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A Climate-Risk-Adjusted Asset Health Index Framework for Railway Infrastructure: Integrating Wireless Sensor Networks, Prognostics, and Intelligent Asset Management Platforms

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ABSTRACT

Railway operators have the double problem of aged infrastructure, which requires cost-effective renovation, and growing risk factors caused by climate change, which increase the risk of failure. Although condition monitoring and predictive, risk-adjusted maintenance are advocated, few organizations, on average, successfully convert data variety into cohesive, decision-supporting risk-prioritization of different assets. In this work, an integrated, advanced framework will be offered to present a risk-adjusted Asset Health Index (AHI) using continuous risk analysis based on WSN, data analytics for RUL, and enterprise-wide integrated risk-aware management planning. This will use literature-reviewed best practices in aggregate risk calculation for Asset Health Index and railway infrastructure health analysis, with an additional "context layer" tailored to assess health based on vulnerability to climate-related risks, including heat buckling, flood and scour, and debris from windstorms. The work will also present decision-support bibliographic libraries for risk practices, aggregation, treatment, and risk thresholds. Two simulation scenarios will also be included to show how climate risk accelerates health degradation and changes prioritization. This research provides a approach blueprint checklist to help railway organizations leap over data fragmentation and move forward in smart, risk-based optimization of infrastructure maintenance.

Keywords: Asset health index, railway infrastructure, predictive maintenance, wireless sensor networks, climate resilience, risk, digital twin, ISO 55000

INTRODUCTION

Railways are critical infrastructure for economic productivity and social mobility but are delivered under very challenging conditions: high demands for availability, long asset lives, and very short windows for access for inspection and renewal. Industries have traditionally employed periodic inspections and prescriptive methodologies for maintenance. Presently, greater demands for use, aging infrastructure, and cost constraints have made time-based maintenance less effective, sometimes less safe. Meanwhile, climate change is imposing new conditions on the environment railways were designed to function in. Higher temperatures increase the temperature of the rail and the likelihood of rail buckling failures; intense rainfall can result in floods, washouts, or erosion under bridge structures; and wind is the cause of numerous line blockages.

Digitalization has supported the continuous condition monitoring based on the use of sensor technology and data analysis. Wireless sensor networks facilitate near-real-time data collection, increased data collection rates compared with physical inspections, and the integration of data collected by multiple types of sensors, which can all serve as the basis for "predict and prevent" maintenance strategies in the railway environment. A missing link, however, still exists: a high amount of data collection can take place without a VoI-supported common and traceable prioritization approach across a whole portfolio. Condition measures across the engineering fields of track, structures, power, signaling, and earthworks are, on the other hand, typically supported by separate condition management processes. Climate risk further adds complexity to condition risk and, consequently, condition prioritization. A specific condition can pose very different risks depending on its vulnerability status.

AHIs have been found to be a helpful intermediary for going from condition data to investment decisions. An AHI combines a variety of indicators into a normalized score which informs on ranking and investment decisions. The data-driven AHI models show how a set of indicators chosen and specific aggregation processes can be utilized to translate disparate data into a cohesive representation. The majority of AHI efforts are on current condition and are not capturing changes to the health score reflecting movement in climate-defined risks of failure.

In this article, a framework of AHI with climate risk adjustments is posed to have a more precise approach for railway infrastructure projects. Three aspects are incorporated: (i) data flows from a WSN and inspection, (ii) prognostic models to calculate a prediction of RUL based upon perceived patterns of degradation, (iii) IAMPs at an enterprise level, which regulate data incorporation, tasks, and tracing of evidence related to decisions (Spyropoulos, et al., 2021; Martínez-Galán, et al., 2020). It brings a new context level, which includes adjustments to health aspects due to vulnerability to climate patterns.

The study is informed by the following research questions

RQ1: Which method can be used to aggregate rail condition and performance metrics into a transparent and comparable index that is appropriate for portfolio consideration?
RQ2: How might the exposure to climate hazard and the vulnerability to it be incorporated into health scoring without compromising interpretability?
RQ3: Which aspects of governance and system architecture are required to implement a climate-adjusted AHI in an enterprise maintenance system?

Contributions

An indicator library and aggregation method for railway infrastructure, ii) a climate context factor to modify health scores, iii) a logic for enterprise workflow to prioritize both AHI and consequence-of-failure, iv) an enterprise workflow blueprint, and finally, an illustrative simulation to demonstrate their behavior. In the case of simulations, these have been clearly labelled to mark them out from other methods, assuming to demonstrate rather than empirically verify their performance.

Section 2 presents a brief survey of related research. Section 3 then continues to explain, with great detail, the methodology that is proposed, including the treatment of uncertainty, weighting, climate adjustment, and a numerical example. Section 4 presents simulation studies, and related aspects of governance, adoption, and impact on decisions. Section 5 then continues to explain the architecture and processes related to an enterprise implementation. Section 6 then presents a related approach to validation and related measures. Section 7 concludes, citing limitations and future studies.

