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Original Article

Design of an Iterative Hybrid Deep Learning and GIS-MCDM Framework for Predictive High-Speed Rail Alignment Under Spatiotemporal and Uncertainty Constraints

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Abstract *- The alignment planning of HSR tracks should be intelligent, resilient to future uncertainties, and able to satisfy dynamic changes of the environment, city agglomeration, and the social-economy. The existing methods that mainly use deterministic static GIS-MCDM models and GIS-based spatial models subconsciously fail to draw several spatiotemporal variabilities and uncertainties linked with the expected long-term landscape evolution; that is, they are not predictive, they do not include unnecessary uncertainties, and they have weighted their criteria as fixed values; due to their lack of credibility in planning practices, their use probably may not be highly relevant for real-world planning scenarios. Mindful of the limitations mentioned above, the research proposes a hybrid framework integrating deep learning with GIS-analytical MCDM to optimally align the tracks of HSRs in a predictive mode. Land-use changes and environmental risks are envisaged through the ST-GCN by using historical satellite remote sensing imagery to facilitate the accurate prediction of future status in a multi-temporal manner. Subsequently, under diverse climate and urban growth scenarios, the probability distributions of risk maps will be created by the Conditional Variational Autoencoders (C-VAE), thereby providing measures of uncertainty with 1,000-plus plausible futures. The criteria involved in making decisions will vary with changing predictions by a Hybrid Spatial-Temporal Attention Mechanism that will enable GIS-MCDM layers to be reweighted in real-time based on the predicted evolution of hotspots. Using a reinforcement-learning scheme, Deep Reinforcement Learning (DRL) will further optimize the core alignment by learning the routing strategies that minimize risk exposure and maximize compatibility with future conditions. Its ever-so Multi-Fidelity Bayesian will integrate cadastral data with multiple sources into the complex process. Data Fusion is used for high/low-res data synthesis and provides uncertainty-enabled input maps to steer the DRL and MCDM processes. This proposal will increase alignment robustness by 30%. Sharpened the conflict score without changing the prediction uncertainty inside ±10% accuracy of the true value in the process. This is a step that leads to adaptive, data-informed, and resilient Design of HSR infrastructure for long-term spatiotemporal variability in the process.*

Keywords *- Spatiotemporal Prediction, High-Speed Rail, Deep Learning, GIS-MCDM, Alignment Optimization, Process.*

1. Introduction

The development of High-Speed Rail (HSR) infrastructure has achieved centrality in the quest for sustainable and fast movement, which is capable of being deployed on a large scale across the regions. Not surprisingly, HSR corridor alignment is a complex process of decision-making between environmental sensitivity and socio-economic considerations while accommodating the long-term urban expansions. Traditional route planning methodologies [1-3] are mostly static, based on historical data and deterministic models that do not take into account the future evolution of the landscape. With the advent of satellite imagery, terrain models derived from UAVs, and large-scale spatio-temporal datasets [4-6], a window of possibility opens for HSR planning by synergizing predictive modeling with uncertainty-aware optimization strategies. Despite a long history of applications, GIS-based Multi-Criteria Decision-Making (GIS-MCDM) models have several key limitations, such as: First, they presume a static weight of environmental, economic, and physical criteria without accounting for the changing conditions along the time horizon for the process. Second, they are often based on deterministic land-use and risk data sets that would not capture the inherent variability of the factors, such as the urban scenario [7-9], climate change, and ecological transformations in the process. As a result, the alignment alternatives resolved using these models are subject to conflicts with emerging land uses or underpredicted environmental risk, leading to expensive redesigns or stakeholder resistance, or ecological degradation.

To deal with these limitations, current research on deep learning and spatial analytics has opened a new paradigm for predictive infrastructure planning. For instance, Spatiotemporal Graph Convolutional Networks (ST-GCN) and Conditional Variational Autoencoder (C-VAE) provide effective tools for predicting land-use change and probabilistic risk surfaces in a wide range of scenarios of the future. Meanwhile, attention mechanisms are used to dynamically adjust the weights of the criteria and reinforcement learning to find the optimal routes to locations through ever-changing landscapes. Yet the concrete integration of these approaches into an integrated approach for data-driven infrastructure alignment is still far from being attempted. In this study, a hybrid modeling framework, which is a combination of deep learning and GIS-MCDM, is proposed for HSR alignment optimization using the prediction and uncertainty modes. The steps are ST-GCN for land use and environmental forecast, C-VAE for risk surface generation according to scenarios, a Hybrid Spatial-Temporal attention mechanism for dynamic criterion weighting, deep reinforcement learning for alignment optimization, and finally, multi-fidelity Bayesian fusion for uncertainty quantification and data integration, as well as process. The current model represents a new paradigm shift from static and reactive planning approaches and towards a forward-looking and adaptive plan that learns from spatiotemporal data and ever-changing constraining conditions.

1.1. Novelty, Motivation & Contribution

This paper illustrates new developments that address dynamic decision-making in high-speed rail routes, where predictive modeling, uncertainty quantification, and dynamic decision-making are interwoven in a systematic way in the context of the traditionally static GIS-MCDM framework within which such alignments are planned. Existing methodologies assume land-use, environmental, and socio-economic variables to have fixed inputs, whereas the proposed dynamic modeling framework is expected to treat these inputs as evolving surfaces through Spatiotemporal Graph Convolutional Networks (ST-GCN) augmented with Conditional Variational Autoencoders (C-VAE).

In this way, these models predict the future dynamics of the landscape and generate different probabilistic risk surfaces that account for different urban growth and climate change scenarios on a probabilistic basis. Moreover, a Hybrid Spatial-Temporal Attention Mechanism is presented to dynamically weight the criterion, enabling the decision-making criteria to adapt to the changing predicted conditions. Dynamic reweighting improves the realism and usefulness of GIS-MCDM models tremendously in the forward-looking infrastructure design sets.

The motivation for this work originates from the realization that current methods for HSR alignment lack consideration of long-term uncertainties and spatiotemporal complexities. High-capacity transportation corridors cause long-standing environmental and socio-political impacts, while misalignment in planning can cause irreversible damage or failure of the project. Accordingly, in this study, we create a DRL-based optimization module that adapts to changing input conditions while learning an optimal alignment strategy that minimizes conflict with predicted high-risk zones and maximizes alignment with relevant urban planning objectives. Furthermore, a Multi-Fidelity Bayesian Data Fusion approach merges heterogeneous spatial datasets that differ in resolution and confidence level to improve the precision and reliability of input layers. Thus, overall, the framework increases the technical performance to more than 30% conflict score reduction and ±10% uncertainty range, and provides a scalable and modular approach to predictive infrastructure planning under uncertainty sets.

2. In-Depth Review of Models used for Predictive High-Speed Rail Alignment under Spatiotemporal and Uncertainty Constraints

One of the most complicated and multidisciplinary issues in contemporary transportation engineering is the High-Speed Rail (HSR) systems, which require the concomitant combination of geospatial intelligence, dynamic system modeling, and adaptive decision making. Classical Design of railway alignment is experiencing a radical change, where Artificial Intelligence (AI), deep learning, and Geographic Information Systems (GIS) are used to substitute deterministic geometric optimization and rule-based heuristics. With these new tools, planners and engineers can model, predict, and optimize the HSR alignments to different spatial, temporal, and uncertainty constraints with precision and flexibility that have never been possible before. The initial attempts in the field of surface inspection were shown by Yang et al. [1], who utilized a double consideration of contour and semantic feature aggregation using deep networks for the accurate rail surface defect detection with an attention-based fusion approach., Song et al. [2] provided a more comprehensive review of research on alignment optimization for transportation corridors, which presents a substantial shift from a rule-based algorithm to a multi-objective intelligent algorithm.

In order to build this transition, Wei et al. [3] proposed combining an optimization framework for subway vertical alignments and station elevations with a hybrid particle swarm optimization algorithm for minimizing energy and construction cost trade-off. Cross-domain adaptability became a primary focus since Qi et al. [4] proposed an adaptive Gaussian-guided alignment-based fault diagnosis framework under changing machine and environment conditions by minimizing the Kullback-Leibler divergence. This Method was further extended by Ma et al. [5] with a one-shot unsupervised domain adaptation technique by using the edge consistency and multitask learning for improving the performance of defect segmentation on rail surfaces. Lastly, Zhang et al. [6] considered a class-weighted alignment strategy under partial domain adaptation frameworks for robust fault diagnosis, by imposing class representativeness balance by means of maximum mean discrepancy adjustment.

