions, and historical performance data.

4**. Predictive Maintenance:** The tool goes beyond load management, providing insights into potential maintenance needs based on weather forecasts and historical wear-and-tear patterns.

2.2.4 Conclusion:

Our Meteorological Analysis Tool combines the power of CanLEAD's long-term climate analysis with state-of-the-art machine learning models for short-term operational precision. This comprehensive approach equips users, especially railway operators, with the insights needed for informed decision-making, ultimately enhancing efficiency and resilience in dynamic weather conditions. As we refine and enhance this tool, we envision a future where organizations can seamlessly integrate climate intelligence into their long-term planning and day-to-day operations.

2.3 InSAR for infrastructure monitoring

Satellite image analysis has become integral to various industries, enabling insights into Earth's surface dynamics. Aposys Technologies employs cutting-edge technology for satellite image analysis, specifically focusing on Sentinel-1 data. This report provides an overview of our approach, utilizing the open-source tools ISCE Interferometric synthetic aperture radar Scientific Computing Environment and StaMPS (Stanford Method for Persistent Scatterers) for analyzing line of sight deformation, generating deformation heatmaps and creating an interactive map interface.

2.3.1 AI/ML tools

- ISCE (Interferometric synthetic aperture radar Scientific Computing Environment)

  ISCE is a framework designed to process Interferometric Synthetic Aperture Radar (InSAR) data. The framework aspects of it have been designed as a general software development framework.

- StaMPS (Stanford Method for Persistent Scatterers)

  StaMPS is a powerful interferometric synthetic-aperture radar (InSAR) analysis tool. It helps identify and track persistent scatterers in satellite images over time, allowing us to study ground deformation and subsidence. By integrating StaMPS with SNAP, we enhance our detailed and accurate analysis capabilities.

2.3.2 Data Source: Sentinel-1 Imagery:

Sentinel-1, part of the European Space Agency's Copernicus program, provides synthetic aperture radar (SAR) data. We leverage Sentinel-1's capabilities to capture high-resolution imagery and monitor changes on the Earth's surface.

2.3.3 Analysis Outputs:

Using Sentinel-1 data, we calculate the line of sight deformation for specific points on the Earth's surface. This information is crucial for understanding ground movement, subsidence, and deformation patterns.

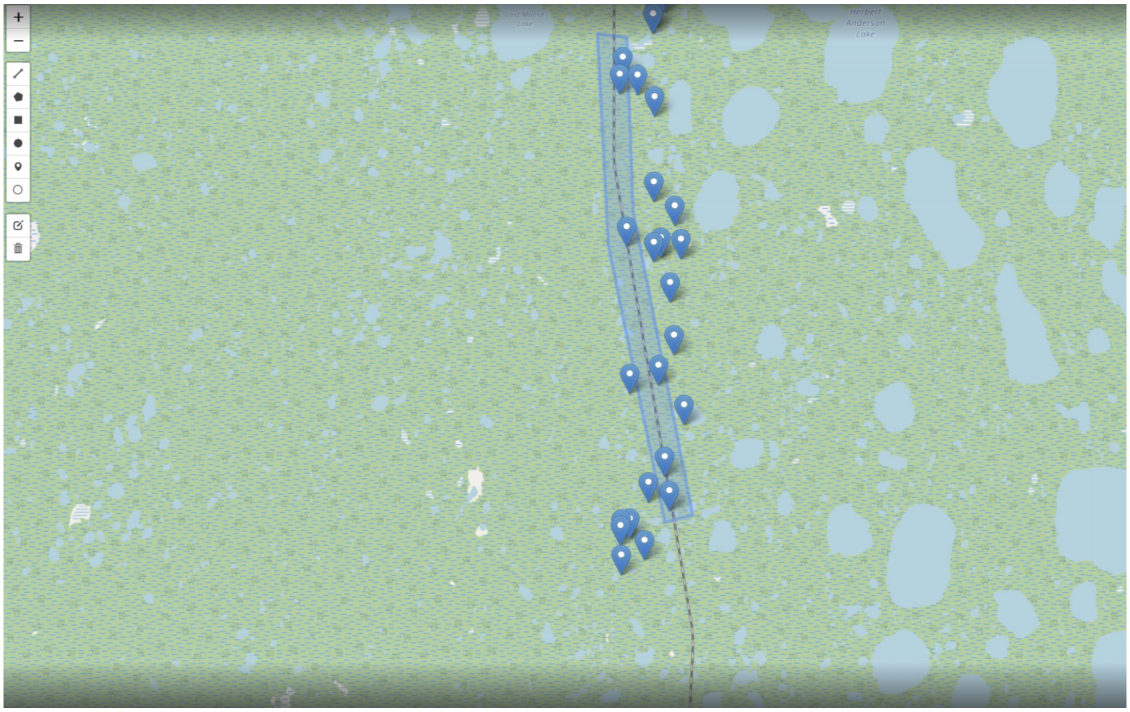


Figure 8: Rail line for satellite analysis (Thompson area)

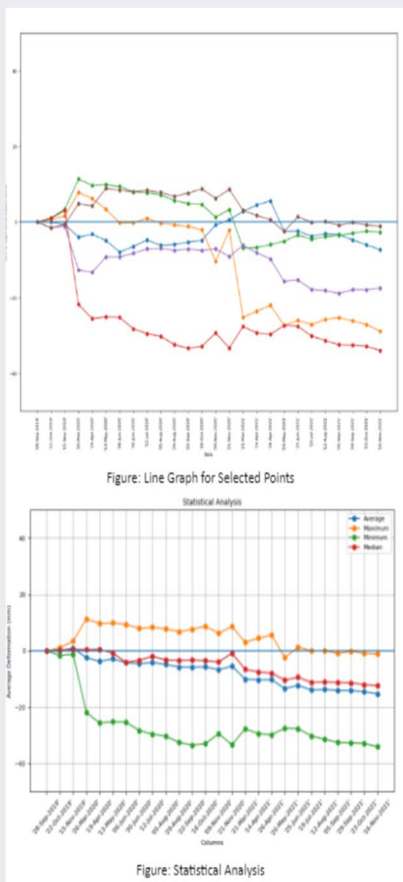


Figure 9: selected points of ground surface deformation (Thompson area)

2.3.4 Deformation Heatmaps:

We generate deformation heatmaps to visualize spatial patterns of ground movement. These heatmaps provide a comprehensive overview of deformation intensity across a region, aiding in identifying areas with significant changes.

