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Original Article

Adaptive AHP and Monte Carlo Simulation for Risk-Informed High-Speed Rail Route Decision-Making Operations

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Abstract - *Deciding on the routes for the HSR involves complex trade-offs within and across the environmental, financial, and social dimensions, all within uncertain and dynamic settings. Whenever traditional decision-making models, such as static Multi-Criteria Decision-Making (MCDM) frameworks, cannot track real-time data or adjust to the ever-changing views of the stakeholders, a new, detailed gap appears. To satisfy this need, the paper proposes a Predictive Multi-Criteria Decision-Making (PMCDM) model, which combines Analytical Hierarchy Process (AHP), Monte Carlo Simulation, and Fuzzy Logic, and presents an adaptive framework. The PMCDM model updates the weights of decisions dynamically based on real-time feedback of IoT sensors and from financial data, and models future possibilities and uncertainties through probabilistic simulations and the fuzzy inference would evolve with changing stakeholder perceptions. Our model, applied to the Californian HSR context, increased route rank by 3.5% better performance alignment margin over exclusive reach in financial risk variance by 6. These findings underscore that PMCDM may be involved in risk-informed adaptive infrastructure decision-making.*

Keywords - *High-Speed Rail, Predictive Analytics, AHP, Monte Carlo Simulation, Risk Assessments.*

1. Introduction

High-Speed Rail (HSR) systems are now an important aspect of sustainable transportation because they offer high capacity, energy efficiency, and low emissions inter-regional mobility. With a growing number of investments across the globe in the HSR infrastructure, the issue of selection of the right rail corridors has become a significant one, which requires planning. Route choices should consider a trade-off between long-term land-use impacts, environmental protection, economic viability, and social acceptability, which is a competing objective and involves intricate trade-offs. The multifacetedness of planning an HSR route is also exacerbated by the presence of numerous stakeholders with changing priorities during different periods, due to uncertainties related to the construction price, compliance with environmental requirements, regulatory development, and social-political circumstances. These aspects bring about a dynamic decision environment where assumptions made at an early stage can be overturned as time goes by, as new information is found. As a result, decision-making tools applied in route selection must be able to react to changing circumstances instead of making MOPs based on fixed assessments. There has been a popular adoption of Multi-Criteria Decision-Making (MCDM) techniques, especially Analytic Hierarchy Process (AHP), as infrastructure planning approaches because of their systematic and explicit approach to assessment of numerous criteria. Nevertheless, the majority of the available AHP-based models implemented in terms of HSR route selection are essentially static. They generally have the assumption that the weight in the criterion is fixed and fail to properly use a real-time stream of data or uncertainty contained in project parameters.

Consequently, these models are constrained in their potential to translate changes in stakeholder preferences, changes in costs, or changes in the environment that take place during the project lifecycle. Even though the application of AHP and corresponding MCDM methods has been proven useful in the past, the combination of weight change mechanisms, the ability to measure uncertainty, and adaptive modeling of stakeholder preferences has not been investigated thoroughly. Specifically, the absence of elaborate models that bring real-time data processing and probabilistic risk analysis together to serve resilient, informed decision support of large-scale HSR projects is lacking. This is of paramount concern, particularly on a project with large implementation windows and where there is high vulnerability to financial and environmental hazards.

The California High-Speed Rail project presents an adequate background to discuss these issues because multiple geographical conditions, seismic factors, nature-sensitive locations, and overcrowded tracks are at play. Adaptive decision-support models can also be developed and tested by facilitating data availability of support systems in the environment, financial reports, and transportation surveys. To address the presented research gap, the current research suggests a Predictive Multi-Criteria Decision-Making (PMCDM) framework, in which the AHP approach will be paired with the real-time weight recalibration, Monte Carlo simulation to assess the risks and uncertainties, and fuzzy logic to reflect the gradual change in preference of stakeholders. The proposed framework is flexible, robust, and incorporates environmental indicators (air quality and emissions), financial (material costs and budget overruns), as well as social pointers (accessibility and public acceptance). The purpose of the PMCDM method is to be used to make resilient and informed route selection choices in dynamic and uncertain situations.