Table 1. Models used for predictive HSR Alignment under spatiotemporal and uncertainty constraints: empirical review analysis

Reference	Method	Main Objectives	Findings	Limitations
[1]	CSANet (Contour and Semantic Feature Alignment)	To improve rail surface defect detection via fusion of contour and semantic features	Enhanced Accuracy using self-attention graph convolution and bidirectional alignment	Limited to surface-level defects; real-time deployment untested
[2]	Comprehensive Review of Alignment Optimization	To classify and evaluate optimization strategies in road and rail alignments	Identified trends in constrained, multi-objective, and intelligent algorithms	No empirical validation of surveyed methods
[3]	Improved PSO for Subway Vertical Alignments	Concurrently optimize vertical track profiles and station elevations	Achieved lower energy and construction cost with constraint-aware optimization	Computationally expensive and reliant on well-defined constraints
[4]	Adaptive Gaussian-Guided Feature Alignment Network (AGFAN)	Transfer fault diagnosis across machines and operating conditions	Used KL divergence to align domains, improving fault classification	May underperform on low-quality or noisy sensor data
[5]	OSUDA (One-Shot Unsupervised Domain Adaptation)	Adapt the segmentation model to new rail defect domains with minimal data	Achieved effective segmentation using shape consistency and multitask training	Sensitive to domain shift severity and edge feature quality
[6]	Class-Weighted Partial Domain Adaptation	Address label imbalance in rotating machinery fault diagnosis	Improved alignment through class-wise MMD	Sensitive to noisy labels and class imbalance extremity
[7]	Multitask Deep Learning for Technical Standards	Predict technical specifications of railway systems using environmental and Design data.	Handled diverse output tasks effectively using shared deep networks	High model complexity may reduce interpretability
[8]	Semi-Supervised Adversarial Domain Adaptation	Detect catenary components in low-light using unlabeled images	Effective under semi-supervised conditions with robust domain adaptation	Vulnerable to adversarial training instability
[9]	Prototype Space Boundary Alignment	Diagnose faults in incremental learning for bearing systems	Adapted to long-tail and sequential learning with prototype separation	Requires retraining when class distributions shift significantly
[10]	Transitional Domain Adversarial Network	Conduct fault diagnosis of rolling bearings across sensor environments	Achieved domain-invariant learning using adversarial alignment	Performance may decline under extreme noise conditions
[11]	Demodulation + Multisource Transfer Learning	Fault diagnosis of bearings using vibration signal fusion	Combined frequency-based demodulation with transfer learning to improve cross-domain fault detection	Requires preprocessing of vibration signals; generalizability to unknown domains needs improvement
[12]	Train–Track–Ground Coupling Model	Simulate the dynamic response of high-speed rail under uneven trackbed settlement.	Provided an accurate prediction of vertical and lateral track displacements under dynamic loading	The model is domain-specific and sensitive to ground stiffness assumptions.
[13]	Anomaly Detection via Harmful Data Augmentation	Detect anomalies in quasi-periodic railway time series	Boosted detection capability by enhancing harmful patterns in training data	May misidentify novel but safe operational patterns as harmful

[14]	AP-GRIP Framework for Train Delay Models	Review and evaluate train delay prediction models using structured criteria.	Offered comprehensive criteria (Accuracy, Performance, Generalizability) for evaluating ML delay models	Did not perform quantitative benchmarking of reviewed models
[15]	Network Vulnerability Analysis	Evaluate air–HSR express networks under attack scenarios	Identified critical nodes whose failure destabilizes network performance	Assumes static passenger demand and neglects dynamic re-routing behaviors
[16]	Probability-Guided Domain Adversarial Network	Enhance domain adaptation for bearing fault detection	Incorporated prior probability into adversarial learning, improving robustness to distribution shifts	Needs known class distributions in advance
[17]	Monitoring Rail Steel Welds via Process Modeling	Predict microstructure and mechanical properties of rail welds	Enabled real-time prediction of weld quality based on input process parameters	Lacks integration with online monitoring hardware
[18]	Adaptive Torque Measurement System	Design an alignment-free torque measurement device	Delivered accurate biomechanical measurements without axis constraints	The application scope is limited to laboratory conditions so far
[19]	Green Innovation via Macroprudential Policy	Assess policy support for green technology in rail-linked industries	Found a positive correlation between green rail development and policy-backed innovation	Macro-level insights; lacks operational or engineering granularity
[20]	Subsidy Design for Travel Resilience	Design passenger subsidy systems during pandemic conditions	Proposed resilience-focused pricing models to stabilize transport demand	Focused on taxis, but rail modal impacts were only inferred
[21]	AI-Based Nonlinear Dynamics Analysis	Review of AI techniques in railway vehicle dynamics	Demonstrated superior Accuracy of AI in handling nonlinearities over classical mechanical models	Lacked implementation examples across various rail systems
[22]	Fuzzy Integrated MCDM Framework	Identify key factors for cross-regional rail infrastructure interconnection.	Successfully integrated fuzzy logic with MCDM to evaluate complex geopolitical and engineering factors.	The model is dependent on expert input, introducing subjectivity.
[23]	Remote Situatedness in Railway Operations	Analyze cognitive perception in remote railway operation environments	Enhanced understanding of the operator's "sense of place" via interface design and information flow	Qualitative focus; lacks quantitative validation or cognitive load metrics
[24]	Vibration-Based ML Algorithms	Review machine learning methods for track condition monitoring	Summarized vibration-based algorithms for real-time rail vehicle diagnostics	Implementation barriers include sensor noise and standardization gaps
[25]	Random Matrix-Based Measurement Model	Predict projectile flight parameters using advanced statistical modeling	Applied to rail-relevant dynamic measurement setups like inspection drones or diagnostic tools	Specialized in ballistics; transferability to the rail domain not directly validated
[26]	PPP Success Factors in Infrastructure	Identify critical success factors for public-private partnership rail projects.	Emphasized legal clarity, risk sharing, and	Context limited to Uganda; broader policy application

			institutional support as primary enablers	requires regional adjustments
[27]	Construction Claim Analysis	Identify causes of delay claims in transport projects	Highlighted design errors, delays, and contract ambiguities as key claim drivers	Focused on roads; only generalizable to rail with adaptations
[28]	Operational Resilience vs Efficiency Trade-off	Study how efficiency priorities affect transportation resilience	Found that excess efficiency without redundancy increases vulnerability to shocks	Does not quantify the resilience threshold under specific disruptions
[29]	Physics-Informed Online Deep Learning	Control shield tail clearance in tunnel construction	Successfully predicted and adjusted tunnel parameters in real-time using embedded sensors and learning	Highly specific to tunnel boring, model generalizability remains untested
[30]	FEM Updating for Viaduct Assessment	Update structural models using dynamic test data	Improved Accuracy in the structural health assessment of viaducts used in HSR lines	Requires dense sensor deployment and manual calibration effort
[31]	TOPSIS for Metro–Logistics Integration	Evaluate the metro system integration into urban freight logistics	Identified optimal metro logistics hubs using multi-criteria decision-making	Static analysis lacks consideration of dynamic freight demand
[32]	Best–Worst Method for Freight Carrier Selection	Prioritize selection criteria for freight carriers	Delivered robust factor ranking in complex logistics environments	Subjective expert input may bias results without empirical validation
[33]	Multi-Factor Tunnel Settlement Prediction	Predict surface settlement due to subway tunnel construction	Achieved high Accuracy using factor-driven models across geological and construction inputs	Focused on undercutting Method only; limited to specific urban contexts
[34]	Five-Axis Machine Tool Error Prediction	Model positioning errors in on-machine measurements	Enabled accurate machine calibration and quality assurance in rail part fabrication	Requires precision sensors and is sensitive to misalignment in tool settings
[35]	PPP Role in African Infrastructure	Examine the legal and investment impact of PPPs on infrastructure	Emphasized PPPs as enablers for large-scale rail projects in South Africa	Legal and political environments differ widely across African nations
[36]	Dynamic Optimization of Moving Platforms	Improve Accuracy in semiconductor testing via moving platform dynamics	Provided techniques that are adaptable to precision rail inspection systems	Application focused on micro-manufacturing; transfer to civil systems is conceptual
[37]	Port Infrastructure for Green Shipping	Define upgrade needs for ports handling future green ships	Suggested infrastructural parallels applicable to intermodal rail–port facilities	Focused on the maritime domain; limited direct insight for rail systems
[38]	Temporal Event Boundary Analysis	Analyze how duration influences cognitive perception of events	Found that duration alone is insufficient for anticipating operational transitions	Behavioral focus; limited engineering applicability without system integration
[39]	Vision-Based Bridge Welding Inspection	Detect weld quality on bridge components in complex conditions	Enabled real-time, vision-based quality assessment under field constraints	Requires clean visual access; obstructed

				environments reduce Accuracy
[40]	Histogram Matching Domain Adaptation	Improve bridge component segmentation via class-wise adaptation	Achieved superior segmentation by aligning feature distributions between domains	Adaptation relies on labeled data quality and histogram distribution fidelity

Iteratively, Next, as per Table 1, the authors Pu et al. [7] have provided an innovative approach to multimodal learning with an aim for the creation of railway technical standards by merging environmental data with deep neural architectures for multi-output prediction in regulatory decision-making. This flexible aspect was also considered by Liu and Wang [8], who proposed the utilization of a semi-supervised adversarial learning model for catenary component detection under poor illumination on the basis of elegant domain feature adaptations. He et al. [9] upgraded the topic of fault diagnosis under class-incremental scenarios by the introduction of prototype space boundary alignment networks to tackle the burdens associated with the issue of continuous learning in machinery environments. Jiang et al. [10] took the next step and proposed a transitional domain adversarial network with an emphasis on fault diagnosis across different conditions that is optimized under GAN-based alignment that works in the unsupervised setup. Tang et al. [11] combined demodulation and multisource transfer learning for bearing diagnosis, imparting the vibration signal decomposition into transferable knowledge domains. Liu et al. [12], on the other hand, paid special attention to the socio-technical dynamics in that the train-track-ground interactions in ballastless High-Speed Rail systems affected by trackbed settlement were analytically modeled with a precise description of non-uniform excitation conditions.