Figure 10: Heatmap of Thompson area

2.3.5 Interactive Map Interface:

Our platform incorporates an interactive map where users can view markers representing analyzed points. Clicking on a marker reveals a detailed line graph depicting the temporal evolution of ground deformation at that specific location. This user-friendly interface enhances the accessibility and interpretability of the analysis results.

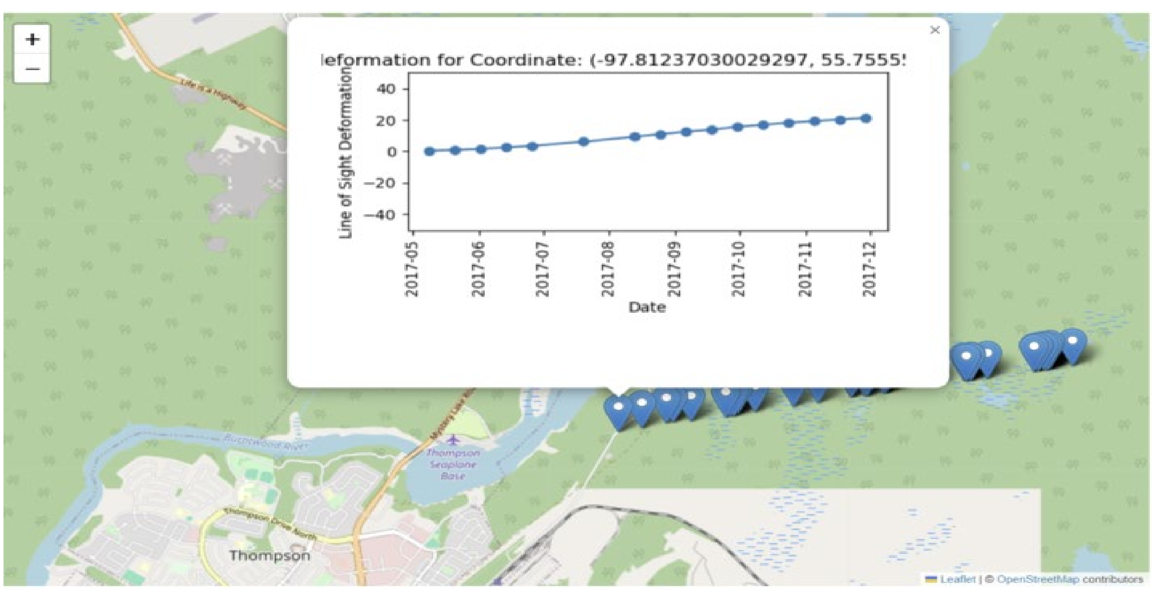


Figure 10: Interactive map inteface

2.3.6 Future Directions:

2.3.7 Future Directions:

- Integration of Machine Learning Algorithms:

Explore the integration of machine learning algorithms to improve the accuracy of deformation detection, automate feature extraction, and enhance the overall efficiency of the analysis process.

- Multi-sensor Fusion:

Investigate the fusion of data from multiple satellite sensors to provide a more comprehensive and accurate understanding of Earth's surface dynamics.

- Real-Time Monitoring:

Work towards developing real-time monitoring capabilities, enabling timely detection and response to dynamic changes on the Earth's surface.

- Cloud-Based Analysis:

Explore cloud-based solutions for scalable and distributed processing of large satellite datasets, facilitating efficient analysis and handling of big geospatial data.

2.4 Track Geometry Algorithms

A gauge calculation method based on LiDAR detection is proposed, and corresponding gauge patterns are analyzed. According to the gauge definition, a nonlinear transformation model of the spatial attitude relationship between two LiDAR camera sensors is established to find the distance between two rails within 16 mm under the rail top tread. The method presented in this paper has the characteristics of high stability, simple structure, fast calculation speed and high detection accuracy.

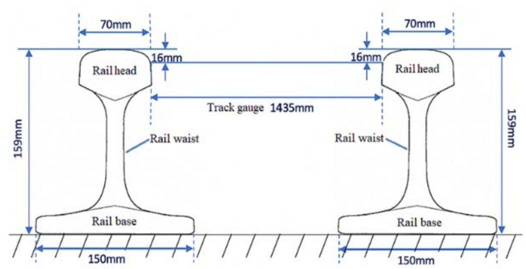


Figure 12. Definition of track gauge (Wu et al., 2023)