2. Review of Existing Models for Optimization of Railway Routing Operations

A large field of research has been gained by the planning, operation, and optimization of the railway systems because of the importance of the contemporary transportation infrastructure system. The studies in this field cut across several dimensions, such as safety assurance, routing optimization, schedule optimization, sustainability, and the incorporation of intelligent decision-support systems. The review in Table 1 on railway systems research reveals a field that is rapidly evolving to meet the demands of modern transportation infrastructure. This part provides a review of the literature in a systematic way to develop a comprehensive background of high-speed rail route decision-making. There exists a body of literature in the field of safety and reliability of systems in relation to railways that runs on formal verification and risk assessment. Iliasov et al. [1] showed that formal modeling techniques were useful in the verification of railway signaling programs and that the safety of the system might be greatly enhanced through mathematically sound properties. To this information, Wang et al. [22] examined the susceptibility of railway infrastructure to natural disasters like floods and earthquakes and emphasized the need to perform long-term resilience planning. These studies underline that safe-critical railway systems must be equipped with stringent analytical instruments, but are usually designed with regard to particular operational settings, and they do not explicitly consider the tactical planning options, including the selection of routes.

The other significant area of research is operational optimization and scheduling, where efficiency and punctuality are the main concerns in high-speed rail networks. Wang et al. [3] also designed synchronized models of service scheduling and routing at the HSR maintenance depot, and the results were very high in terms of operational efficiency. Zhou et al. [4] dealt with the issue of timetable rescheduling during large-scale disruptions, which included combined schemes that minimise delay propagation. Sharma et al. [5] also continued to modify real-time traffic management by using ant colony optimization methods to maintain passenger connectivity in times of disruption. Whereas these optimization models have been shown to be efficient in operations, they are mostly oriented to the short-term or tactical level decisions as opposed to the long-term infrastructure planning in an uncertain situation. The issues of routing and scheduling are not limited only to passenger operation in rail and road systems, but also to the freight systems. Frisch et al. [27] combined freight car routing and train scheduling in an attempt to enhance operational stability, and Ivina and Ma [28] tested the ability of trackwork scheduling under long-term maintenance constraints. Krauth and Haalboom [29] analyzed economic measures to bypass wagons to improve network congestion with a focus on cost-benefit. The contributions highlight the significance of combining routing choices, but by and large, they presuppose a comparatively steady system state and neglect dynamic choices of the stakeholders and risk factor fluctuations.

Another important research theme is the analysis and management of delays. Dekker [8] used the geographic modeling techniques to classify the railway delay patterns, which also facilitates the identification of delay hotspots. Sharma et al. [30], a representative of the literature on the topic, presented a review of the passenger-oriented rescheduling strategies, emphasizing the transition to passenger-focused performance metrics. Although such studies are rich with valuable insights on service reliability, most are diagnostic and reactive and would hardly help with predictive and strategic decision-making in the process of route planning. Simulation-based methods have been used in more railway studies as the complexities of the system increase. In a study by Pu et al. [15] based on the integrated railway and pedestrian simulations, passenger hub capacity was calculated, including human movement and interaction with infrastructure.

Flammini et al. [17] used stochastic activity networks to simulate virtual coupling operations, enhancing the safety of operations functions. These simulation schemes provide high-performance evaluation, although they may be very computationally intensive and not usually incorporated in adaptive decision-making within large-scale planning issues. The past several years have been characterized by a rapid increase in the number of machine learning and artificial intelligence applications in railway systems. Zhou et al. [14] used attention-based capsule networks to automatically classify faults in onboard equipment with high diagnostic accuracy. Yu et al. [19] used deep reinforcement learning to enhance the data transfer efficiency in high-speed railway communication networks. Kumar and Mishra [20] introduced the EEDLNN algorithm to evaluate vulnerabilities in railway networks to increase resilience to network-disruptive events. These methodologies have various issues pertaining to scaling of data, computational complexity, and compatibility with top-level decision-making, although they have strong technicality.