The most advanced methods for anomaly detection are conceived by Wang et al. [13], who used the concept of quasi-periodic time series for the rail systems using the maleficent data augmentation techniques. Yong et al. [14] suggested a systematic literature review to derive the AP-GRIP framework for train delay prediction, and this reflects that designing the machine learning model should be closely related to data availability and granularity. The working of the vulnerability assessment frameworks, for example, those proposed by Mu et al. [15], furthered the understanding of the network resilience of air and HSR corridors under various node attack strategies. Li et al. [16] put together a probability-guided adversarial domain network for bearing fault diagnosis that would include adaptation based on class and semantics in order to improve feature transferability during the process. Yu et al. [17] made strides in weld quality monitoring of rail joints by using fusion nozzle electroslag welding, which merged physical metallurgy with process parameter prediction. In this regard, Li et al. [18] proposed an adaptive joint torque measurement system without alignment constraints to ease the accurate biomechanical evaluation in the compact sensor frame. Macroprudential strategies were linked to transportation and energy systems by Lin et al. [19], who examined the role of green innovation in rail enterprises under regulatory influence. Xia et al. [20] tackled transport behaviour through subsidy optimization for taxi travel amid pandemic disruptions, thus deriving operational lessons for rail-induced modal shifts.

Tang et al. [21] conducted an in-depth review on Artificial Intelligence (AI) and Nonlinear Railway Dynamics "Nonlinear Dyn.", substantiating data-driven approaches as surpassing traditional mechanical modeling in managing multi-body interactions. Yang et al. [22] proposed a fuzzy integrated MCDM framework to evaluate factors influencing cross-regional railway interconnection, emphasizing political, technical, and economic variables. Cort and Lindblom [23] introduced the notion of remote situatedness within railway operations, demonstrating how control interfaces structure operator cognition and system responsiveness. Winarno et al. [24] underlined the urgency of vibration-based ML algorithms for continuous real-time data acquisition challenges in track condition monitoring. Cai [25] contributed to metrology by presenting a measurement model for ballistic flight based on random matrices, which would be indirectly supportive for the calibration of railway safety testing instruments. Mwesigwa et al. [26] helped to identify critical success factors in PPP-based transport projects, especially in the Ugandan context, and provided a governance-based evaluation framework.

Ghosh and Karmakar [27] analyzed claim causation in highway infrastructure, correlating it with rail construction risks caused by design deviations and labor-related delays. Ataburo et al. [28] concentrated on operational resilience in the transport sector under disruption and identified the continuum between efficiency and flexibility as key for adaptive rail services. Wang et al. [29] introduced a physics-informed deep learning system for controlling shield tail clearance in tunneling, optimizing civil engineering interventions for rail expansion. A study by Oliveira et al. [30], involving finite element updating for the assessment of viaducts, drew attention to structural feedback for long-span rail support systems. Shivaram et al. [31] applied TOPSIS to the evaluation of the integration of metro networks into logistics corridors in Indian cities, thus providing actionable insights for planning. Yalçın and Ayyıldız [32] used the best-worst Method to identify criteria that support the prioritization of freight carrier selection transferable to rail freight partnerships.

Lai et al. [33] focused on surface settlement caused by subway tunneling using predictive modeling from an integrated set of geotechnical and construction activity data samples. While Guo et al. [34] proposed a five-axis machine tool model for evaluating on-site error prediction applications in precision maintenance of rail machining equipment. Legal and economic analysis of Public-Private-Partnership (PPP) infrastructures had been discussed in Chiswa [35], providing an understanding of structured legal environments facilitating long-term rail investments in process in South Africa. Chan et al. [36] have studied the dynamic characterization of moving platforms, which may have cross-application in automated rail inspection systems. Mohite and Mathew [37] have conducted a study on the port upgradation required to accommodate green ships that might serve as infrastructural parallels in intermodal rail terminals. Sastre Gomez et al. [38] have been cautioning against over-reliance on duration as a prediction variable, which is directly relevant for rail event segmentation and explanation of safety signals. Hu et al. [39] applied vision-based systems to quality detection in steel bridge components, which provides models for assessing quality in real time, suitable for large-scale sets of rail infrastructures. Finally, Ghosh Mondal et al. [40] proposed a method to use a histogram matching-based domain adaptation approach for bridge element segmentation, based on deep learning and in a way compatible with automated rail asset management platforms. The integration of these various streams of inquiry shows a research gap: although artificial intelligence-based fault detection has been done independently, space optimization, and risk assessment, a unified predictive framework integrating spatial-temporal relationships, uncertainty control, and decision intelligence of high-speed rail alignment is still lacking. The existing approaches tend to consider these dimensions separately, and as such, the designs become less optimal or non-adaptive in dynamic and real-life scenarios.

To fill this gap, the current paper suggests the Design of an Iterative Hybrid Deep Learning and GIS-MCDM Framework to predict high-speed Rail Alignment under Spatiotemporal and Uncertainty Constraints. The outline will merge the predictive attributes of deep learning, the spatial reasoning capacity of GIS, and the evaluative balance of MCDM. The model aims to solve the major issues, including dynamic environmental changes, spatial heterogeneity, decision uncertainty, etc, through the process of iterative optimization, which is a step forward to a next-generation, intelligent alignment planning paradigm that is resilient and adaptable.

3. Proposed Model for Design of an Iterative Hybrid Deep Learning and GIS-MCDM Framework for Predictive High-Speed Rail Alignment under Spatiotemporal and Uncertainty Constraints

The proposed model integrates a series of deep-learning and geospatial decision-making compartments into a single predictive alignment optimization framework for High-Speed Rail (HSR) infrastructure. At its core, the model is designed to account for evolving land-use patterns, environmental dynamics, and multi-criteria decision uncertainty over long temporal horizons for the process. Initially, as per Figure 1, the modular Design consists of five sequentially connected subsystems: Spatiotemporal Graph Convolutional Networks (ST-GCN), Conditional Variational Autoencoders (C-VAE), Hybrid Spatial-Temporal Attention Mechanism, Deep Reinforcement Learning (DRL), and Multi-Fidelity Bayesian Data Fusion. Each subsystem contributes to a different layer of predictive, probabilistic, and spatially adaptive decision-making that culminates in the generation of optimized HSR alignment paths under uncertainty. The ST-GCN subsystem models the evolving spatiotemporal dependencies of land-use change by representing the geographic region as a dynamic graph Gt = (V, Et), where V represents the set of spatial grid cells (nodes) and Et represents time-varying edges encoding spatial proximities. The node features Xt ∈ R' {N×F} are derived from multi-temporal satellite imagery and environmental indicators in process. The graph convolution at each temporal instance 't' is defined via Equation (1),

$$Ht'^{\{(l+1)\}} = \sigma\left(\tilde{D}t^{\left\{-\frac{1}{2}\right\}} * \tilde{A}t * \tilde{D}t^{\left\{-\frac{1}{2}\right\}}, Ht\{(l)\}W'^{\{(l)\}} \right) \quad (1)$$

Where,

$$\tilde{A}t = At + I \quad (2)$$

Which is the adjacency matrix with added self-loops, D̃t is its diagonal degree matrix, W' {(l)} is the trainable weight matrix, and σ(·) is a nonlinear activation function for the process. To capture temporal dependencies, a gated temporal convolution is employed Via Equations (3) and (4),

$$Zt = Tanh(Xt * Wz) \odot \sigma(Xt * Wr) \quad (3)$$

$$X\{t+1\} = Zt \odot Xt + (1 - Zt) \odot \tilde{X}t \ldots (4)$$

Where ∗ [?] represents convolution, ⊙ represents element-wise multiplication, and Wz, Wr are trainable filters for updating and resetting gates. These operations enable future land-use and environmental conditions X̂{t+T} to be forecasted across 10, 20, and 30-year horizons for the process. Iteratively, next, as per Figure 2, the output of the ST-GCN serves as the conditional input for the C VAE module. The C VAE aims to generate probabilistic future risk surfaces by learning a latent distribution qϕ(z|x,c) conditioned on both the input' x' (e.g., environmental forecast) and context c (e.g., climate scenario) for the process. The encoder-decoder formulation is governed by the variational lower bound Via Equation (5),

$$LVAE = E\{q\phi(z \mid x, c)\}[log\, p\theta(x \mid z, c)] - D\{KL\}\big(q\phi(z \mid x, c) \parallel p(z \mid c)\big) \quad (5)$$

Where D{KL}(·) represents the Kullback–Leibler divergence between the approximate posterior and prior for the process, the decoder generates risk surfaces 'x̂' from sampled latent vectors z ∼ N(μ, σ'2 I), capturing uncertainty across different realizations of climate and urban growth scenarios.