LITERATURE REVIEW

Wireless sensor systems and condition monitoring in railways

WSNs have been proposed for various railway infrastructure monitoring tasks, including track monitoring (vibration, temperature), bridges (strain, modal analysis), points and crossings (actuation signals), and environmental conditions (humidity, water level). Reviewing WSN applications in the railway domain, various advantages of WSNs include continuous, near-real-time data acquisition, operation without human intervention, enhancedAccessibility and centralized analysis, sensor data fusion, and the feasibility of shifting from schedule-based to prediction-based maintenance planning (Hodge et al., 2015). Similarly, this literature review identifies limitations of practical applications, including noisy sensor measurements, potential failure of sensor systems and wireless communications in difficult environments, and the need for appropriate management of bulk data for a meaningful system status representation (Hodge et al., 2015).
The first crucial observation is that degradation levels as well as sensor measurements are heavily dependent on the environment and operational conditions; for example, a temperature change may affect strain measurements. Thus, analytics performed on sensor data that is decoupled from context may flag variation as anomalies and vice-

versa or may not be able to detect changes in risk levels due to context. It is precisely this observation that brings us directly to the climate context layer proposed by this paper.

Asset Health Indices and Composite Scoring Techniques

Composite indices are intensively used in asset-intensive sectors as they reduce a multi attribute condition into a single indicator that matches the process of decision-making, such as ranking and budget allocation. Data-intensive AHI deployments stress the importance of reproducibility, governance of the indicators, and cross-portfolio comparison. A data-intensive AHI method for the industrial port assets domain demonstrates how a designed indicator framework and aggregation scheme can lead to meaningful scores, which are then used as inputs for the subsequent step related to fleet planning (Crespo del Castillo et al., 2024). While the basic idea can also be applied to railway infrastructure, the uniqueness arises in the fact that the distributed assets and respective diverse data, along with the requirement for prioritization, are similar. Yet, the potential drawbacks for composite indices include the fact that the weights can lead to index bias and the missing values in the index calculation can lead to the rewarding of better-monitored rather than poorly conditioned assets, and the loss of uncertainty regarding index values, potentially appearing to offer more detail than the inputs.

i) Use indicator definitions and thresholds.
ii) Explain the choice for weights.
iii) Drill-down from index values to indicators.
iv) Mark index values according to uncertainty and data quality.

Prognostics and Remaining

Useful Life Estimation Prognostics allows the prediction of the future state or remaining life. A comparison discussion regarding the options for prognostic models highlights that the choice between knowledge-based solutions, stochastic reliability models, or data-driven models relies on the amount of information regarding the situation that could be obtained, operating variability, or the timeframe of the decision-making process (Sikorska et al., 2011). There is considerable variety in the asset base that is present at the railway infrastructure, where physics models or geotechnical models may be appropriate for the bridges and earthwork, statistics models may be appropriate for the geometry issues, and signature data-driven models may be appropriate for Points/switch issues. Recent studies on rail systems are an exemplary case of applying machine learning skills in defect prediction and anomaly detection according to the increasing trend of available operational data streams. For example, prediction of track defects according to data-driven forecasting for precise maintenance ahead of time is covered by Jiménez-Cabas et al. (2024). Online predictive maintenance according to an explainable prognostic framework with metro datelines underscores that explainability is an enabler that allows practitioners to really implement the method. Systematic reviews also underline that implementation and integration into decision-making procedures are essential challenges. AHI stands in this case for a portfolio translation layer because prognostic values are translated into consistent scores and thresholds, operator-executable.

Digital Twins and Model Calibration

Use of digital twins to combine models of assets with real data has been noted in literature to be emerging in relation to monitoring and decision-making. Methods of developing digital twins in relation to civil infrastructure repair have been identified in literature to combine data from sensors, models, and repair strategies. In the railway field, digital twins appear to be promising in complex areas, like train dynamics and interactions between tracks and vehicles, founded on the ability to use data from sensors aboard trains in motion to detect the state of infrastructure. The literature review on train motion model calibration examines model calibration, data, and model significance to observations for interpretation. Although train motion model calibration is itself not an AHI approach, it is indirectly relevant to AHI, in that the quality of inference is dependent on calibration, if the data is to be inferred for conditions on the track. Thus, a climate smart AHI program has to address model calibration and model drift too, for the use of onboard data for proxying infrastructure conditions.

Climate change impact on railway infrastructure

Climate change poses a twofold challenge on the probability level. The literature on the impact on railway infrastructure examines heavy rainfall, which leads to flooding and shutdown; extreme temperatures, which may lead to rail dilation, buckling; and in the case of prior protection, shutdown speeds, additional inspection, in prep to close derailment threats that are caused by flooding contribute to derailment threats, while events connected to the windstorm lead to blockage (Palin et al., 2021). Importantly, each infrastructure type has its set sensitivities to the impact, namely track, earthwork, bridges, tunnels, points, and switches. 2.6 Smart asset management platforms and systems Analytics is hardly ever a source for innovation on its own or within its smart universe. The IAMP & IIoT platform enables the connectivity, data, data analysis, analytics, and management system. Research on the comparison on IAMP stresses the need for the associated features for a successful implementation in the maintenance paradigm Martínez-Galán et al., 2020. Research on maintenance management on IAMP has noted the current trend is developing areas such as integrated information, decision support systems, and standardized data models, where the most suitable areas for continuing impact are Spyropoulos et al., 2021. The literature is extremely relevant to the appropriate management for AHI—versions on definitions, auditing, data integration, work orders, and reports. 2.7 Summary on the gap Expressed simply, while the ingredients for the solution—monitoring, prognosis, health indexing, impact awareness, and management systems—do already exist in the literature, their integration is incomplete. Climate, for example, is rarely, if ever, factored into the balance for the score on the basis of interpretation. This is now to be remedied by the current paper.