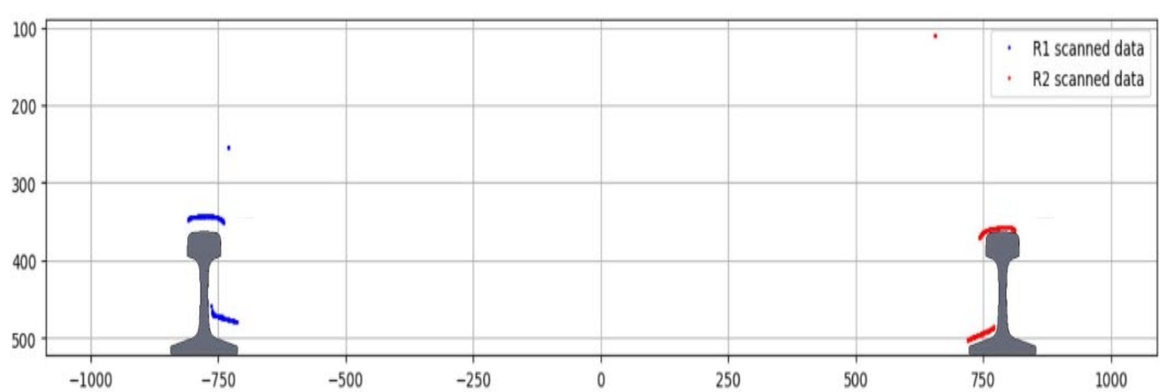


Figure 13: Track geometry overlay

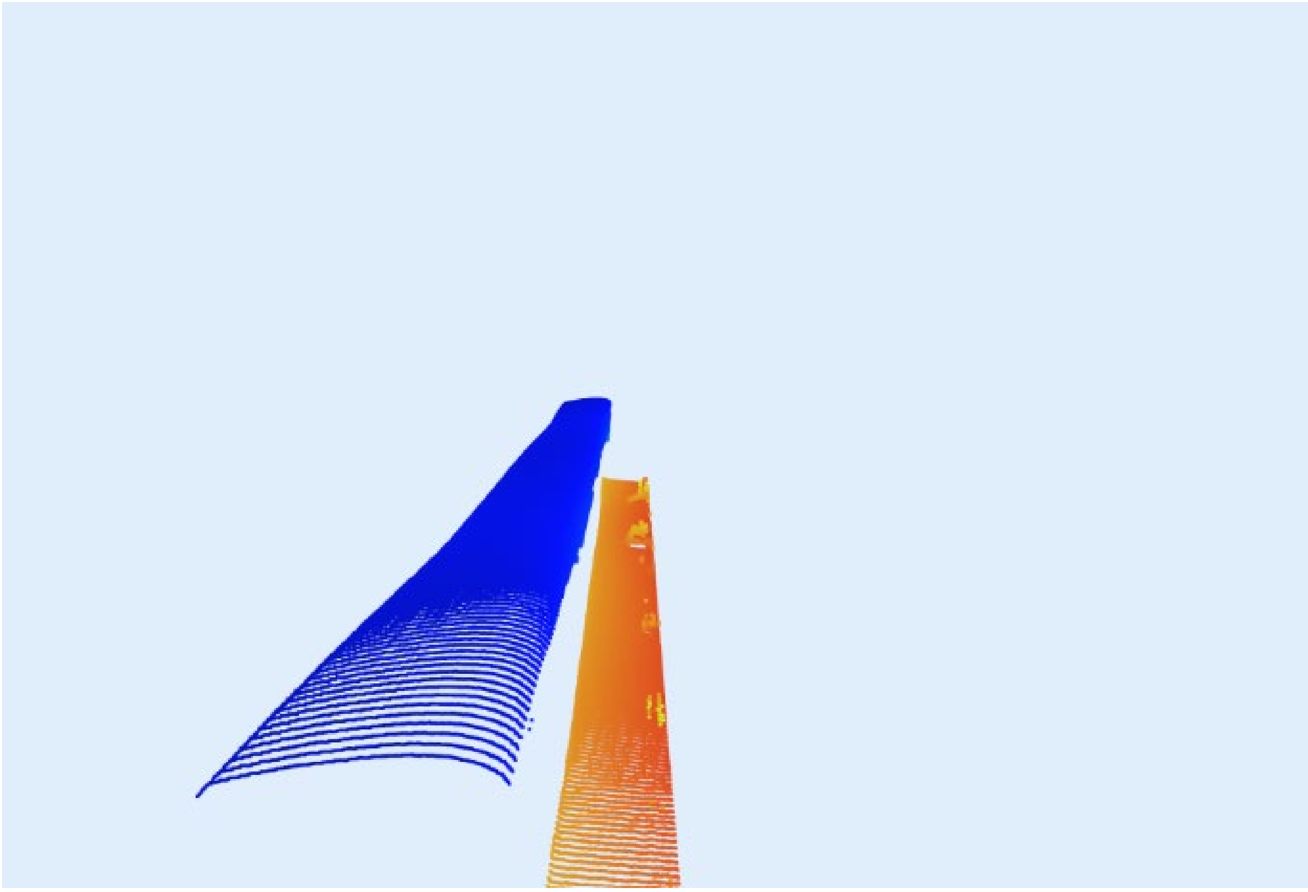


Figure 14: Closed-up version of 3D profile

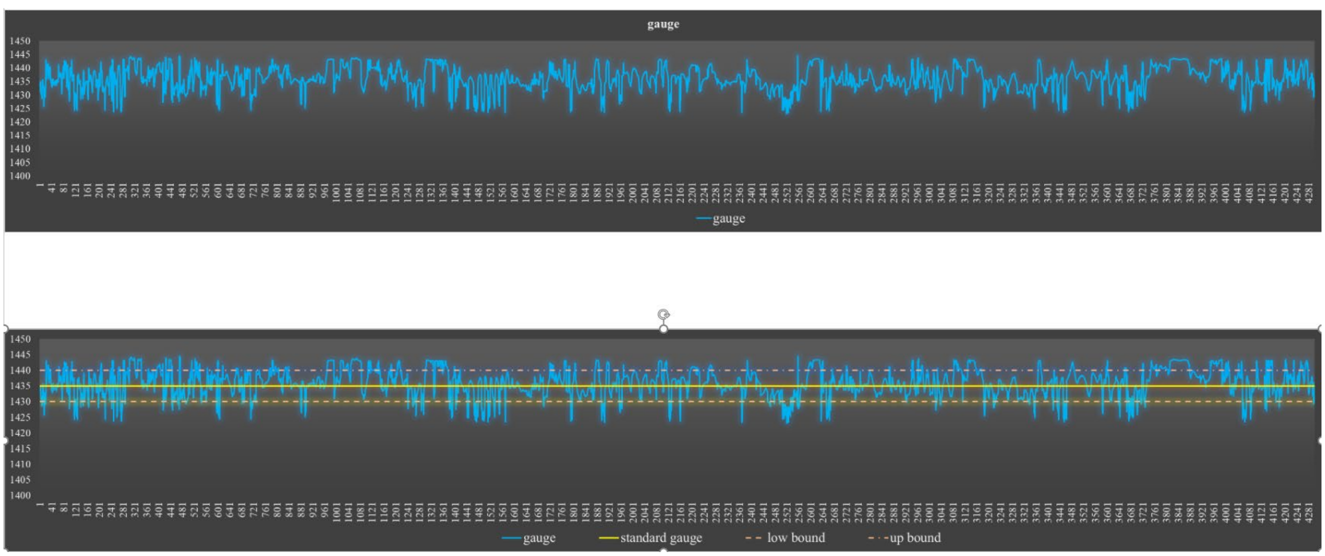


Figure 15: Brush Chart- WIP

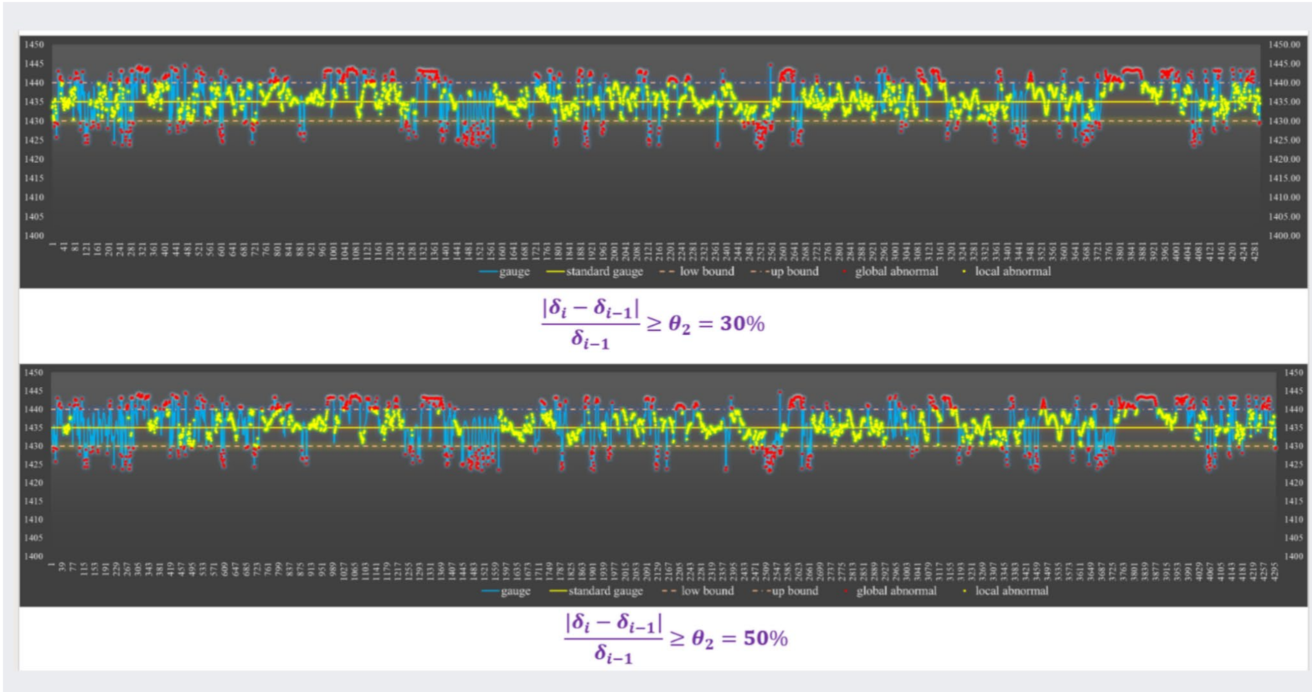


Figure 16: Statistic model of brushchart

2.4.1 Further development

The next phase in LiDAR technology development will focus on field validation to ensure data accuracy and extend its range for broader infrastructure monitoring. Enhancements will also target more precise defect detection and anomaly identification in track parameters. These improvements aim to increase the reliability, repeatability, consistency, and comprehensiveness of railway assessments, ultimately enhancing infrastructure safety and efficiency.

2.5 GPR

Ground Penetrating Radar (GPR) will be utilized to assess ballast and substructure conditions, identifying issues like entrapped ice water and evaluating drainage capacity, crucial for maintaining track integrity and ensuring a smooth train ride. By integrating GPR data with track geometry measurements, we can efficiently detect and address underlying track bed problems before they escalate into visible faults, enhancing overall railway safety and performance.

Based on the current data, we have identified the material layers including air gap, snow, ballast, ice layer, wet materials, soil. From the further analysis, we can also identify the water pockets, sinkholes. We will need asset location information to achieve.