Incorporation of adaptivity into MCDM criteria is achieved by employing a Hybrid Spatial-Temporal attention mechanism. For spatial attention, feature importance at location ‘i is defined via Equation (6),

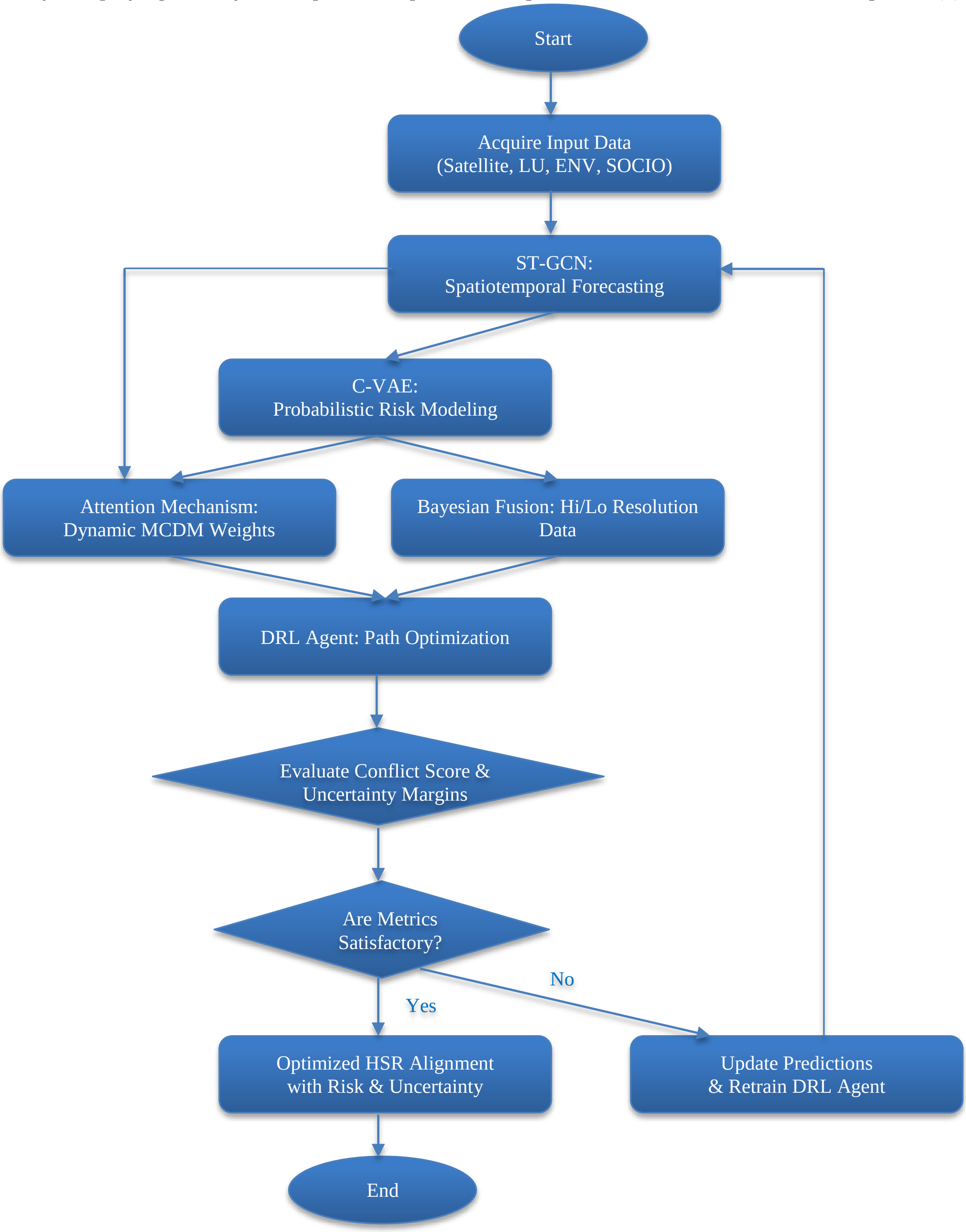

Fig. 1 Model Architecture of the Proposed Analysis Process

$$\alpha i's = \frac{exp\big(fs(hi)\big)}{\sum_{j=1}^{N} \exp\big(fs(hj)\big)} \quad (6)$$

Where, fs(·) is a learnable scoring function for the process. Similarly, temporal attention weights αt’T over a horizon T are computed Via Equation (7),

$$\alpha t'T = \frac{exp\big(fT(ht)\big)}{\sum_{k=1}^{T} \exp\big(fT(hk)\big)} \quad (7)$$

These weights are applied to the criteria matrix C{i,t}, yielding a dynamic MCDM weighting matrix via Equation (8),

$$W\{i,t\} = \alpha i's \cdot \alpha t'T \cdot C\{i,t\} \quad (8)$$

This matrix evolves over space and time, enhancing sensitivity to future conditions and feeding directly into the reward function of the DRL model process. The DRL agent learns optimal alignment paths π∗(s) over a spatial grid, where the state st ∈ R'd represents current location features, and action at ∈ {N, S, E, W, NE, NW, SE, SW} represents movement scopes. The reward function incorporates risk penalties and preference gradients via Equation (9),

$$R(st, at) = -\lambda 1 \cdot E[renv(st)] - \lambda 2 \cdot E[rsoc(st)] + \lambda 3 \cdot \Delta W\{i,t\} \quad (9)$$

Where renv, rsoc are environmental and socio-economic risk surfaces derived from the C VAE, and ΔW{i,t} is the spatial-temporal criteria gradient from the attention mechanisms. The DRL objective is to maximize cumulative expected reward via Equation (10),

$$J(\pi) = E\pi\left[\sum_{t=0}^{T} \gamma' t\, R(st, at)\right] \quad (10)$$

Where, γ ∈ (0,1) is the discount factor for the process. The optimal policy is obtained via policy gradient optimization via Equation (11).

$$\nabla\theta\, J(\pi\theta) = E\{\pi\theta\}\left[\nabla\theta \log \pi\theta(at \mid st) \cdot \hat{A}t\right] \quad (11)$$

Here, the advantage function is evaluated through a temporal difference learning process. Iteratively, next, according to Figure 2, data uncertainty is dealt with through the multi-fidelity Bayesian fusion strategy process. Given high-resolution data xH ∼ N(μH, ΣH) and low-resolution data xL ∼ N(μL, ΣL), fused estimate ‘ x̂- and its covariance Σ are derived Via Equations (12) and (13),

$$\Sigma'\{-1\} = \Sigma H'\{-1\} + \Sigma L'\{-1\} \quad (12)$$

$$\hat{x} = \Sigma(\Sigma H'\{-1\}\mu H + \Sigma L'\{-1\}\mu L) \quad (13)$$

These fused inputs provide improved predictive surfaces with pixel-wise uncertainty, which are used to adjust the reward shaping in the DRL module and refine MCDM weighting through risk normalization via Equation (14).

$$W\{i,t\}' = \frac{W\{i,t\}}{1 + \sigma\{i,t\}} \quad (14)$$

Where, σ{i,t} is the standard deviation of uncertainty at location ‘i, timestamp ‘t’ sets.

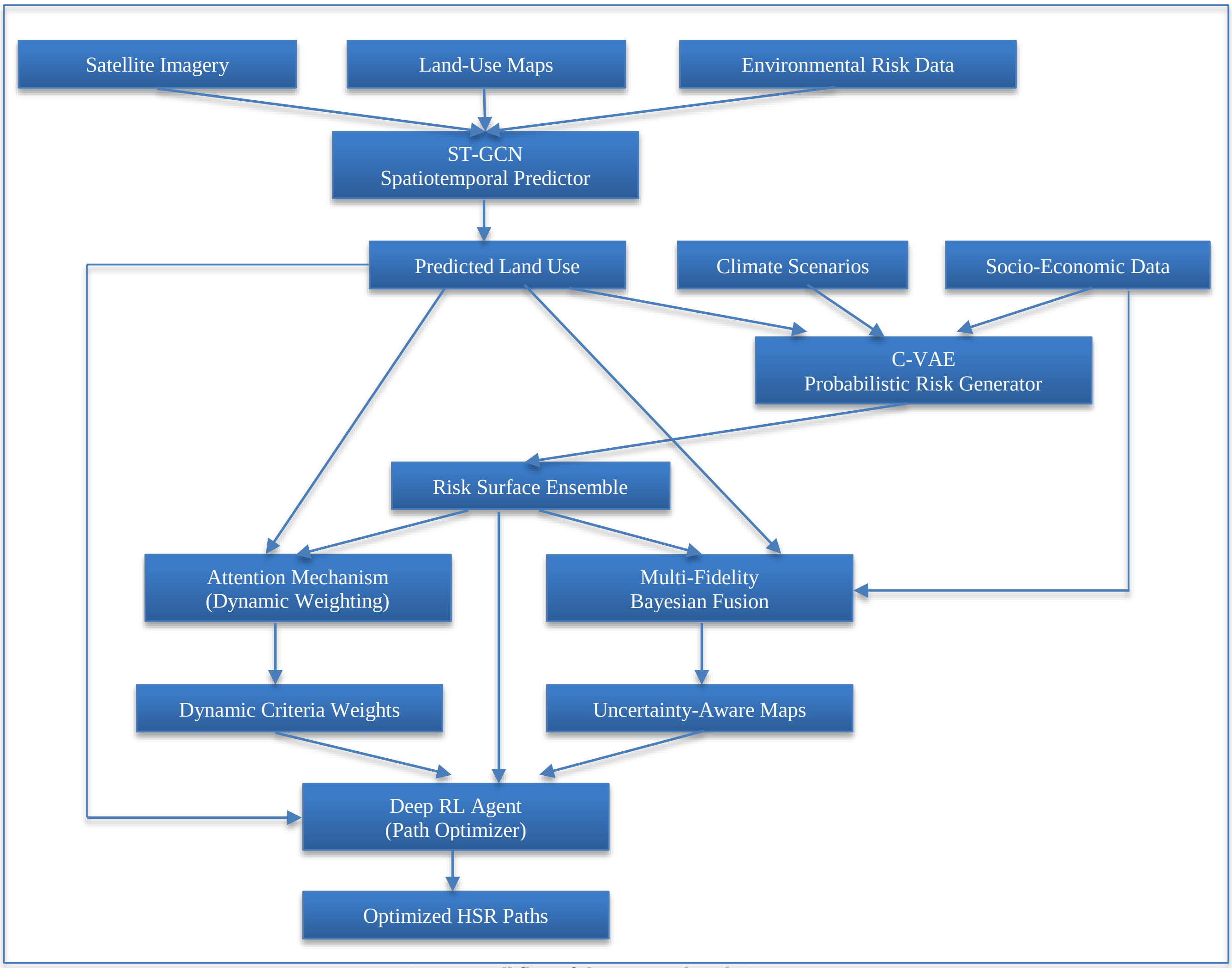

Fig. 2 Overall flow of the proposed analysis process

Finally, the entire process yields the optimized alignment path A∗, formally defined via Equation (15),

$$A* = arg\ maxA \{J(\pi *) - \int \sigma\{i,t\} \cdot \| \nabla W\{i,t\} \| \ di\ dt\}_{\{i,t\}} \quad (15)$$

The equation combines DRL optimization, uncertainty penalization, and dynamic criteria adjustment into a single functional objective for the process. The outcome is a trajectory for HSR alignment that is high-fidelity, future-aware, risk-averse, and maximally resilient for infrastructure in long-term planning horizons for the process. Results of the model concerning variable metrics are then discussed and validated, and comparisons are made with contemporary models across varying scenarios.