In line with these developments, technologies of digitalization and intelligent infrastructure have become promising in the management of the railway. SAT-based techniques of generating detailed railway infrastructure schematics were proposed by Luteberget and Johansen [13] to enhance the consistency of design. Trembearth et al. [35] introduced the concept of a spatial digital twin to help provide a real-time vehicle warning and rerouting at critical crossings. Although digital twins provide the ability to monitor in real-time, their extensive utilization is limited by the complexity of systems and data integration. The issue of environmental sustainability has recently received a crucial role in the research on railways. Sun et al. [18] also solved the problem of green road-rail intermodal routing when there is uncertainty by using approaches of fuzzy programming, leading to a significant reduction of emissions. Castillo et al. [31] also optimized the urban logistics with agile routing to aid in more environmentally friendly urban distribution systems. Sarma and Ganguly [10] examined the possible allocation of hydrogen refuelling stations to facilitate the hydrogen-powered locomotive, which is a potential low-emission substitute. But these sustainability-based studies are frequently fraught with sophisticated trade-offs of environmental advantage and economic plausibility, and do not directly apply to large-scale HSR route choice. One more dimension is the importance of the infrastructure and energy systems. Hu et al. [25] made an overview of the history of traction power systems, along with a trend toward electrification and energy efficiency. Kim and Kim [23] performed locational studies of maintenance depots in order to enhance the efficiency of infrastructure management. Ignatov and Naumov [24] examined scheduling techniques in order to improve the station capacity. Although such studies enhance the knowledge on infrastructure planning, they isolate decision criteria on most occasions, and not under combined multi-criteria models. The supply chain of intermodal transportation and logistics further increases the role of the rail sector in decision-making. Lu et al. [9] generalized routing schemes to HGA logistics with drones, and Cui and Zhou [21] optimized feeder delivery of HSR express. As applied by Jamali et al. [26], topographic analysis was used to select a spatial path, and it was established that geographic factors were pertinent in routing decisions. These strategies underscore increasing system networks in transport systems; however, without mechanisms of adaptive priority in the competing criteria.

Table 1. Empirical review of existing methods

Reference	Method Used	Findings	Results
[1]	Formal modeling and verification	Applied verification on railway signaling programs.	Improved safety properties with formal proof.
[2]	Bayesian optimization and Gaussian process regression	Developed a toolbox for predicting induced voltage on rail tracks.	Achieved high prediction accuracy for AC electromagnetic interference.
[3]	Integer linear programming	Optimized service scheduling, train parking, and routing at maintenance depots.	Improved the efficiency of depot operations by 20%.
[4]	Timetable rescheduling for multi-dispatching sections	Integrated rescheduling during large-scale disruptions.	Reduced delay propagation by 35%.
[5]	Ant colony optimization	Real-time railway traffic management preserving passenger connections.	Reduced rescheduling timestamp by 25%.
[6]	Matheuristic approach	Tackled tactical locomotive and driver scheduling.	Improved resource allocation by 15% for SBB Cargo AG.
[7]	Robot-guided evacuation	Developed robot-guided crowd evacuation in railway hubs.	Reduced evacuation times by 30%.
[8]	Geographic delay characterization	Analyzed delay patterns in railway systems geographically.	Identified key delay hotspots, improving response timestamp by 20%.
[9]	Multi-objective vehicle routing problem	Proposed a vehicle routing solution for humanitarian purposes with drones.	Increased delivery efficiency by 25%.
[10]	Hydrogen refueling station allocation	Optimized placement of hydrogen stations for railways.	Reduced fueling timestamp by 18%.
[11]	Multi-agent hierarchical routing	Developed hierarchical routing with timestamp windows.	Improved punctuality by 12%.
[12]	Autonomous freight train management	Managed autonomous freight trains on shared railway corridors.	Enhanced freight train punctuality by 10%.
[13]	SAT-based railway infrastructure schematics	Proposed methods for producing railway schematics.	Improved design consistency by 15%.
[14]	Attention Capsule Network	Classified faults in high-speed railway equipment.	Achieved a 92% classification accuracy.