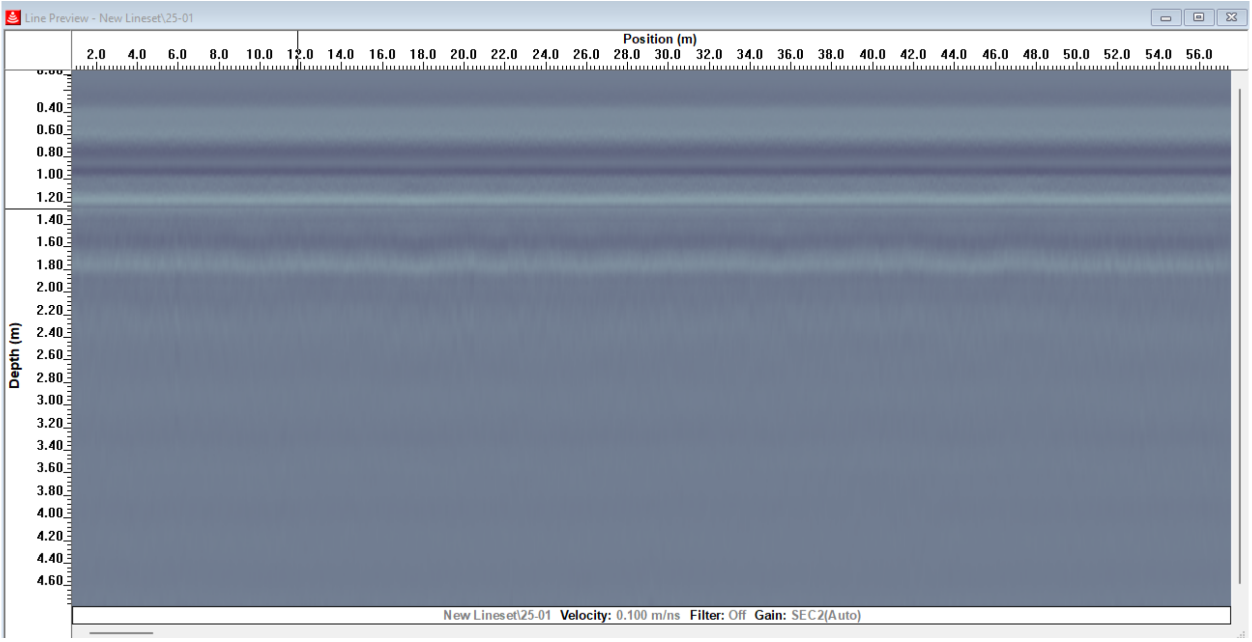


Figure 17: GPR raw data display

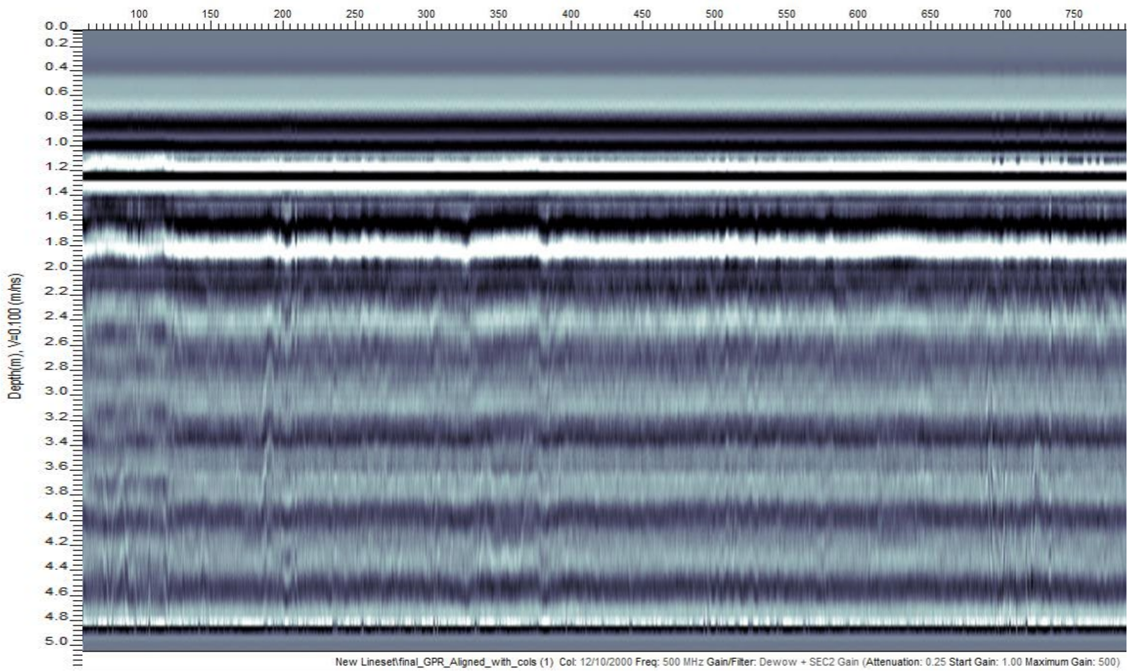


Figure 18: Low contrast GPR data

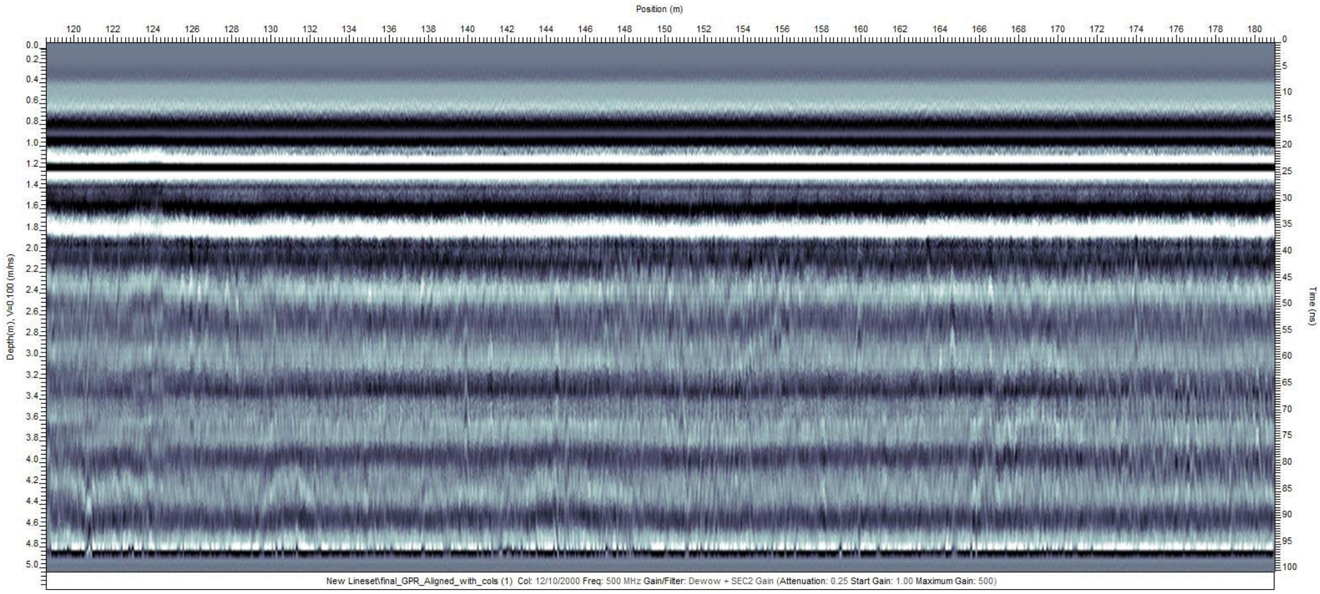


Figure 19: small section

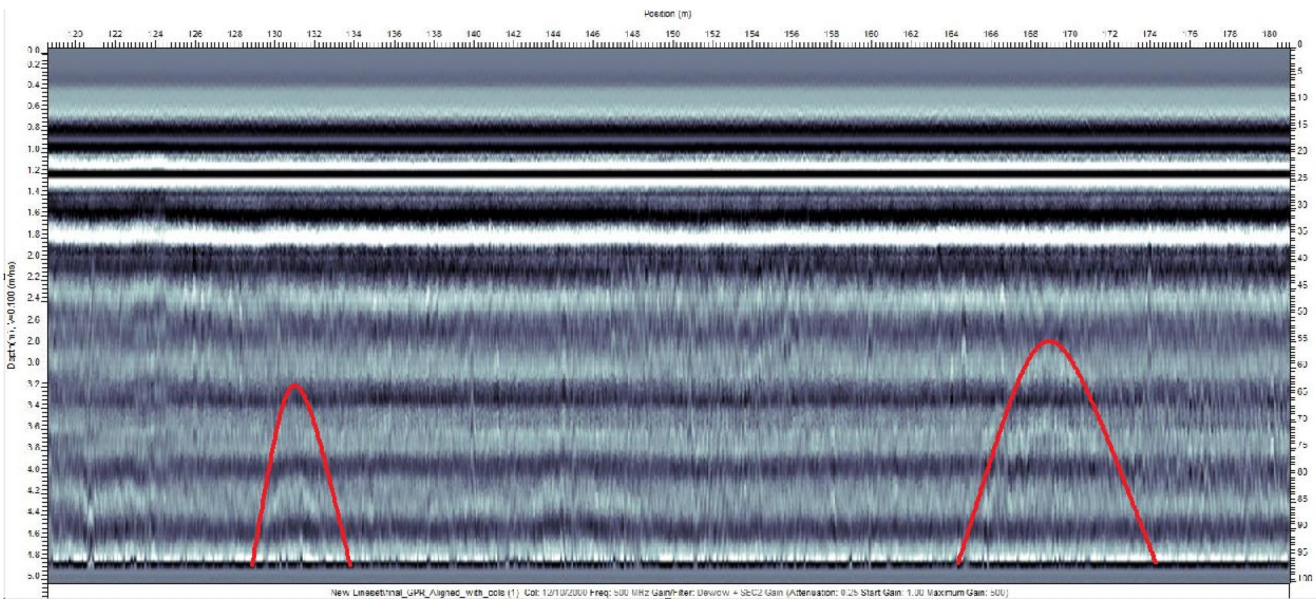


Figure 20: Hyperbolic for potential water pockets

2.5.1 Further development

In the upcoming phase, we plan to enhance Ground Penetrating Radar (GPR) analysis capabilities to cover longer distances, enabling more extensive and detailed infrastructure assessments. Additionally, we aim to integrate machine vision technology to automatically identify patterns, streamlining the detection of irregularities and potential issues within the railway infrastructure. Furthermore, we will incorporate a deep learning training process to facilitate numerical data-based analysis, significantly reducing human interference and increasing the accuracy and efficiency of our diagnostic processes. These advancements are geared towards improving the precision and scope of our infrastructure monitoring techniques.

2.6 Platform and Dashboard

RIMF is developed as an integral platform for data aggregation, processing, management, distribution and storage, report generating, and a visualized dashboard for users' access. It includes: data network, web portal, cloud service and database. AWS is used as a data cloud hosting platform to run application programs, database setup, and web portal hosts. As well, the local network has been used for preprocessing and data storage.

A dashboard as a customer access portal has been developed.