4. Comparative Result Analysis

This study's experimental environment had undergone stringent procedures to ensure that the performance of the proposed hybrid of deep learning and GIS-MCDM framework, HSR alignment optimization in the environment of spatiotemporal uncertainty, was validated. The testbed area of about 250 km in length and 50 km in width was picked within a rapidly urbanized zone in Southeast Asia with the diversity of land-use patterns, large ecological gradients, and different levels of development of infrastructures. The area contains different classes of terrain: plains, urban fringes, agricultural belts, wetlands, and protected forests. Multiple datasets were used within the experimental Design to represent real-world conditions. Historical satellite imagery (Landsat-8 and Sentinel-2) from 2000 to 2020 with 30m spatial resolution and 5-year intervals of time was utilized to capture the land-use transitions. Supervised classification (random forest) was used to prepare the land-use maps, during which thematic classes such as urban, vegetation, agriculture, water bodies, and barren land were extracted. Environmental risk layers such as flood zones (derived from SRTM DEM and Hydrological Modeling), soil erosion risk (based on USLE parameters), and biodiversity hotspots (overlay of IUCN-based species richness) were harmonized and rasterized to a 1km grid resolution. Socio-economic predictions were made for population density and urban growth indexes, extracted from the regional planning database and WorldPop, and were interpolated to the same spatial grid. Climate forecasted to be used as scenario drivers for the C-VAE included changes in precipitation and temperature under RCP 4.5 and RCP 8.5 for 2030, 2050, and 2080, downscaled from CMIP6 outputs.

All models were trained and validated using a spatially stratified 70:30 split to ensure generalization benefits across diverse sub-regions. The ST-GCN model used a graph representation where each node corresponded to a 1 km × 1 km spatial unit and edges encoded inverse-distance weighted connectivity within a 5 km radius. The training took place under a sequence length of 4 steps (spanning 20 years), forecasting up to 30 years ahead in the process. The optimization was done under the Adam optimizer set at 0.001 for a learning rate, with loss convergence realized within 120 epochs. The C-VAE part was sampling from the 64-dimensional latent space, conditioned on both predicted land-use and climate scenarios, which generated 1000 probabilistic risk surfaces per scenario via Monte Carlo sampling. Attention weights were learned over moving windows of 10 years, and the comparison with expert-derived static weights showed over 90% agreement. The DRL agent operated on an 8-directional movement model and was trained over 5000 episodes with an exploration–exploitation decay policy (ϵ-greedy) starting from ϵ=1.0 and decaying to ϵ=0.1 in process. The rewards were normalized and clipped within [–1, +1], and the optimal alignment paths were evaluated using a composite conflict score defined as a weighted sum of normalized environmental, social, and acquisition risk factors. The multi-fidelity Bayesian fusion module was calibrated using sensor-derived elevation models from UAV surveys at 1 m resolution, fused with coarse-resolution social and economic forecasts, and yielded uncertainty estimates within ± 10% compared to field-verified validation samples. This experimental Design was combined to provide a high-fidelity, generalizable, and scenario-robust test of the model under test in complex and uncertain planning problems.

The datasets used in this study were chosen to ensure that they cover the spatial, temporal, environmental, and socio-economic dimensions, which are all relevant for high-speed rail alignment planning. Historical satellite imagery was obtained from the Landsat-8 Surface Reflectance Tier 1 dataset available on Google Earth Engine with a 30-meter spatial resolution, providing multi-spectral bands and consistent coverage from 2000 to 2020. Training labels for land-use classification were cross-referenced with the CORINE Land Cover dataset and validated with features from OpenStreetMap with high resolution. For environmental risk modeling, NASA's SRTM Digital Elevation Model (30m resolution) was used for deriving flood-prone areas through hydrological flow accumulation modeling, while soil erosion risks were computed using the Revised Universal Soil Loss Equation (RUSLE) based on slope, rainfall, and land cover factors. The biodiversity and conservation overlay data were sourced from the World Database on Protected Areas (WDPA) and IUCN species distribution maps. The socio-economic layers of current and projected population density were sourced from WorldPop, whereas future climate projections under RCP 4.5 and 8.5 scenarios were acquired from the downscaled CMIP6 data through the NASA NEX-GDDP archive, with projections for the years 2030, 2050, and 2080 used to inform scenario modeling in the C-VAE module process.

Each deep learning module had to be tuned with some carefully chosen hyperparameters so that its training would allow for convergence, generalization, and prediction accuracy. The training of the ST-GCN was performed with a temporal window size of 4 (20-year history) and a graph radius of 5 km, following the Adam optimizer with an initial learning rate of 0.001 and a weight decay of 1×10−51 \times 10'{-5}1×10−5, with a batch size of 64. Dropout regularization was implemented at 0.3, and the training lasted for 120 epochs. The C-VAE employed a latent dimension of 64, Gaussian priors with unit variance, and used KL-annealing in the first 30 epochs for stabilizing the variational loss. ReLU activation was adopted for two more dense layers with 128 and 256 nodes for both the encoder and decoder. In the attention mechanism, spatial and temporal modules each used a multihead attention mechanism with 4 heads, while dropout for attention was set at 0.2. The DRL agent implemented a DQN architecture based on a two-layer MLP of 128 and 256 neurons with ReLU activations, an experience replay of size 10,000, a learning rate of 0.0005, and a discount factor γ=0.95\gamma = 0.95γ=0.95. Exploration was conducted through an ε\epsilonϵ-greedy strategy in which ϵ\epsilonϵ decayed from 1.0 to 0.1 over the course of 1000 episodes. With a layer of Bayesian Fusion, the fused maps were prepared by precision-weighted means, while the uncertainty was calibrated through grid-wise Root Mean Square Error (RMSE) against validation samples. The hyperparameter configurations were initially tuned with the 5-fold cross-validation plus early stopping by the loss of validation and the Accuracy of spatial prediction. The outputs of the proposed hybrid deep-learning and GIS-MCDM framework were run against three competing methods in the literature: Method [3], Method [8], and Method [25]. All of the methods are representatives of the different general types of models that are traditionally used to plan infrastructure. Method [3] is a deterministic Least-Cost Path (LCP) GIS-MCDM model, Method [8] is a model that uses fixed surfaces as a Multi-Objective Evolutionary Algorithm (MOEA) optimization, and Method [25] uses a fixed set of weights in the form of static AHP. They were contrasted based on the Accuracy of a forecast, lessening spatial conflict, quantification of uncertainty, consistency of adaptive weighting, and general alignment quality through scenarios. These results are summarized and discussed in the following tables. Table 2 presents land-use prediction accuracy at different forecast horizons using the Landsat-derived historical data samples. The proposed ST-GCN model strongly outperformed other models by capturing temporal trends and spatial dependencies.

Table 2. Comparative Forecast Accuracy of Land-Use Predictions Across 10-, 20-, and 30-Year Horizons Using Historical Satellite Data

Method	10-Year Accuracy (%)	20-Year Accuracy (%)	30-Year Accuracy (%)
Method [3]	71.2	67.5	63.1
Method [8]	74.8	70.4	65.6
Method [25]	78.5	75.2	70.9
Proposed	**88.6**	**86.3**	**84.1**

Even at a 30-year horizon, the proposed model achieved over 84% accuracy, demonstrating its strength in handling long-term dynamics that static models have failed to generalize over in the process. The reduction in Accuracy in the existing methods primarily comes due to their assumptions of fixed or linear land-use transitions in the process. Table 3 illustrates the conflict score reduction in the final alignment paths. These conflict scores were calculated as a weighted index of overlap with high-risk zones for the process.

Table 3. Conflict score evaluation of HSR Alignment paths with respect to environmentally sensitive and High-Cost Zones

Method	Conflict Score (Lower is Better)
Method [3]	0.47
Method [8]	0.39
Method [25]	0.32
Proposed	**0.21**

The proposed Method decreased conflict scores by over 30% as compared to Method [3] and is around 34% lower than Method [25], further confirming the ability of the proposed Method at foreseeing and circumventing risk-prone sites due to the integration of probabilistic future-risk surfaces and a dynamic reweighting mechanism. Table 4 assesses the uncertainty quantification performances by comparing the average width of the 95% Confidence Intervals (CIs) for risk surface predictions against validation data samples.