Table 1. Proposed indicator library for a railway AHI (example)

Asset class	Indicator	Typical data source	Example measurement	Decision relevance
Track	Rail temperature exceedance risk	Rail temp sensors + weather feeds	Max rail temp vs stress-free temp	Buckling risk; speed restrictions; stress management
Track	Geometry exceedance rate	Geometry car + inertial systems	Alignment/twist exceedance per km	Tamping/lining renewal targeting
Track	Flood/washout susceptibility	Hydrology alerts + drainage inspections	Flood alerts; drainage condition score	Pre-storm inspections; drainage works
Bridges/Earthworks	Scour/erosion risk	Water level sensors + inspections	Scour proxy; river stage percentile	Foundation protection; closure planning
Bridges/Earthworks	Vibration/strain anomaly	Accelerometers/strain gauges (WSN)	Modal frequency drift; strain peaks	Crack monitoring; load limits
Signaling/Power	Point machine actuation anomalies	Current/position sensors	Actuation current spikes; cycle time	Preventive replacement; lubrication
Signaling/Power	Cable/relay temperature & humidity	Environmental sensors	Cabinet humidity %, temperature °C	Condensation/corrosion mitigation

METHODOLOGY

Design Principles

It is developed with consideration to the following five principles: (i) Transparency: Each score can be explained on the use of indicators and parameters, (ii) Comparability: Each score should be normalized to get comparisons possible for different asset types, (iii) Scalability: Scalable for big datasets with varying availability levels for varying assets, (iv) Relevance to Climate: In-built consideration for vulnerability and exposure to risks, and (v) Operationalization: Easy connections to investment and maintenance.

Data architecture and sources

The new architecture has three levels of data:
(a) Condition layer: readings from WSWS & IoT sensors, and inspection data.
(b) Layer of performance: performance in action, incidents, delays, and maintenance.
(c) Context layer: Climate factors (climate, environment, temperature extremes, rainfall intensity, flood risk, coastal influences, and wind-storm risk) and operation factors (traffic flow, axle load, speed, and geometry).

WSns are involved in the monitoring and multi-sensor fusion. WSns, however, are linked with reliability and quality control (Hodge et al., 2015). The inspection and geometry cars are involved in actions like adding standardized data. Data extraction can occur through weather stations, hydrological warning systems, as well as climate maps.

Indicator library and failure modes mapping

It is dependent on an indicator library for calculation of AHI.
Table 1 Below proposes a possible "operation flow" for set covering tracks, structures/earthworks, and signaling/power. These indicators would necessarily need to refer to failure types and possible operation actions. Examples:
Heat condition monitoring is linked with buckling risk, which requires the following indicators:
1. Stress management
2.Intensive surveillance
3.Speed restriction

Flood-related indicators: Washouts and scours; methods include drainage systems, river-level observation, and temporary closure.
The actions involving the activation indicators of the pointer machine switches and failure include lubrication, replacement, and reduction of temperature and humidity in the cabinets.

Normalization and the indicators are then standardized to a results ∈ [0,1], where 1 is regarded as the optimal value for each indicators. With the following normalization procedures:
1. Engineering threshold scoring: The scores may be obtained either through scoring on standards or through empirical thresholds obtained as a result of measurement.
2. Percentile scoring: Comparison based on peers for individual variations.
3. Scoring: by probability of failure, then reverse for status.

Normalization also has to ensure that there is no loss of interpretability. For any discourse regarding percentile-based scoring, there has to be consideration regarding reference group and update rate.

Aggregation and Base AHI

The simple formula of AHI applied to asset "a" at time "t" can therefore be expressed in terms of the scores obtained on the following indicators:
Function subjected to the condition ∑ w_i = 1. The weights can vary based on the asset. The handling of the weights is very important. The weights must be authorized and given numbering.

Missing data handling, Data quality

In other cases, the data may not actually be available. Missing values should be dealt with by the following guiding principle that "it is

(i) Weight re-normalization, where there is missingness associated with
(ii) imputation with decay when applicable;
(iii) Explicit Penalization where the values are not present but inferred and could imply danger, like the absence of a sensor system which is strategically located.
Data quality metrics like (Availability, Latency, Drift) can be measured too. These can be used for creating indicators that project a degree of uncertainty too.

Climate Exposure and Vulnerability: The Context Factor Climate Exposure

The important methodological change brought about by the researchers in relation to this problem is the adoption of the new climate variable CF(a,t), which helps in reducing the former value of AHI in respect of their susceptibility and sensitivity to the threat. Climate variable ranges from 0 to 1. As the values are small, the stress on the climate will be high.

CF(a, t) = 1 – g(H(a, t

where H is the degree of the hazard, V is the degree of vulnerability, and R is the degree of resilience/adaptive capacity. This function, g, maps the input variables into a certain bounded penalty. This could be done by the use of standardized indicators for hazards and multipliers for vulnerabilities:

M among dangers, C among risks.

g=clip(sum(α_k * z_k(H_k) * v_k * (1 - r_k)), 0, g_max)

Consequently, the domain of the function "CF" is given from (1 – g_max) to 1.

Climate Hazard

In order for CF to be implemented, there needs to be a defined hazard library that includes measurable proxies in an organization. The measurable proxies could include:
- Heat: Chances of train temperature going beyond a certain level, Number of days with high temperature.
- Flooding: flood warnings, rainfall intensity percentile, floodplain proximity, drainage inspection results.
- Wind speed: wind speed percentile; historical debris events.

Surge from coastal waters: notices related to severe weather, topographic relief, drainage. There would be a correlation between each type of hazard proxy and its corresponding assets and failure mechanisms.

3.8 *Risk-Adjusted AHI:

AHI risk (a,t) = A

AHI risk + Consequence of Failure (CoF) for priority

C1 | C2 | C3 | C4

CoF can be calculated based on safety impact, service importance, traffic density, and recovery cost.