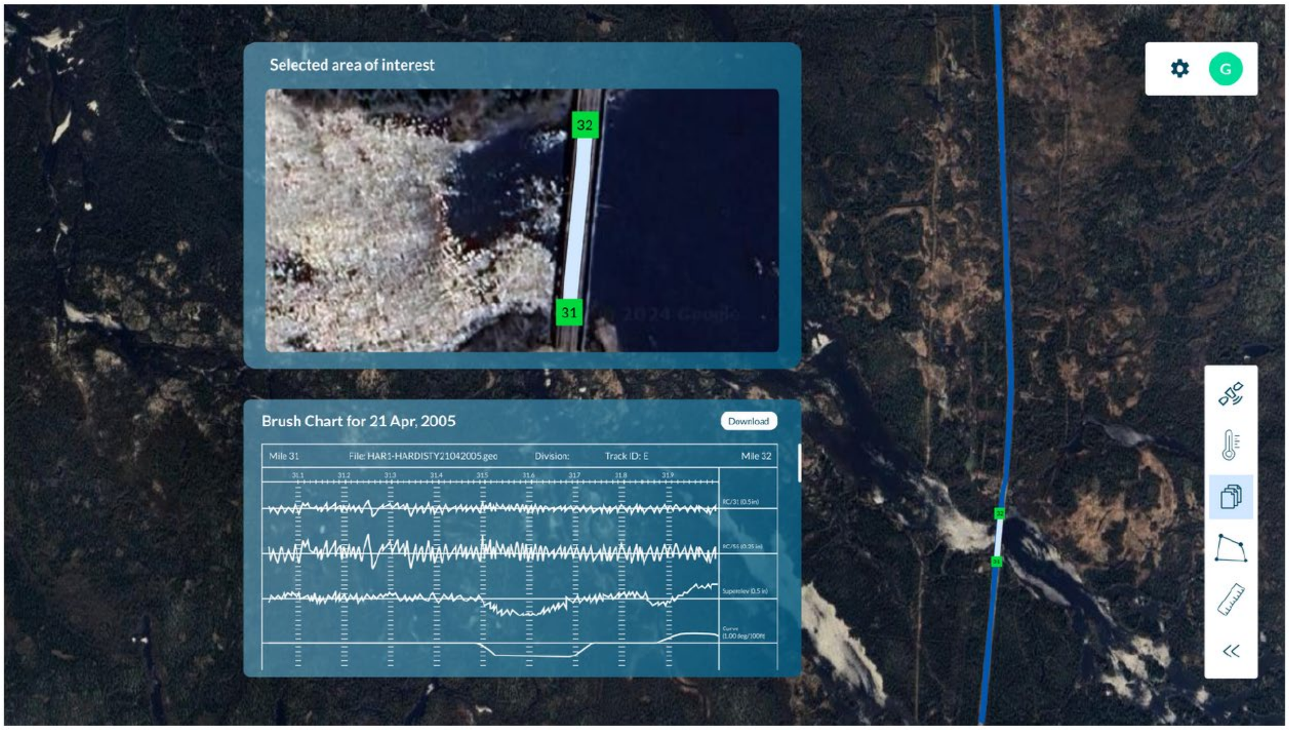


Figure 18: Dashboard track geometry display examples

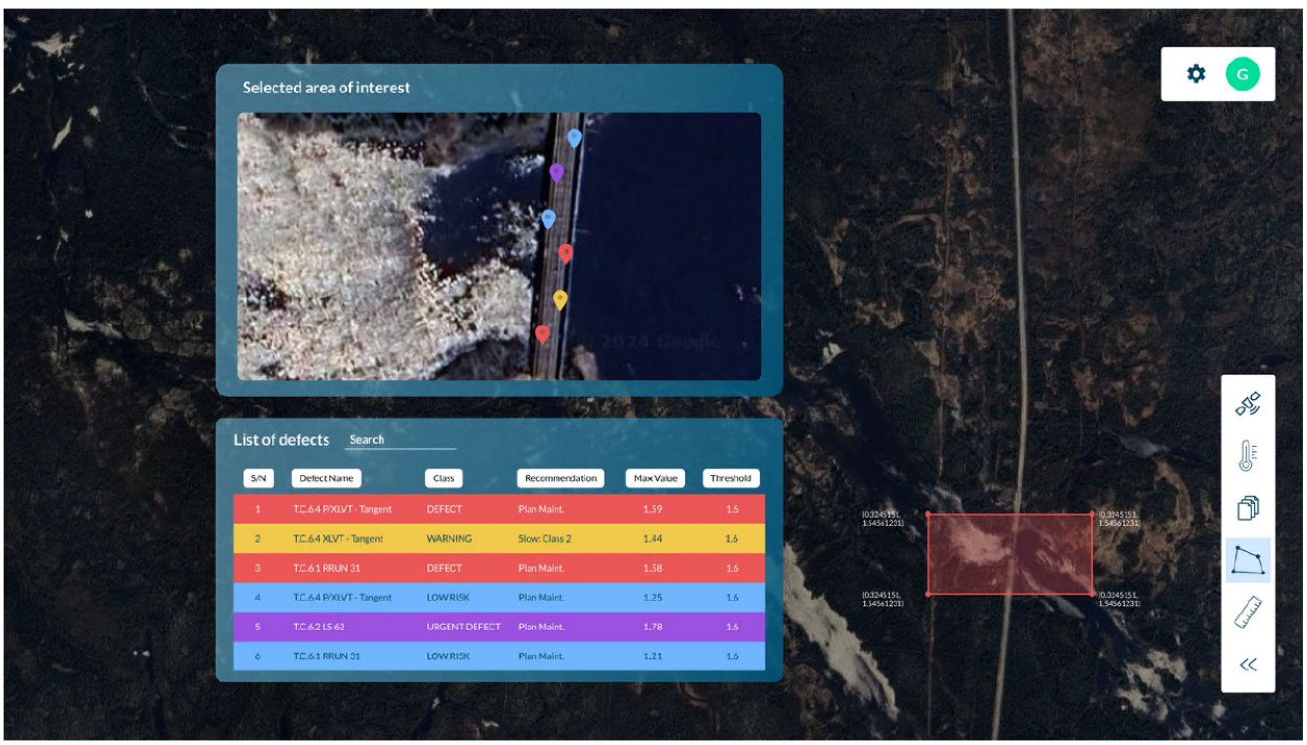
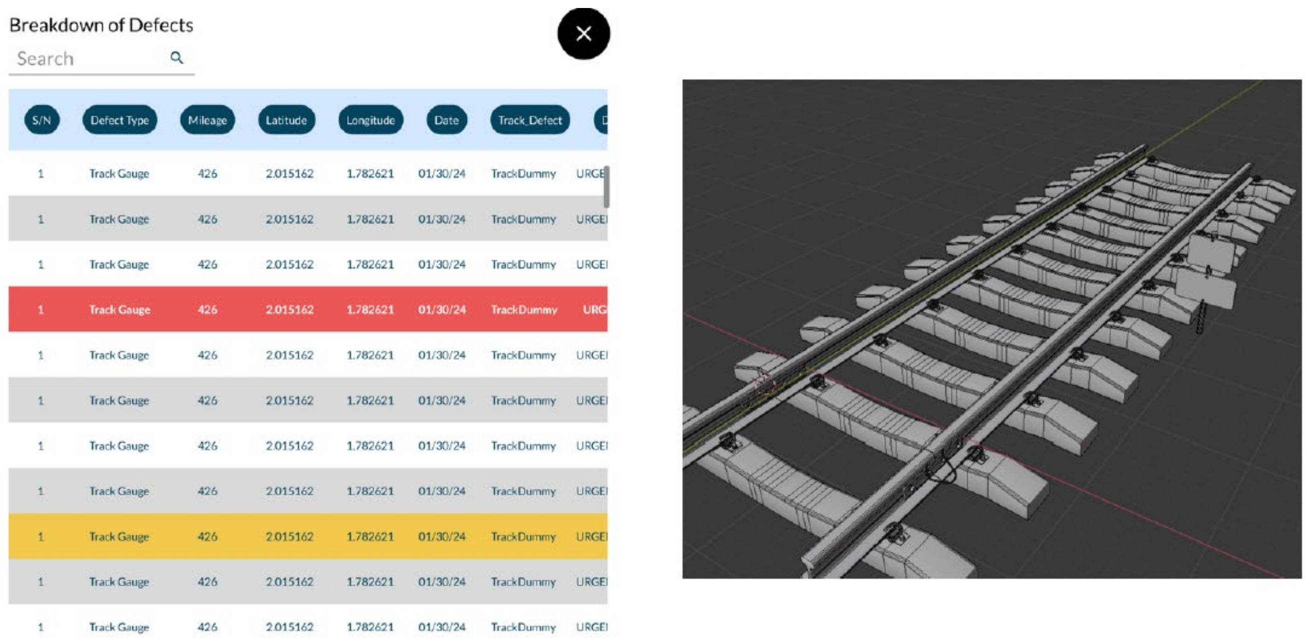


Figure 19: track defect display examples

2.7 Predictive analytics

With existing trends deviation, the system can predict future defects using advanced methods. By combining the different components: ground surface deformation, underground mapping, track geometry, and climate data, RIMF has capability to make short term predictions and long term predictions. The prediction will be shown with the elbow prototype dashboard.



S/N	Defect Type	Mileage	Latitude	Longitude	Date	Track Defect	D
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URG
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE
1	Track Gauge	426	2.015162	1.782621	01/30/24	TrackDummy	URGE

Figure 20: Digital twin for predictions

3 Conclusion

In the R-CCAP final report by ApoSys for HBRY, the project aimed at enhancing railway safety and efficiency through innovative technologies and methodologies.

Component and features development:

- Ground Penetrating Radar (GPR): Utilized to assess ballast and substructure conditions, identifying issues like entrapped ice water and evaluating drainage capacity, which is crucial for maintaining track integrity and ensuring a safety operation.
- ATMU Development: Two versions were developed to collect comprehensive data including track geometry, environmental conditions, and underground mapping.
- Climate Modeling: Advanced Meteorological Analysis Tool integrating the CanLEAD climate model with machine learning for both long-term and short-term operational planning.
- InSAR Monitoring: Employed Sentinel-1 data and advanced InSAR techniques for detailed ground movement and infrastructure deformation insights.