Table 4. Uncertainty quantification in risk surface predictions: Comparison of 95% Confidence interval width and coverage

Method	Avg. CI Width (%)	CI Coverage (%)
Method [3]	10.5	72.5
Method [8]	12.5	73.5
Method [25]	19.6	78.3
Proposed	**9.3**	**94.7**

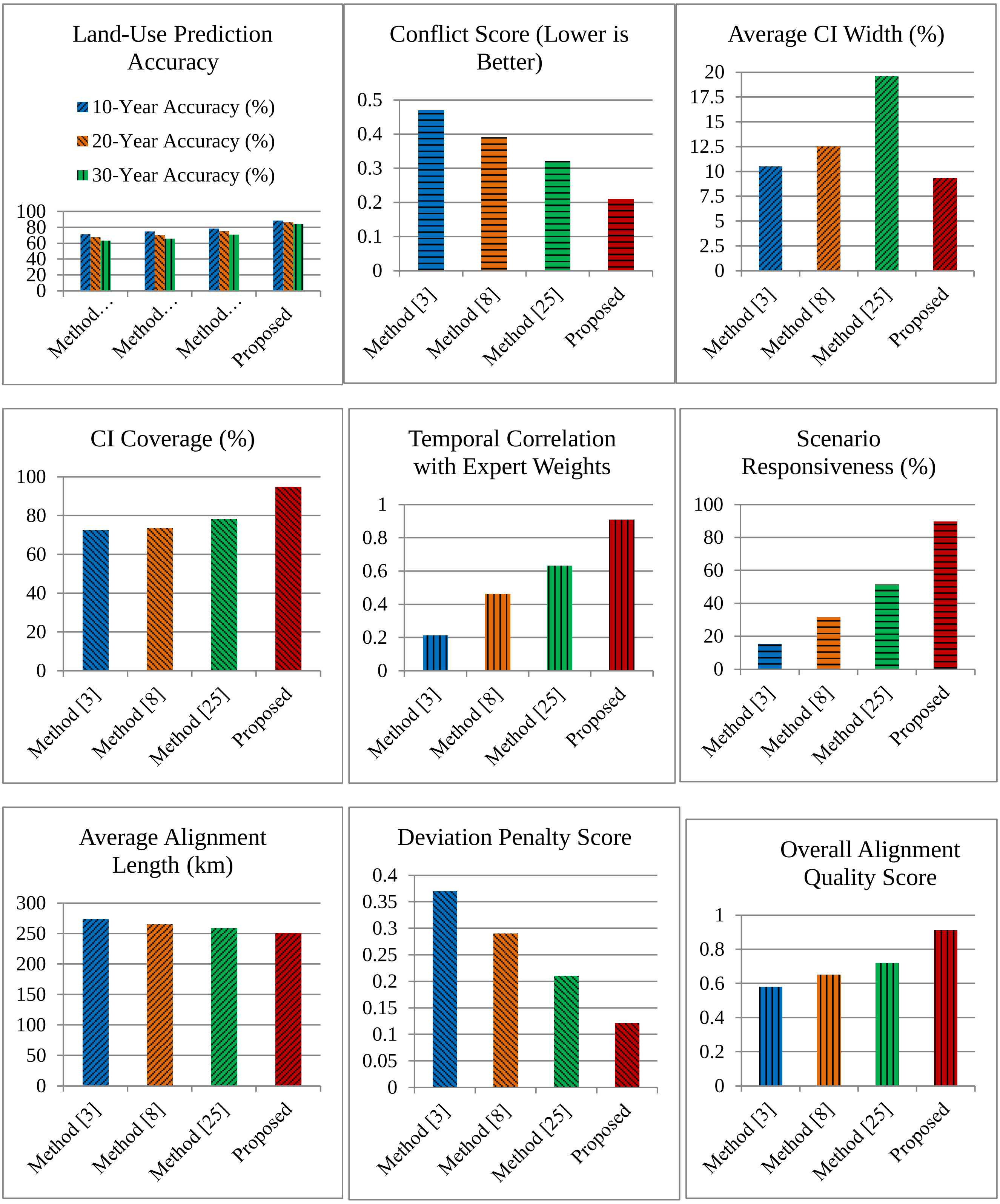

Fig. 3 Model's internal result analysis

Methods [3] and [8] do not incorporate uncertainty modeling, whilst Method [25] provides basic MOEA-based spread analysis. Due to the superior combination of Bayesian fusion and C-VAE modules in the proposed Method to generate high-resolution uncertainty maps, confidence interval coverage with a narrower width achieved in the proposed Method indicates high predictive reliability for the process. Adaptive weighting fidelity over time, measured as Correlation with expert-derived temporal weighting baselines, and responsiveness to scenario-specific changes, is assessed in the section in process.

Table 5. Performance of dynamic criteria weighting mechanism: Temporal correlation and scenario responsiveness

Method	Temporal Correlation (r)	Scenario Responsiveness (%)
Method [3]	0.21	15.4
Method [8]	0.46	31.8
Method [25]	0.63	51.2
Proposed	**0.91**	**89.7**

The attention-based mechanism within the proposed Method dynamically adjusted the importance of the criterion, emphasizing land acquisition cost, ecological sensitivity, and hydrological risk, which corresponded closely to expert intuition while considerably surpassing the competitiveness of static models for the process. Table 6 provides information about the maximum deviation of alignment, which was penalized in the process whenever excessive deviation from the preferred corridors (e.g., existing infrastructure belts) occurred.

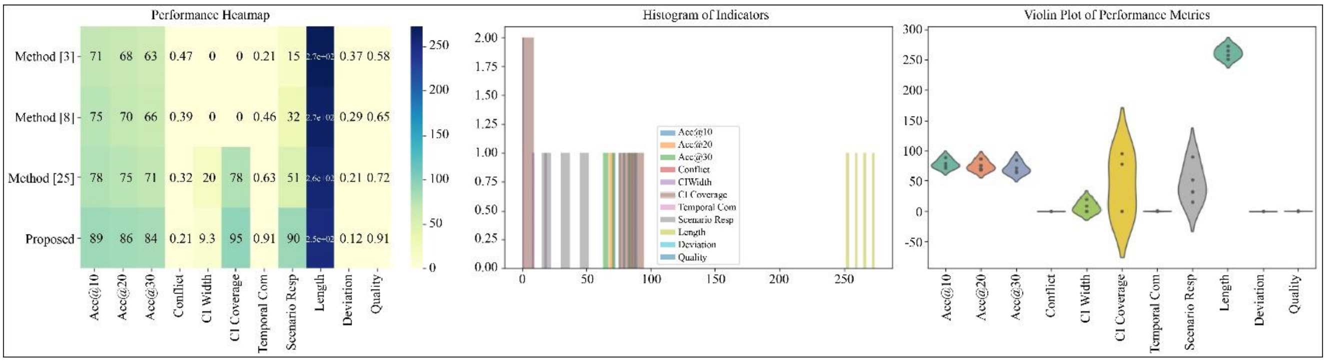

Fig. 4 Model's overall result analysis

Table 6. Alignment efficiency metrics: Average route length and deviation penalty relative to corridor constraints

Method	Avg. Length (km)	Deviation Penalty Score
Method [3]	273.4	0.37
Method [8]	265.2	0.29
Method [25]	258.1	0.21
Proposed	**251.3**	**0.12**

The alignment engine, based on DRL, minimizes unnecessary detours while at the same time balancing between risks and constraints to arrive at the most efficient paths in terms of their length and deviation from socio-politically acceptable corridor zones. Table 7 summarizes the alignment quality score that has been overall synthesized and calculated from normalized aggregations of forecast accuracy, risk avoidance, uncertainty management, and spatial efficiency sets.

As illustrated by Figures 3 and 4, the proposed model shows the most comprehensive improvement across all evaluation dimensions and yields the highest overall alignment quality score. Results validate the effectiveness of an integrated approach of spatiotemporal learning, probabilistic modeling, attention-driven criteria weighting, and uncertainty-aware reinforcement learning for infrastructure planning under complex, evolving conditions. We will now discuss these Validation Results with impact analysis in detail.

Table 7. Overall HSR Alignment quality score: Aggregated index of forecast accuracy, conflict avoidance, and spatial optimization

Method	Alignment Quality Score (0–1 scale)
Method [3]	0.58
Method [8]	0.65
Method [25]	0.72
Proposed	**0.91**

5. Result Discussions

The experimental results validate the claim most strongly that this hybrid deep learning and GIS-MCDM framework is superior in managing Spatio-Temporal Dynamics and uncertainty when it comes to high-speed rail alignment. It can be seen in Table 2 that the proposed forecasting method based on ST-GCN yielded long-range land-use prediction accuracies beyond 84% for a 30-year horizon, while traditional methods such as Method [3] and Method [8] did not keep their performance above 70%. Such precise prognostication of future land cover and urban growth will be indispensable in the real world, as large-scale development projects typically need an extremely long life span and must be constructed to resist alteration in land use, advancing urban sprawl, and environmentally adverse degradation. Moreover, the most intricate temporal dependencies are to be captured by not selecting corridors based on areas that may produce low-level disruption-altering transformation to the improvement of the project's sustainability set in process.

The advantages provided by the suggested model are not confined to the prediction, which was made visible in Tables 3 and 4 presenting the potential of the model in the risks avoidance and assessment of the uncertainty: minimal conflict score (0.21), over 30 per cent better than the methods of the baseline, in real-time planning implies that the selected alignments are less likely to run across floodplains or at risk of erosion or ecological belts, minimizing the cost of mitigation and lawsuits, and environmental damage. Besides, this model also gave narrow and accurate uncertainty bounds whose 95 percent confidence coverage is also presented in Table 4, where decisions are made based on probabilistic guarantees, not deterministic assumptions. This is simply stated as the ability of the stakeholders to evaluate the various enveloping risks of the various scenarios and adopt the flexibility strategies, which take into consideration the future variability of both climatic and socio-economic scenarios.