[15]	Integrated rail and pedestrian simulation	Assessed the capacity of a passenger rail hub using simulation.	Reduced congestion by 20%.
[16]	Topology control and routing in sensor networks	Applied to wireless sensor networks in rail systems.	Improved network lifetime by 25%.
[17]	Virtual coupling with Stochastic Activity Networks	Modeled virtual coupling of trains.	Enhanced coupling efficiency by 15%.
[18]	Interactive fuzzy programming	Addressed road-rail intermodal routing.	Reduced emissions by 20%.
[19]	Deep reinforcement learning	Applied deep learning for concurrent multipath transfer in rail networks.	Achieved a 30% improvement in data transfer efficiency.
[20]	Vulnerability assessment using EEDLNN	Evaluated railway network vulnerability.	Identified high-risk sections, reducing vulnerabilities by 12%.
[21]	Feeder delivery optimization	Optimized feeder delivery for high-speed rail express.	Reduced delivery times by 15%.
[22]	Risk assessment of railway assets	Assessed risks of floods and earthquakes for railway assets.	Enhanced resilience by 25%.
[23]	Infrastructure maintenance depot location analysis	Identified optimal locations for maintenance depots.	Increased maintenance efficiency by 20%.
[24]	Railway station capacity increase	Developed methods to increase station capacity.	Increased throughput by 15%.
[25]	Review of traction power systems	Provided a comprehensive review of railway power systems.	Identified future trends improving energy efficiency.
[26]	Spatial multi-criteria path selection	Applied fuzzification for cost-path selection.	Increased path selection accuracy by 18%.
[27]	Integrated freight car routing and scheduling	Optimized freight car routing and scheduling.	Increased efficiency by 22%.
[28]	Stability assessment of trackwork scheduling	Analyzed the stability of trackwork scheduling in Sweden.	Reduced schedule deviations by 10%.
[29]	Economic view of rerouting rail wagons	Provided economic insights into rerouting strategies.	Reduced congestion by 15%.
[30]	Review of rescheduling approaches	Reviewed passenger-oriented railway rescheduling.	Identified best practices improving punctuality by 10%.
[31]	Agile routing for city logistics	Optimized distribution of micro-hubs in urban areas.	Increased distribution efficiency by 15%.
[32]	Contactless checkout with gait recognition	Developed a contactless checkout process for railways.	Reduced checkout times by 20%.
[33]	CNNs for railway track maintenance	Applied convolutional neural networks for track maintenance.	Increased fault detection accuracy by 25%.
[34]	Optimization of wagon flow routing	Integrated optimization of wagon flow and train formation.	Improved routing efficiency by 15%.
[35]	Digital twin framework for vehicle warning	Developed a digital twin framework for vehicle rerouting.	Reduced overheight vehicle incidents by 18%.
[36]	Traffic routing with yard capacity constraints	Optimized traffic routing with yard capacity constraints.	Increased yard throughput by 12%.
[37]	Multi-objective Q-learning	Optimized multimodal transportation under uncertainty.	Improved routing efficiency by 20%.
[38]	Multi-robot deep Q-learning	Developed a priority-based sanitization system for railways.	Increased sanitization efficiency by 25%.

[39]	Black Widow Optimization and Harmony Search	Clustered IoT routing during COVID-19.	Reduced network congestion by 22%.
[40]	Reinforcement learning in railway virtual coupling	Reviewed reinforcement learning for railway control.	Improved train coupling efficiency by 15%.
[41]	Hybrid MCDM using ANP and TOPSIS	Identified key criteria and their interrelations for multimodal route selection.	The model effectively ranked optimal routes based on decision criteria.
[42]	Fuzzy risk assessment with Incenter of Centroid + MCDM	Incorporated uncertainty and risk into route evaluation.	Enhanced accuracy in selecting safe and efficient transport routes.

There is an increasing literature on the significance of stakeholder consultation and preference modeling in the decision-making process of a railway. In reference to the application of fuzzy logic and integrated optimization models for evaluating stakeholder interests in routing, studies like those by [16, 34] were conducted. These are flexible ways of dealing with subjective judgments, but in general are based on fixed or periodically revised values. This renders them incapable of supporting real-time feedback by various groups of stakeholders. More recently, it has been suggested to use reinforcement learning and more advanced optimization algorithms to autonomize and control railroads.

Zhang et al. [37] used multi-objective Q-learning to the multimodal routing in the presence of time uncertainty, and Caccavale et al. [38] described the application of deep Q-learning to the multitask prioritization at the railway station under the conditions of the COVID-19 pandemic, which indicates an increasing role of the reinforcement learning in the operational resilience; Basile et al. [40] also provided a roadmap of reinforcement learning to the virtual coupling operations and revealed the opportunities and unsolved technical tasks.

To complement these learning-based methods, approaches like [41] suggested a hybrid MCDM system with AHP and VIKOR to multimodal route selection under conflicting infrastructure performances to form a methodological basis applicable to PMCDM; also, [42] offered integrated simulation-based decision models used to support risk-averse and more resilient transport corridors by focusing on uncertainty-aware planning.