RUL models are applicable in relation to important indicators for critical assets. The requirements for selecting RUL models are comparative guidelines. KS techniques apply in the situation where expert models have high quality, stochastic models with specified failure distribution, or data-driven models with continuous sensor variables (Sikorska et al., 2011). RUL forecasting could be one way to determine how to predict the AHI traces under climate stressed conditions.

For the business side, the AHI engine is integrated into or with an IAMP. The capabilities of device integration, data quality assessment, control of analysis results by indicators, scheduling of computations, and connection with work orders may then be accessed via the platform. Tracing capabilities may also then be available for all outputs from the AHI process. The portfolio rank is recognized in the dashboard view. In-depth analysis may also then be conducted by the engineers themselves.

RESULTS AND DISCUSSION

In order to make this observation simpler, Figure 1 has permitted the graphical simulation of the time series for the period of five years, monthly for the set of assets classified into three groups: track, bridges/earthing, and signaling/power. The simulation for climate stress index is also shown, depicting an increase with the passing period and seasons. The Base AHI will see its decrease affected by climate-related stresses. These trends show that the effect of emerging risk by growing climate change can lead to acceleration of degradation as well as a change in the type of base assets more at risk at any point in time. These trends reflect the reality that has been put forward by the reviews on the effect of climate change, where rising temperatures lead to a risk of buckling due to flooding by heavy rainfall, whereas a lack of access by a wind storm leads to blockages (Palin et al., 2021). It can be inferred that in adverse climate conditions, a change in base conditions changes completely in a short span, whereas base conditions change slowly.

Illustrative Simulation 2

Figure 2 shown above indicates an example for priority evaluation with an equal underlying AHI for each of the

four corridors. In this calculation, it is clear that this priority metric reveals that climate exposure could reverse the priority.
Therefore, this allocation does not allocate resources solely on priority without taking into account the risk associated with hazard.

When considering whether a choice or a decision is:

With `AHI_risk`, three improvements can be obtained in the following way:

(1) Dynamic Prioritization. Priority updates within the intervention list occur due to increased levels of exposure, for example, heatwave alerts and flood alerts.
(2) Budget targeting: assets in the high-risk region with intermediate conditions could need an active investment budget.
(3) Evidence-Based Trade-Offs: "Leaders are able to understand why a corridor is prioritized—whether it is for poor condition, for high climate exposure, or for a combination of factors like"

Alignment with Predictive Maintenance and Explainability

Research on predictive maintenance has increasingly incorporated the explainability dimension to facilitate uptake. The inclusion of metro data streams to this explainable online pipeline demonstrates the integration of the model and the explainability component to improve its trustworthiness (García-Méndez et al., 2025). This is an addition to the above contribution through the AHI framework that includes the dimension of explainability on the portfolio level where the salient features underlying the new risk variable (AHI_risk) are explainable (indicator scores and context factor parts).

Governance and Equity for Data-Dominated & Data-Starved Assets

That which can be pointed out as possible in the context of digital execution has risk tilted more in favor of well-surveilled assets. When there exist instances which can potentially involve calculation of the value of an index feasible only if there were sensor readings, portfolios can reveal the absence of any consideration for the aspect of poorly surveilled assets. The system can, however, overcome this challenge by taking into consideration signs of inspection and missing data. Furthermore, the effectiveness of leadership choices can also be established with regard to confidence.

Climate context and Operational Readiness

Climate could also be applied in preparedness rather than only at the ranking level. For instance, in the event that CF decreases under the flood warning forecast, then the workflow service can prepare inspections/crews and escalate the rates for the at-risk segments. The rationale for this is because AHI_risk transitions to 'situational awareness.'

Cost and Value Discussion

Although an empirical cost model was not presented in this paper, a basis for the quantification of values does exist. The common basis with which all other calculations will be built upon is the determination of the cost of failure, which is given as E[Cost] = P(failure)•CoF. Having established that a cost of failure proxy exists, which is denoted by AHI_risk, a comparison can now be made, which offers value with a consequent increase of cost of failure savings due to an increase in failure probability due to the climatic factor.
In this paper, an example will be provided by way of a framework, rather than being an example that has been tested and shown to exist or function well in its field. The specific choice of weight and the choice of the factors or parameters for the specific environment being considered will require local validation for the consideration of appropriate levels of weight and the choice of the factors or parameters.

Enterprise Implementation Architecture & Workflow

Why Enterprise Architecture Matters

Moreover, AHI projects may also experience failure if they continue on the lines of analytics projects, and not as full-fledged systems. In this case, what is required is an architectural capability that can address the issues of ingestion, computation, governance, workflow, as well as feedback. This, according to research work done by the Institute of Advanced Manufacturing Analytics and Physics (IAMP), about defining functionality and relevance of device integration, data models, and decision support systems with regard to the effectiveness of maintenance in the view of this particular industry (Spyropoulos et al., 2021).

Components

(A) Asset Registry and Hierarchy: Ids, Geospatial locations, characteristics of vulnerability by type (e.g. type of fastening, drainage).
(B) Data Ingestion Layer
The module which handles incoming feeds for WSN, uploads for inspection, work orders, as well as context feeds.
(C) Indicators calculation service: Computes raw values of the indicators, like geometry exceedances per km, and normalized values s_i. It also retains historical data to be analyzed.
(D) AHI Engine: combines base AHI, with CF to calculate AHI_risk. Versioned for weighting, thresholds, and hazard, with audit logging.
(E) Decision workflows: This is relevant to the assignment of thresholds to processes like inspections, work orders, or escalation, followed by integration with Enterprise Asset Management and ticketing systems.
(F) Dashboards & Reporting: views of the portfolio for executives, drilling down into engineers; provides measures of UQ & data quality.
(G) Feedback/Learning: the results of the intervention procedure give feedback on the adjustment of the indicators, weights, and models.