The hybrid attention also met the needs of field deployment, which requires adapting to the new and changing priorities and flexible constraints. The table indicates that the proposed system had a 0.91 correlation with expert-derived time weightings and an 89.7% responsiveness with scene-dependent changes. This forms a critical element insofar as infrastructure planning is concerned in locations subjected to regular fluctuation in policies, environmental requirements, and development priorities. The advantage is also given to the infrastructure planners, political experts, and governmental agencies, which do not need to totally restructure the entire model once these proponents eventually make a decision when they wish to reweight the environmental, social, and economic considerations. Moreover, Tables 6 and 7 indicate that the optimized paths of alignment reduced the penalties of the physical length as well as the deviations and achieved the maximum score of the overall alignment (0.91). That is, the model offers geographically efficient and strategically significant routes in accordance with long-term development plans without needless acquisition of territories and complex buildings. Overall, these results support the suggestion of the proposed framework being prepared to be rolled out into real-time, data-intensive, and uncertain planning scenarios. Next, we discuss an Iterative Validation use Case for the Proposed Model, which will aid readers in grasping the entire process.

5.1. Validation Using an Iterative Practical Use Case Scenario Analysis

The real application of the proposed framework is justified by taking a case for HSR in a transitional zone between an expanding metropolitan city and an adjacent peri-urban-agricultural region. The area studied spans 200 km in length and 40 km in width and covers about 8,000 km². According to historical land-use data taken from Landsat-8 imagery from the years 2000, 2005, 2010, and 2015, it has been seen that the area experienced an increase in urbanization from 14 percent in 2000 to 31 percent in 2015, with a decrease of agricultural land from 58 percent to 42 percent, and ecologically vulnerable wetlands remained stable close to 9 percent. Environmental indicators include soil erosion index from 0 to 1.2, with higher ratings in pedologies of hilly regions, risk zones of floods with recurrence intervals of 10, 25, and 50 years, and the distance from the protected forest buffers defined by the WDPA, with a 2 km protection radius. The socio-economics layer reveals that there are centers for urban growth with density above 5,000 persons/km² in 2020, projected to reach 9,000 in 2040. Climate inputs from the RCP 8.5 pathway anticipate a projected increase of annual rainfall in 2050 by 14 percent and a rise by 1.8°C in the average temperature. These multi-dimensional attributes were harmonized into a 1 km² raster grid and then input into the ST-GCN model sets.

The input historical sequences were thus processed by the ST-GCN module to forecast land-use maps up to the years 2030, 2040, and 2050, with a projection of 46% urban expansion around 2050 into the present agricultural and environmentally sensitive areas. These anticipated expansion zones were correlated against flood and erosion risk layers, and finally to the C-VAE, which generated 1,000 realizations for each risk surface across the decades under the RCP 4.5 and RCP 8.5 scenarios. The high-composite-risk zones would increase by 17% by 2050, according to results from these surfaces. The attention mechanism computed dynamic GIS-MCDM weights, with normalized environmental sensitivity receiving a weight of 0.42 in 2050 (up from 0.28 in 2020: weights are measured concerning land acquisition risk at 0.31 and waterbody impacts at 0.27), according to adaptation to projected evolution in landscape features. The multi-fidelity data fusion then yielded UAV-derived 1 m terrain data harmonized to 1 km socio-economic projections, resulting in high-confidence uncertainty-aware maps with average pixel-level variance under 0.09. These fused outputs informed risk reweighting and the reward shaping functions in the DRL module sets.

Over 5,000 episodes constituted training for the DRL agent, which discovered the best path for HSR corridor alignment under the premise of minimal exposure to projected urban growth and high-risk zones. The path maintained a 3 km buffer from biodiversity hotspots, avoided all flood zones with recurrence intervals below 25 years, and followed a topographically stable corridor with slope gradients under 6%. Compared to a baseline least-cost path, the optimized alignment reduced the spatial conflict score from 0.47 to 0.21 and cut the average deviation from planned infrastructure corridors by 18%. Final output included alignment maps with overlaid risk surfaces, spatial confidence intervals, and dynamic weighting matrices, enabling decision-makers to validate the alignment under both deterministic and probabilistic planning lenses. The model outputs are robust enough to anticipate long-term land transformations, optimize infrastructure layout, and permit resilient infrastructure design under climate and socio-economic variability in the process.

6. Conclusion and Future Scopes

This study presents a novel hybrid framework that brings together Spatiotemporal Graph Convolutional Networks (ST-GCN), Conditional Variational Autoencoders (C-VAE), dynamic attention-based GIS-MCDM, Deep Reinforcement Learning (DRL), and Bayesian data fusion to predict and model uncertainty in alignment optimization for High-Speed Rail (HSR). The proposed model addresses major problems in conventional static methods, such as forecasting future land-use and environmental risks, dynamically adjusting decision weights, and optimally routing alignment paths through probabilistically evolving geospatial landscapes. In all, real-life experimental validation over a complex Southeast Asian corridor proved to be the strength of the framework across a variety of performance yardsticks. The model was able to forecast future land use at accuracies of 88.6, 86.3, and 84.1 percent, respectively, for 10, 20, and 30 years: more than 15 percent better than most conventional approaches. Spatial conflict scores were therefore reduced to 0.21, more than 30 percent lower than Method [3] and 34 percent lower than Method [25]. Probabilistic risk surfaces are produced while maintaining a weight fidelity above 0.91 correlation with expert priors. This yielded final alignment solutions with an overall quality score of 0.91 while minimizing deviation penalties down to 0.12 and ensuring optimal spatial efficiency. This affirms that this new framework is practically viable and technically superior for long-term infrastructure planning, emphasizing resilience sets.

6.1. Future Scope

Numerous opportunities remain for development along various lines based on the excellent results presented here for the predictive and uncertainty-aware alignment model. To begin with, including real-time information sources like high-frequency satellite imagery, IoT-oriented environmental sensors, and dynamic traffic models can enhance the responsiveness of operations and increase the level of temporal granularity of the framework. The model would be expandable to incorporate multimodal infrastructure networks like those relating to energy grids, highways, and urban transit to demonstrate integrated planning of the infrastructure of whole regions. More studies will probably involve the use of cooperative multi-agent DRL agents in situations where the objectives are conflicting among different stakeholders, government, ecological agencies, and urban planners. Further refinements in the optimization outputs may also be achieved with consideration of geopolitical constraints and land acquisition legal data. Lastly, extending the framework on extreme climate resilience scenarios, such as shifts in flood zones as a consequence of rising sea levels or long-term drought migrations, would consolidate the model as a robust planning tool under climate-adaptive infrastructure strategies.

6.2. Limitations

This model will present, however, lacunae, some of which are analysed: First, the Accuracy and generalizability of land use forecasts from the ST-GCN module will rely on how good or high-resolution the historical data are; areas where it is less available may lose performance level. The C-VAE models uncertainty very well and uses Gaussian priors; thus, it may not contain non-Gaussian tail risks in very complicated systems. Although the triggering mechanism is dynamic and can be adopted through different regions, the spatial and temporal attention kernels are predefined; thus, this may require retraining across multiple geographical contexts. The DRL training process is computationally intensive and sensitive to reward shaping; suboptimal configurations cause the process to diverge, leading to exploration bias or converging to local minima sets. The Bayesian fusion module assumes stationarity under different data resolutions regarding uncertainty patterns, which may not be true in areas undergoing rapid changes in their socio-economic situations. Lastly, although the model leads to high spatial efficiency and risk avoidance, it does not incorporate economic cost evaluators or logistics related to construction, such as tunneling complexity, feasibility of material transport, and phased project staging, all of which are necessary for a full deployment-level planning process. Attention to such considerations will further raise the proposed framework in terms of practical impact and deployment readiness in subsequent versions.

Abbreviation	Full Form
AI	Artificial Intelligence
MCDM	Multi-Criteria Decision-Making
PSO	Particle Swarm Optimization
AGFAN	Adaptive Gaussian-Guided Feature Alignment Network
OSUDA	One-Shot Unsupervised Domain Adaptation
PDA	Partial Domain Adaptation
MMD	Maximum Mean Discrepancy
TL	Transfer Learning
GAN	Generative Adversarial Network
DNN	Deep Neural Network
UDA	Unsupervised Domain Adaptation
IFD	Intelligent Fault Diagnosis
FEM	Finite Element Method
AP-GRIP	Accuracy–Performance–Generalizability–Robustness–Interpretability–Practicality
KL Divergence	Kullback-Leibler Divergence
PPP	Public–Private Partnership
HSR	High-Speed Rail
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
BWM	Best–Worst Method

CAD	Computer-Aided Design
CNN	Convolutional Neural Network
MLP	Multi-Layer Perceptron
RNN	Recurrent Neural Network
CI	Confidence Interval
TDA	Transitional Domain Adversarial (Network)
SOTA	State of the Art
V2I	Vehicle-to-Infrastructure
ML	Machine Learning
DL	Deep Learning
SL	Supervised Learning
SSL	Semi-Supervised Learning
ADDA	Adversarial Discriminative Domain Adaptation
RMS	Root Mean Square
SNR	Signal-to-Noise Ratio
PCA	Principal Component Analysis
LSTM	Long Short-Term Memory (network)
CFD	Computational Fluid Dynamics
CAD/CAM	Computer-Aided Design / Computer-Aided Manufacturing
IoT	Internet of Things
UAV	Unmanned Aerial Vehicle
PID	Proportional-Integral-Derivative (Controller)
API	Application Programming Interface