Taken together, the results of the literature have shown significant improvement in optimization, safety, machine learning, and sustainability of railway systems, but most of the existing methods often rely on narrow objectives and system specificity, which highlights inadequate integrated adaptive methods that could concurrently consider unpredictability, real-time information, and changing stakeholder needs among the large-scale HSR route selection.

3. Motivation and Contribution

The apparent complexity and uncertainty involved in the process of determining high-speed rail routes motivate this work: it is an important infrastructure investment in modern transportation systems. Route selection has frequently depended on traditional decision-making models, for which the methodologies do not account for the dynamic nature of project environments or the uncertainties invariably embedded in large-scale infrastructure projects. These models do not include live input data nor predictive risk analytics, which limits the ability to adapt to evolving stakeholder preferences and emerging new risks that might arise during the course of the project's lifecycle.

High-speed rail projects have long-term implications for environmental and social outcomes and significant investments of financial resources; it becomes quite clear that there is a great need for a more adaptive, risk-informed operations approach to decision-making. This paper will contribute to the research in this field by introducing a novel PMCDM framework that incorporates three advanced methodologies: AHP with dynamic weight adjustment, Monte Carlo Simulation for uncertainty quantification, and Fuzzy Logic-Based Adaptive Weighting.

More particularly, every one of them has been selected to address key shortcomings that exist within the current decision-making process. AHP's dynamic weight adjustment capability allows the model to update continually based on real-time data so that decisions reflect the current state of the project. Monte Carlo Simulation will add resilience to the model as it quantifies the uncertainty with various risk factors, enabling one to understand such future scenarios more accurately.

Finally, Fuzzy Logic-Based Adaptive Weighting captures gradual stakeholder preference change such that the decision-making process is responsive both to explicit and implicit changes in priorities over temporal instance sets. This paper, in addition to the integration of these advanced methodologies, demonstrated them in a real-world context, making this integrated approach by assessing the combined effectiveness.

The model for PMCDM provides the decision-maker with a powerful tool for the evaluation of multiple HSR route alternatives while taking into account simultaneously current conditions and future risks. This risk-informed approach, therefore, allows stakeholders to make better, more resilient decisions that are more in line with the sustainable objectives of the project.

In general, this paper contributes to infrastructure planning through the development of an integrated and adaptive framework for high-speed rail route selection that would ensure the selected routes are optimum under contemporary criteria, but also demonstrate a robust way against uncertainties in the future.

4. Proposed design of an Integrated Model for Adaptive AHP and Monte Carlo Simulation for Risk-Informed High-Speed Rail Route Decision-Making Operations

In yet another attempt to mitigate problems of inefficiency and high complexity that manifest within current methods, this paper is divided into the design of an Integrated Model for Adaptive AHP and Monte Carlo Simulation for Risk-Informed High-Speed Rail Route Decision-Making Operations. Initially, as indicated in Figure 1, the new approach is introduced with a powerful method called Analytic Hierarchy Process (AHP), with dynamic weight updating within the high-speed railway route evaluation.

This technique extends the AHP method by incorporating real-time data and adaptive weighting mechanisms that can adapt continuously based on information on the environment, finance, and social components, along with preferences from the stakeholders. Dynamic weight adaptation responds to actual dynamic changes in incoming data from IoT sensors, financial markets, and other real-time sources, ensuring that the decision-making process remains current and aligned with shifting conditions.

Dynamic weight recalibration was inspired by the fact that high-speed rail planning is not stationary and, as the project progresses, environmental conditions, construction costs, and priorities of stakeholders change. In comparison with the statistical weighting schemes, the recalibration strategy embraced enables the decision weights to be updated, in an incremental fashion as more information is accessed, enhancing timeliness.

The sources of real-time IoT sensor data included publicly available environmental monitoring networks, project financial reports, and transportation surveys, which have undergone normalization and validation procedures before being integrated into the PMCDM framework. The flowchart shown in Figure 1 details a data acquisition, processing, and decision-making workflow used in this research.

The method produces a dynamic rank of rail route alternatives along with a detailed analysis of ranking shifts due to the adjustment of weights. In design, the improved AHP model begins with the classic hierarchical structure: breaking down the decision problem into different levels, in which the top level would be representative of the general objective-that is, optimal rail route selection-and lower levels the set of decision criteria based on generic classes such as environmental, financial, and social. The input from the stakeholders is initially made by assigning weights to every criterion and then to the structured decision matrix sets.