Operational Workflow Patterns

Are found the following three patterns of the workflow:
Pattern 1 (Threshold triggered inspection): If AHI_risk exceeds or is equal to the threshold value (for example, 0.60), then a targeted inspection is triggered. Scoring takes place based on the results of targeted inspections.

Pattern 2 (Intervention planning):

On crossing a lower threshold value (0.40) for a high CoF value in the expression "AHI_risk," an intervention plan will be formed.

/*Pattern 3: Hazard escalation mode*/

If it is a situation related to the potential acute hazard based on the projections regarding heat wave or flood warnings, the responsibility is focused on increasing the corresponding thresholds.

Data Governance & Auditability

The governance output or deliverables consist of the indicator dictionary, weight/threshold registry, hazard library, and the change log. This restarts the discussion on the reason and effect assessment that is embedded in every change that occurs, for example, the weight update. This supports the defensibility of the index to the regulator and the internal audit function.

Cybersecurity & Data Protection

WSNs & IIoTs are prone to cybersecurity risks. Cybersecurity risks can be overcome through authentication checks on the hardware, encryption on communication, segmentation of the network, and role-based network management. Cybersecurity is out of the scope of the research paper. However, it holds utmost significance in reliable monitoring systems in public places and semi-public areas in relation to the remote control of monitoring nodes.

Scaling and Performance Considerations

Thousands of assets produce an unconceivable amount of data. The generation of the data should occur through an interface that recognizes the difference in the storage of raw and indicator data. Also, the raw data sources should be stored in either a time series database or object storage. Then comes the storage of the indicators inside the structured records. This allows efficient querying that takes place during the generation of dashboards. The AHI calculations should take place on both a scheduled basis and an event-driven manner.

Integration with Digital Twin Projects

In infrastructure pertaining to railways, within the implementation of Digital Twins for digitization, AHI_risk could basically act as a standard "health state" for this Digital Twin. In Digital Twins pertaining to maintenance research, combining sensor measurements, models, and actions, along with intervention actions, is well-supported (Bretones-Guerrero et al., 2022). In this respect, AHI_risk encourages a standard "health state," making it feasible to simulate this "health state" for intervention actions and climate change situations.

Validation Plan & Evaluation Metrics

The validation process would provide confirmatory evidence for the following: (i) technical validity—AHI_risk is related to observed failures and defects, (ii) operational validity—AHI_risk has the ability to optimise planning outcomes, and (iii) business values—decreases in AHI_risk correspond to increased commercial values.
Based on the historical data, the values for AHI_base and AHI_risk can be generated for the asset variables. Hypotheses may be tested with respect to whether lower scores on the asset are related to a higher rate of defects, the rate of corrective maintenances, or incidents. The comparisons on the distribution of scores given to the failure versus the non-failure data may be carried out using statistical tests or by employing the survival analysis on the AHI scores and the time to failure.

The outcome metrics with the elapse of time: defects identified, number of emergency calls, delay minutes, cost of maintenance, comparison among them. When referring to the climate factor component, for this pilot, emphasis has to be on seasons with hazards such as the summer season, rainy season, and so on.

Model and decision metrics

In the technological metrics: precision/recall for defect prediction tasks, calibration over risk scores. Decision metrics: stability (turnover-free) ranking, sensitivity to weight changes, coverage (percentage of assets with data available). Or, possibly, stabile top-N ranking with sensitivity to hazard escalations.

Business Metrics

Business metrics would be the reduction in failures, the reduction in delay minutes, the improvement in inspection efficiencies, and the reduction in cost per asset km. Then the differences in the rates of incident and the incident response times before and after the hazard periods can be used to establish the benefits for the climate-aware options.

Threats to Valid

Issues associated with inconsistencies in asset identification, confusing change, and biased data due to imbalanced sensors. These issues underpin the importance of good governance and quality data. 6 In addition, it is integration that must be incorporated into the validation plan concerning both performance and potential. This is in line with challenge areas defined by systemic reviews, such as the role of decision-making and deployment in railway predictive maintenance systems (Binder et al., 2023).

CONCLUSION

The rail companies are employing more sensors and analytical capabilities, yet it is ultimately the ability that is difficult, given the climate risks that are pouring into the scenario, that the integration capability of the various sets of data concerning the informative prioritization at the level of the overall portfolio. In this paper, there has been a proposition of an Asset Health Index that is climate risk-adjusted. This takes into consideration the WSN-based monitoring/inspection results, Remaining Useful Life prediction analysis, and intelligent asset portfolio management. This integration and proposition took into consideration an indicator library, an example calculation, and actions mapping. There were also two case study simulations that demonstrated the stressors introduced by climate factors that accelerate the trend toward deterioration and prioritized actions. In future studies, it may also consider a comparison test on the framework using actual train communication system setups, or perhaps extracting an even more suitable transformation of the AHI_risk into the notion of probable failure or even evaluating the actual cost and actual benefits that may be incurred by the climate-infused prioritized maintenance. On one side, it is true that the climate risk-adjusted AHI has, instead, become the next useful tool that could lead toward more innovative and closed-loop maintenance realization concerning the concepts of monitoring toward decision toward actions toward results realization concerning reduced risks and costs.