- Track Geometry Analysis: Enhanced gauge calculation methods based on LiDAR detection for improved track measurement accuracy.

Achievements:

- Successfully extended GPR operational range for broader infrastructure assessments.
- Integrated machine vision with ATMU prototypes for automated defect detection.
- Developed a comprehensive climate analysis tool aiding in weather-related decision-making.
- Advanced infrastructure monitoring using InSAR technology for valuable ground deformation insights.
- Improved track geometry algorithms for higher detection accuracy and stability.

Challenges Overcome:

- Overcame environmental impacts on sensor performance, especially under varying weather conditions.
- Addressed data fusion and management issues for timely processing of large datasets.
- Resolved failed heating system challenges and mechanical design issues for different

locomotives.

Further Development:

- Plan to enhance GPR technology for increased resolution and data processing capabilities.
- Aims to expand machine vision functionalities for a wider range of defect types and conditions and apply it to onboard processing modules
- Will continue to refine deep learning models for improved predictive accuracy and applicability to different environmental conditions.

In conclusion, the ApoSys project with HBRY has made significant development in railway infrastructure monitoring by integrating cutting-edge technologies such as GPR, LiDAR, machine vision, and deep learning. These developments will not only improve safety and efficiency but also set a strong foundation for predictive maintenance and climate adaptation strategies in railway operations. The project's ongoing and future enhancements are expected to further revolutionize infrastructure monitoring and management practices.