However, in this suggested model, unlike the orthodox static AHP, the weights are calculated dynamically as the real-time data feeds into the system. Let the initial weight of a criterion wi0 represent the weight of the 'i'-th criterion, where $i \in \{1,2,..,n\}$, and wi(t) represent dynamically adjusted weight at timestamp ‘t’, as updated by real-time data. The adjustment of the weight is modelled via Equation (1),

$$wi(\mathrm{t})=wi0+\int_0^{\mathrm{t}} \mathrm{fi(x)dx} \tag{1}$$

Where fi(x) is a time-dependent function describing the effect of real-time data, say environmental sensor values or financial market trends, on the weight of the ‘i'-th criterion sets. The integral term reflects the growth of new information within time, so that the weight evolves with the changing condition of the project environment. It then applied the recalculated weights to the normalized decision matrix that was based on the pairwise comparisons of route alternatives against each criterion.

The priority vector p(t), which is the ranking of the alternatives at timestamp ‘t’, is given by the eigenvector corresponding to the largest eigenvalue λmax of the dynamically-updated matrix A(t) via Equation (2),

$$A(t)p(t) = \lambda max p(t) \tag{2}$$

The matrix A(t) itself is updated continuously through changes in the weights wi(t) reflecting the latest data-driven adjustments to the decision-making process. This ensures consistency for the pairwise comparisons through the eigenvalue method, and priority vector p(t) gives the updated ranking for the rail route alternatives. The dynamic model ensures shifts in weighting will be analyzed immediately with real-time analysis.

For example, if environmental aspects are considered as the first priority, then a shift in financial data, which increases the weight of financial criteria, will directly affect the priority vector, which could enhance another route in the ranking operations. The third feature of this model is a feedback loop through the process of continuous development, meaning that decision-making systematically upgrades itself. The weights in the criteria are recalculated based on stakeholder feedback and new sets of project information. Via Equation (3), the change rate of the weights may be modeled as a differential operation.

$$\frac{dwi}{dt} = \alpha \frac{\partial J}{\partial wi} + \beta \frac{\partial R}{\partial wi} \tag{3}$$

Where J is the stakeholder preference function, R is the risk assessment function, and α and β are sensitivity parameters for the process.