Figure 1. Illustrative AHI trends with climate stress (simulated example)

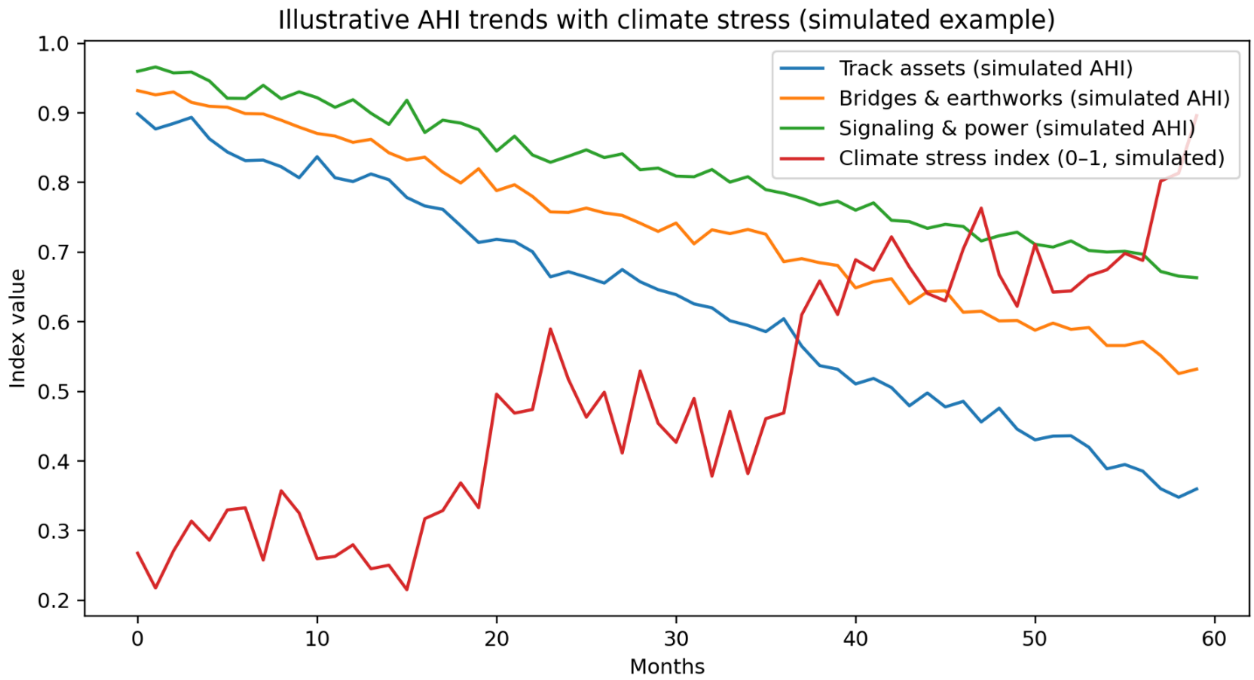

Figure 1. Simulated example showing how an increasing climate stress index can accelerate deterioration and shift priorities.

Figure 2. Illustrative risk-aware prioritization snapshot (simulated example)

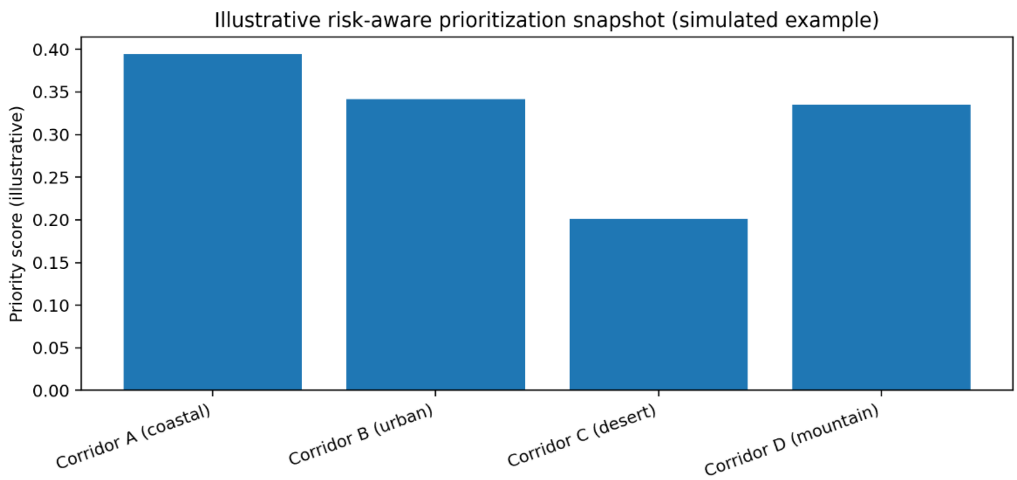

Figure 2. Simulated prioritization score across corridors using base AHI, climate context factor, and consequence-of-failure.