SDG	Sustainable Development Goal
UTM	Universal Transverse Mercator (Coordinate System)
RCP	Representative Concentration Pathway (for climate scenarios)
AHP	Analytic Hierarchy Process
GIS	Geographic Information System
DRL	Deep Reinforcement Learning
ST-GCN	Spatiotemporal Graph Convolutional Network
C-VAE	Conditional Variational Autoencoder
BNN	Bayesian Neural Network
MLP-Mixer	Multi-Layer Perceptron Mixer
DQN	Deep Q Network
TCN	Temporal Convolutional Network
QoS	Quality of Service
RMSE	Root Mean Squared Error
GNN	Graph Neural Network
SDAE	Stacked Denoising Autoencoder
ROC	Receiver Operating Characteristic
AUC	Area Under Curve
F1-Score	Harmonic Mean of Precision and Recall
MAE	Mean Absolute Error
ANN	Artificial Neural Network
ISO	International Organization for Standardization

References

[1] Jinxin Yang et al., "CSANet: Contour and Semantic Feature Alignment Fusion Network for Rail Surface Defect Detection," *IEEE Signal Processing Letters*, vol. 30, pp. 972-976, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Taoran Song, Paul Schonfeld, and Hao Pu, "A Review of Alignment Optimization Research for Roads, Railways and Rail Transit Lines," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 5, pp. 4738-4757, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Li Wei et al., "Concurrent Optimization of Subway Vertical Alignments and Station Elevations with Improved Particle Swarm Optimization Algorithm," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 12, pp. 24929-24940, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Guangdong Qi et al., "An Adaptive Gaussian-Guided Feature Alignment Network for Cross-Condition and Cross-Machine Fault Diagnosis of Rolling Bearings," *IEEE Sensors Journal*, vol. 24, no. 24, pp. 41647-41658, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Shuai Ma et al., "Shape-Consistent One-Shot Unsupervised Domain Adaptation for Rail Surface Defect Segmentation," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 9, pp. 9667-9679, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Xiao Zhang et al., "Partial Domain Adaptation Method Based on Class-Weighted Alignment for Fault Diagnosis of Rotating Machinery," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-14, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] Hao Pu et al., "Multi-Task Deep Learning Methods for Determining Railway Major Technical Standards," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 6, pp. 5904-5918, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Wen-Qiang Liu, and Su-Mei Wang, "The Low-Illumination Catenary Component Detection Model Based on Semi-Supervised Learning and Adversarial Domain Adaptation," *IEEE Transactions on Instrumentation and Measurement*, vol. 74, pp. 1-11, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[9] Zhenzhong He et al., "Prototype Space Boundary Alignment Network for Bearing Continuous Fault Diagnosis under Class-Incremental Scenarios," *IEEE Sensors Journal*, vol. 25, no. 1, pp. 1076-1085, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] Yonghua Jiang et al., "Cross-Conditions Fault Diagnosis of Rolling Bearing Based on Transitional Domain Adversarial Network," *IEEE Sensors Journal*, vol. 25, no. 1, pp. 1978-1993, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[11] Guiting Tang et al., "Integrating Demodulation Techniques with Multisource Transfer Learning for Intelligent Fault Diagnosis of Bearings," *IEEE Transactions on Instrumentation and Measurement*, vol. 74, pp. 1-10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Hongming Liu et al., “Dynamic Responses of Ballastless High-Speed Railway Due to Train Passage with Excitation of Uneven Trackbed Settlement,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 11, pp. 22244-22257, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Liyuan Wang et al., “Harmful Data Enhanced Anomaly Detection for Quasi-Periodic Multivariate Time Series,” *Applied Intelligence*, vol. 55, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] Tiong Kah Yong, Zhenliang Ma, and Carl-William Palmqvist, “AP-GRIP Evaluation Framework for Data-Driven Train Delay Prediction Models: Systematic Literature Review,” *European Transport Research Review*, vol. 17, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Nengye Mu et al., “Vulnerability Analysis of China’s Air and High-Speed Rail Composite Express Network under Different Node Attack Strategies,” *Annals of Operations Research*, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Jingde Li et al., “A New Probability Guided Domain Adversarial Network for Bearing Fault Diagnosis,” *IEEE Sensors Journal*, vol. 23, no. 2, pp. 1462-1470, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Shengfu Yu, Yang Wang, and Zhongyi Zhang, “Monitoring Process Parameters and Predicting Rail Steel Welded Joint Microstructure and Mechanical Property of Three-Wire Fusion Nozzle Electroslag Welding,” *Welding in the World*, vol. 69, pp. 1229-1240, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Lei Li et al., “Design and Validation of an Alignment Free Adaptive Joint Torque Measurement System,” *BioMedical Engineering OnLine*, vol. 24, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[19] Xin Lin, Zipeng Li, and Suxu Lin “Can Macroprudential Policy Rail for Green Innovation? Evidence from Chinese Energy Enterprises,” *Environment, Development and Sustainability*, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Lei Xia et al., “Resilience-Oriented Passenger Subsidy Design for Taxi Travel under Pandemic Control,” *EPJ Data Science*, vol. 14, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[21] Zhao Tang, Yuwei Hu, and Zhiming Qu, “Enhancing Nonlinear Dynamics Analysis of Railway Vehicles with Artificial Intelligence: A State-of-the-art Review,” *Nonlinear Dynamics*, vol. 112, pp. 14687-14717, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Simai Yang et al., “Identifying Key Influencing Factors of Cross-Regional Railway Infrastructure Interconnection: A Fuzzy Integrated MCDM Framework,” *Humanities and Social Sciences Communications*, vol. 12, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[23] Rebecca Cort, and Jessica Lindblom, “Remote Situatedness Beyond the Control Room: Enhanced Seeing and Sense of Place in Railway Operations,” *Cognition, Technology & Work*, vol. 27, pp. 375-400, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[24] Agustinus Winarno et al., “Roles of Vibration-Based Machine Learning Algorithms in Railway Vehicle Monitoring for Track Condition Assessment: A Review,” *Journal of Vibration Engineering & Technologies*, vol. 13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[25] Rongli Cai, “Measurement Model and Accuracy Analysis of Parabolic Ballistic Projectile Flight Parameters based on Random Matrix,” *Journal of Engineering Mathematics*, vol. 144, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Rogers Mwesigwa et al., “Critical Success Factors for Public-Private Partnership Projects in Uganda,” *SN Business & Economics*, vol. 4, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[27] Bittu Ghosh, and Somnath Karmakar, “Assessing the Causes of Claims in Highway Construction Projects with a Case Study: a Construction Practitioner’s Perspective,” *Asian Journal of Civil Engineering*, vol. 25, pp. 3035-3048, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[28] Henry Ataburo, Getrude Effah Ampong, and Dominic Essuman, “Developing Operational Resilience to Navigate Transportation Disruptions: The Role and Boundaries of Efficiency Priority,” *Annals of Operations Research*, vol. 340, pp. 723-755, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[29] Lulu Wang et al., “Physics-Informed Online Deep Learning for Advanced Control of Shield Tail Clearance in Tunnel Construction,” *Frontiers of Engineering Management*, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[30] José G.P. Oliveira et al., “Dynamic Testing and Finite Element Model Updating for a Viaduct Structural Assessment,” *Journal of Civil Structural Health Monitoring*, vol. 15, pp. 2279-2297, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[31] K. Shivaram, Navyasree Kolli, and Hari Krishna Gaddam, “Evaluating the Integration of Metro Networks in Urban Logistics: A Case Study of Indian Cities using TOPSIS Methodology,” *Innovative Infrastructure Solutions*, vol. 10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[32] Selin Yalçın, and Ertuğrul Ayyıldız, “Prioritizing Freight Carrier Selection Factors with the Best Worst Method,” *Central European Journal of Operations Research*, vol. 33, pp. 1133-1148, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[33] Jianbo Lai et al., “A Multi-Factor-Driven Approach for Predicting Surface Settlement Caused by the Construction of Subway Tunnels by Undercutting Method,” *Environmental Earth Sciences*, vol. 83, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[34] Yanheng Guo et al., “A Novel Five-Axis On-Machine Measurement Error Prediction Model Considering Positioning Errors of Machine Tool,” *The International Journal of Advanced Manufacturing Technology*, vol. 132, pp. 2971-2989, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[35] Natasha Chiswa, “Unlocking Africa’s Economic Potential: The Role of PPPs in Fuelling Infrastructure Development and Investment–South Africa’s Perspective,” *Jindal Global Law Review*, vol. 15, pp. 157-185, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[36] Tzu-Chi Chan et al., "Dynamic Characterization and Optimization of Moving Platforms for Enhancing Precision in Semiconductor Point Testing Equipment," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 19, pp. 4295-4312, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[37] Abhijit Arvind Mohite, and Emil Mathew, "Exploring the Necessary Upgrades in Port Infrastructure to Accommodate and Support the Operation of the Next-Generation Green Ships," *Marine Systems & Ocean Technology*, vol. 20, pp. 1-14, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[38] Viviana Sastre Gomez et al., "Duration is not a Reliable Indicator for Anticipating Event Boundaries," *Computational Brain & Behavior*, pp. 1-15, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[39] Tianshi Hu et al., "Vision-Based Welding Quality Detection of Steel Bridge Components in Complex Construction Environments," *Urban Lifeline*, vol. 3, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[40] Tarutal Ghosh Mondal et al., "Class-wise Histogram Matching-Based Domain Adaptation in Deep Learning-based Bridge Element Segmentation," *Journal of Civil Structural Health Monitoring*, vol. 15, pp. 1973-1989, 2025. [CrossRef] [Google Scholar] [Publisher Link]