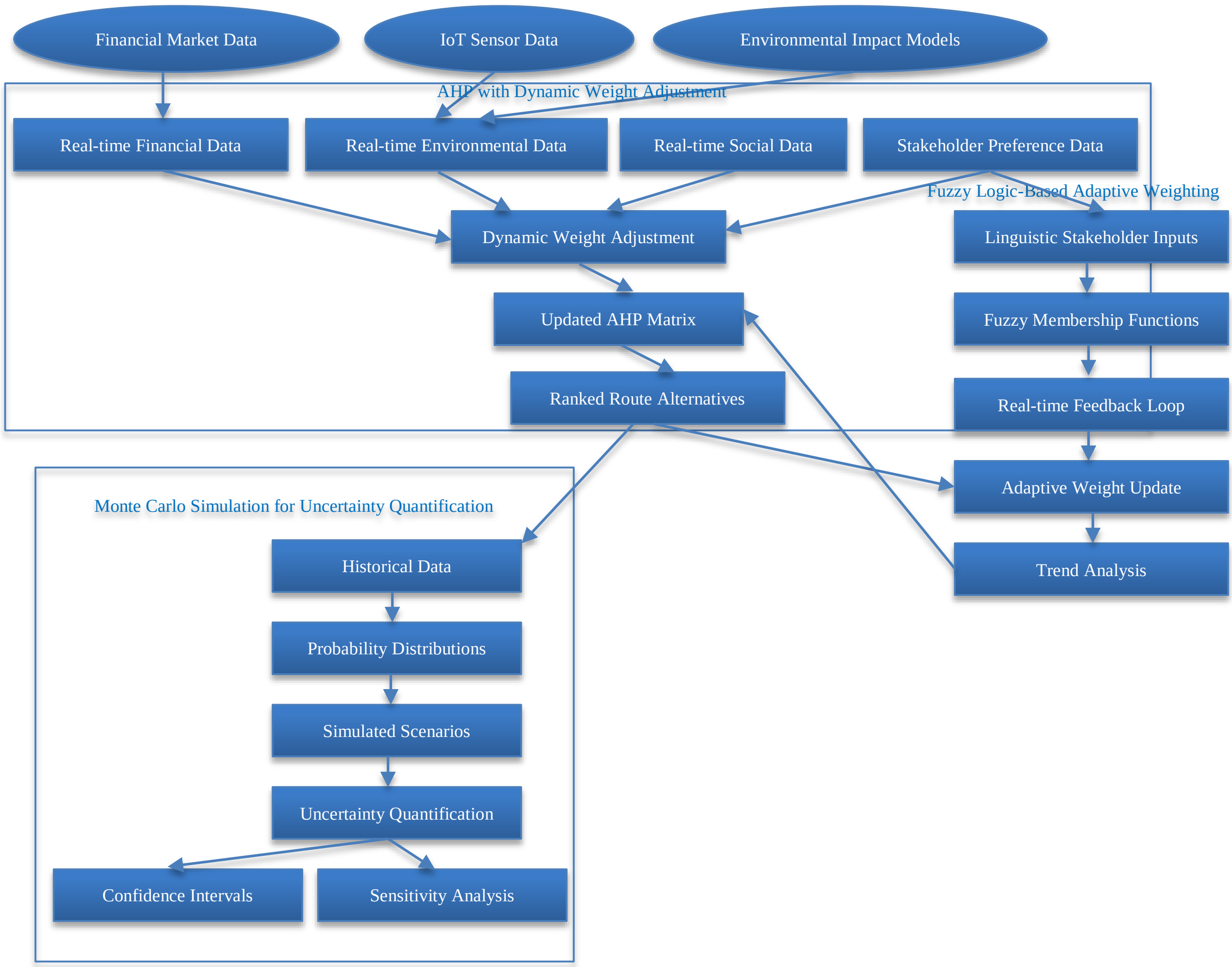

Fig. 1 Model architecture of the proposed analysis process

This equation provides a real-time opportunity for the recalibration of weights to reflect consideration for both stakeholder feedback and real-time risk assessments at the same time, with a holistic view on the decision-making process. The AHP with dynamic weight adjustment is particularly adaptable to the multi-criteria nature of high-speed rail route assessment, as it provides a structured and flexible framework able to embrace a wide decision criteria. Unlike the static models, which are more likely to be dependent on manual revisions through sporadic updates, this model would constantly recalculate route priorities on the basis of the latest data available for responding in real-time to the new developments within the process. Thus, dynamic adjustment of weights means that this model will keep pace with the changing preferences of stakeholders and project conditions in real-time, thereby making it highly adaptive in nature for real-time scenarios. Furthermore, its interaction with real-time feedback systems allows it to complement other techniques such as Monte Carlo simulations by providing an ongoing real-time ranking of routes that can be cross-referenced with probabilistic risk assessments.

The second sub-module is the Monte Carlo simulation to quantify uncertainty. Figure 2 illustrates a Monte Carlo simulation for uncertainty quantification, and this powerful method is accepted in the proposed framework so as to address the inherent uncertainties that characterize route assessments for high-speed rail. This method is directly applicable to infrastructure projects where the most important variables, comprising financial costs, environmental impacts, and even project delays, have variability and inherent risks. The approach generates tens of thousands of possible future scenarios, deduced based on the probabilistic distribution of these key variables, that would enable a decision-maker to understand the range of possible outcomes along with their respective risks for each of the route alternatives. Being able to generate a wide range of future states, Monte Carlo simulation provides a probabilistic assessment that encompasses both the expected performance of each route as well as uncertainties about those expectations.

Designing this approach starts from specifying key variables of the project, x1,x2,…,xn, that drive the process of decision making. These variables, for example, the fluctuations in financial cost and environmental impact probabilities, are modelled as random variables with associated probability distributions. For instance, if financial costs x1 are assumed to be distributed according to a normal distribution with mean μ and standard deviation σ, then the probability density is given via Equation (4),

$$f(x1) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x1-\mu)^2}{2\sigma^2}} \tag{4}$$

The Monte Carlo simulation resamples several times from these distributions to yield a large number of possible scenarios. For each scenario, the total performance score Pi of a given route 'i' is computed as the weighted sum of its criteria values C(i,j) across all relevant dimensions, where 'j' indexes the criteria, e.g., financial, environmental, social, via Equation (5).