Table 2. Example action mapping from risk-adjusted AHI to interventions

AHI_risk band	Meaning	Recommended action	Typical SLA / timeline
0.80–1.00	Good health; low risk	Routine monitoring; optimize inspection frequency	Standard cycle
0.60–0.79	Moderate; early degradation	Targeted inspections; minor repairs; update prognostic models	4–12 weeks
0.40–0.59	Poor; risk rising	Plan intervention; consider operational mitigations under heat/flood alerts	1–4 weeks
< 0.40	Critical; high failure likelihood/impact	Immediate engineering review; emergency renewal/closure if needed	0–7 days

Extended Discussion: Case Study Blueprint and Cost-Benefit Model

In the previous studies "What does success look like in a real corridor, and how do we prove success quickly?" is a common question with railway infrastructure projects. Solutions were provided in a process simulation and some simulations within the preceding sections. Now, this section provides a ready-to-apply tool for testing in a pilot and for creating, testing, and embedding the climate risk adjustment AHI into an optimal operating process from a pure innovation effort in the field of engineering. The emphasis is strictly on what can and what does already exist with respect to data, already existing decisions of maintenance managers, and already existing risk management controls (ISO, 2018) and asset management (ISO, 2024).

Pilot Design

"A pilot design should be 'small enough to deliver, large enough to matter.'" Usually, the scope for a pilot design needs to address one corridor (or a set of relevant ones, up to 2-3, which are demonstration ones) that is expected to reflect the diversity of infrastructure types and is subjected to one or more typical kinds of climatic hazards, such as, for example, flooding and salt damage in the case of the ocean-fronting corridor, high temperature in the case of the inland corridor, etc.

Thus, with the selection of demonstration corridors, there will be greater external validity, and a business case will emerge.

A starting criterion for the pilot line would include: (i) the availability of data on the baseline state (track geometry records, inspection records, work orders); (ii) the risk of hazards (heat season, flood events); (iii) its operational significance (strength of railway use according to the density of passengers and nominal freight value); and (iv) the possibility of intervention during the timeframe for the pilot project (enough for the results to be analyzed). Palin et al. (2021) also indicate that the lack of safety hazards like heat and floods has physical and operational aspects, therefore lines for which the data for hazard periods is already known raise the probability for the evaluation for the climate context factor CF.

Asset Registry and Indicator Dictionary Establishment

The pilot must start with an asset registry that allows strong, direct mappings between the source data. It can be assumed that most railway organizations have their asset information stored in a variety of IT systems (EAM systems, GIS systems, engineering spreadsheets). It will not be necessary that the pilot itself fully implements master data but that it does have (a) a permanent reference for each type of asset section or component, (b) a common reference frame (route reference, chain age, or geographic coordinates), and (c) key elements regarding vulnerability categories like track form, drainage system, and type of foundation under bridges.

A very important field in which the structures of the data as well as the processes of their combination will have great impact through the effect of IAMP-enabled management of maintenance practices has been identified as follows by *Spyropoulos et al. (2021)*, and this was embodied in the asset registry.

Furthermore, set up an indicator dictionary that has a range of 8 to 15 indicators. This is because it is more convenient to handle a shortlist of indicators with high operational relevance rather than working with a long list that may appear overfit. Each indicator should include the following fields: definition, unit, sources of information, level of updates, type of normalization, threshold values, and owner. This ensures that at least one type of hazard proxy indicator ("Consecutive hot days," "Rainfall intensity percentile," "Flood alert flag"), at least one type of resilience indicator ("Drainage improvement status," "Completion of stress management status"), or both should not cause CF a lack of specificity by simply being a non-trackable part.

Mapping AHI_risk results to decisions and work execution

The important point about this framework is that it assumes that AHI_risk has a positive effect on changes in behavior. To test, one needs an understanding of decision mapping prior to a pilot trial. A good understanding of that mapping would involve: (1) 'top-N risk list' that occurs on a weekly cycle, which is related to maintenance; (2) exception processing related to a sharp, big drop in AHI_risk, such as escalation related to hazard; and (3) engineered escalation processing related to crossing important thresholds.
Because of this consideration, because the risks could occur within a short period, there is a need for development of what is called "hazard mode." In this regard, once the indications for the heat wave cross specific levels, there is a need for this system to (a) bring additional CF penalties on track sections with risks, (b) monitor those sections with increased frequency, and (c) undertake other operation measures, including run restrictions on ground. It has been asserted by Palin et al. (2021) that run restrictions and additional inspections within a state with heat stress are operations and therefore designated as "index operational credibility" within hazard mode.

Data quality, uncertainty, and 'trust' engineering

Trust will typically be the critical factor for the adoption of analytics. Trust-related problems can be considered a technology problem during the pilot phase. Some approaches have been proposed:
• Traceability: Each value for AHI_risk has to relate to values for the indicators as well as the raw data for the evidence.
• Uncertainty visibility: In areas where data may be incomplete or uncertain, the dashboard will have to signify the degree or metrics of missing or uncertain data in such a way that it will be possible to assess where the index is strong or weaker.
• Reconciliation: If it is found, after using the index-based inspections, that there is no problem, it may be looked upon as a learning experience and not an issue for the program. It may be that it is mis-calibrated, it could be due to seasonality or it could be due to sensor drift. The presence of noise, as stated above, affects environmental factors, according to WSN research (Hodge et al., 2015) and is dealt with via reconciliation.

Evaluating the climate context factor CF in the field

The test hypothesis for the study of CF is to be followed by the asking of this question: "Does the addition of climate context enhance the capability to forecast imminent problems and direct preventive resources?" There are two ways that the evaluation question can be addressed in the real-world train environment.
(A) Event-based evaluation: Identify the hazard windows (for example, the days on which heat-wave thresholds exist, days on which flood warnings are active). Within each hazard window, assess the base ranking by AHI versus the risk ranking by AHI_risk. If more segments in an incident ranked by AHI_risk have entered top-N positions, then it proves the effectiveness of CF. The results may be inspections, speed restriction, failures, and disruptions.
(B) Operation effort alignment: This is evaluated by monitoring how well the operation effort for inspections/maintenance aligns with the portion of the pipeline in the hazard exposure areas during the hazard windows. Although the probability of occurrence is very low, the alignment indicates that the operation is adapting to its risk exposure.
These outcomes of assessments can, and should, also be supplemented with professional reviewing sessions where engineering teams can verify whether the fines for CF are appropriate compared to danger mechanisms as described in literature related to assessments of climate impact (Palin et al., 2021).

Cost-benefit model for the business case

The railway administrations should be able to justify their spending on sensing, analytics, and resilience. A simple cost versus benefit analysis could be framed with respect to the disruption cost and maintenance efficiency.
Step 1: Evaluate a consequence-of-failure (CoF) value for every type of asset. CoF may be estimated by any of the following methods: Delayed minutes worthed in money units, Cost of freight disruption, Emergency repairs, Safety costs, or finally, Reputation damage. It may turn out that none of these methods is apt at assigning a value for CoF.
Step 2: Calibrate AHI_risk into a probability proxy. This may be completed with the help of data concerning past failures by forming a survival curve that suggests lower AHI_risk has a higher probability of failure. On the other

hand, without data, one may establish a direct association, like banding. Ever since work has begun under the subject of prognostics, there has been a belief that model type and calibration data rely on data available and the time horizon (Sikorska et al., 2011).

Step 3: Calculate the cost of avoidance. The cost for a given intervention (inspection, repair, drainage upgrade) to improve AHI_base and/or reliability (measured by the increase in CF) can now be estimated by the reduction in probability of failure multiplied by the cost-of-failure factor over the term, less the cost of intervention. The natural mapping between the value and cost of investment is then given by:

Step 4: Identify the benefits of operational efficiencies. While the benefits of increased reliability may not readily lend themselves to short-term measurement, benefits related to operational efficiencies will likely include a reduced number of unnecessary inspections and improved concentration on tampering and renewal activities. The model must track the latter.

Scaling strategy and maturity roadmap

Scaling is to be accomplished through progressive implementation. In Stage 1, the indicators are centered on inspection-driven indicators and climate indicators with simple climate conditions (alert levels, temperatures, and rainfall). In Stage 2, WSN indicators are taken into account from strategic locations, with the assurance of quality data formalized based on knowledge gained from the current WSN operations, wherein "harsh environmental operating conditions and a concern for reliability are seen as the norm" (Hodge et al., 2015). In Stage 3, predictive RUL models are incorporated with emphasis on critical failure modes, enhancing the risk environment by incorporating local conditions for higher risk. In Stage 4, the addition of scenario planning with the concept of capital planning includes adaptation investment projects, wherein the parameters of resilience are changed to model the risk pathway with different investment plans.

In particular, there is the aspect of scaling, which has to occur in a governance setting. Then, there's the aspect of data models and decision support systems, which, according to the platform studies, have to be standardized (Spyropoulos et al., 2021). At the level of the AHI_risk scale, this means that there will be a common dictionary used in relation to the indicators and the change log, in addition to the establishment of a cross-functional steering group that will involve the engineering, operation, safety, and data groups. These groups will approve the weights, thresholds, and hazard definitions. In addition, these groups will determine the frequency of reviews, such that there will be reviews done quarterly in relation to weights, reviews done monthly in relation to the health of portfolios, and weekly reviews in relation to hazard mode when in extreme seasons.

Integration of train movement calibration and onboard data in advanced implementations

As a result, as the maturity level of these organizations increases, onboard data becomes a preferable option due to the ability offered by accelerometers, inertial sensors, and vehicle systems to provide frequent data readings. However, as a condition to extract data readings to determine the status of the infrastructure, there exists a demand for models of train motion and interaction models with tracks. Cunillera and Bešinović (2023) argue that calibration models and train motion models are considered critical to this objective. Accordingly, from the perspective of AHI, the recommendations adopted can thus be considered to include: (i) to adopt status of calibration as a data quality metric (de-emphasis or reduce weight to indicators, such as those which are outdated, for example, out-of-date calibrations), and (ii) adjust motions due to seasonal and climatic changes, which are extraneous indicators due to increased hardness of tracks associated with hot climatic temperatures. Ideally, this marks the second occurrence where "context matters."

Summary of the Extended Discussion

This article has provided a practical guide to piloting and scaling, based on corridor identification, creation of an indicator dictionary, conceptualization of workflows, CF analysis, and business cases development, using an expectation of cost construct consistent with risk management literature (ISO, 2018). As AHI_risk is a governed asset that can be integrated into platform-level logic (Martínez-Galán et al., 2020; Spyropoulos et al., 2021) and, based on that, Railway transport systems should be enabled to transition from climate change monitoring to climate change closed-loop climate change resilient maintenance planning, as it is described in examples from the literature (Palin et al., 2021). 8.10 Checklist for readiness to implement at scale. Prior to scaling from a pilot, it is necessary that, for instance, (1) the asset IDs are agreed upon and standardized, (2) that a nominating owner and a standard for normalizing their data is defined for each indicator, (3) that weights and thresholds are approved by a workflow, (4) that a quality check on sensor data and messages of context is carried out, (5) that protocols for hazard mode operation are agreed on with operational and safety teams, (6) that indexes of AHI_risk/estimates of uncertainty are provided on dashboards, (7) that work orders generated from the calculation of the index can be attributed to evidence, and (8) that results post-intervention are documented for recalibration. These ensure a closed-circle process from a management standpoint, for (asset and risk management)-focused management, ISO (2024, ISO, 2018).

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