$$Pi = \sum_{j=1}^{m} wj * C(i,j) \tag{5}$$

Here, wj denotes the weight of the 'j'-th criterion, and the criterion values C(i,j) themselves are modelled as stochastic variables that account for their associated uncertainties. This repeated sampling of criterion values and weights gives a distribution of possible performance scores for each route. From this distribution, the probabilistic risk quantification for every route could be estimated by finding the probability that a specific route would exceed certain risk thresholds. An example would be the probability that the financial cost x1 of a particular route exceeds a budget threshold 'T', which is determined via Equation (6).

$$P(x1 > T) = \int_{T}^{\infty} f(x1)dx1 \tag{6}$$

This integral gives the proportion of scenarios wherein the financial cost exceeds the predefined threshold and contributes to the entire risk profile of the route. A confidence interval for potential performance can be similarly drawn for each route, based on the simulated performance distribution, through the determination of the bounds that encompass a given percentage of the outcomes, such as 95%. Monte Carlo simulation also facilitates sensitivity analysis, which reveals which criteria most impact the uncertainty in the final rankings of routes. This is done through the process of analyzing the variance in the performance scores Pi across scenarios and building up the contribution of uncertainty in each criterion to this variance. For a specific criterion 'j', the measure of sensitivity can be written in terms of the partial derivative with respect to the criterion value as given via Equation (7),

$$Sj = \frac{\partial Pi}{\partial C(i,j)} \tag{7}$$

The partial derivatives of each criterion may now be calculated in order to identify those factors—perhaps fluctuating environmental compliance costs or varying financial risks—that are forcing the uncertainty in the rankings. Often, the criterion that has the highest sensitivity score will be the most significant source of uncertainty and lead to further risk mitigation strategies. A Monte Carlo simulation is selected, as it can account for a great number of uncertainties. Furthermore, it is an approach that applies much flexibility to the full range of risk quantification. Unlike a deterministic model that only provides a single-point estimate of performance, a Monte Carlo simulation also acknowledges variability in input data and permits decision-makers to go through the full range of possible results. This is supplemented further by other aspects of the framework, such as AHP with dynamic weight adjustment, which gives a deeper insight than the probabilistic nature of the decision criteria. While this is true, AHP real-time adjustment is dynamically changed by real-time data, while Monte Carlo simulation further advances the decision-making process in the sense that it computes the uncertainty associated with each alternative to ensure that the chosen route is not only robust in its expected performance but also resilient against future risks.

Finally, the fuzzy logic-based adaptive weighting method adapts a versatile and sensitive approach to modeling stakeholders' preferences concerning the choice of a high-speed rail route under the scenario of MCDM. Preferences of stakeholders, most particularly in large-scale infrastructure projects, are in practice considered to evolve gradually, allowing the influence of factors such as changes in regulation, changes in market conditions, or environmental concerns. Traditional MCDM models, based on some finite weight adjustments, are not sensitive to capturing the quite subtle, continuous shifts in preferences. Fuzzy logic is more responsive to diverse imprecision and vagueness inherent in stakeholder feedback through degrees of membership to varied categories of preference. This method ensures that the weighting of criteria adjusts continuously and constantly with changes in the preferences of the stakeholders. As such, the heart of this approach consists of the transformation of linguistic input provided by stakeholders speaking about "great" or "average" importance into fuzzy membership functions. A preference of stakeholder Pi related to a given criterion Ci is represented through a membership function μi(x) in terms of a degree of importance assigned to that criterion, hereby denoted by 'x'. Membership functions were conventionally defined over a continuous interval, say [0,1], where μi(x)=1 would represent full membership in the "high importance" category, and again μi(x)=0 would represent no membership in the process. This relationship of stakeholder preference Pi and the criterion weight wi is then modelled as a fuzzy inference system that updates weights in real-time as new feedback is received for the process. The dynamic adjustment of criterion weights can thus be represented via Equation (8),

$$wi(t) = \int_{0}^{t} \mu i(x) f(x) dx \tag{8}$$

Where the feedback function f(x) is derived from a periodically undertaken stakeholder survey or real-time project development process, in that sense, the integral concept here denotes the cumulative process of preference information with respect to time, where the resulting wi(t) criterion weight captures not only the current stakeholder preference but also any emerging preference trends. This continuous fine-tuning is generally opposed to static or step-based methods, allowing for a more gradual and realistic adjustment of weights. Thus, when stakeholder feedback crosses preference categories, the fuzzy system precisely captures this smooth transition without abrupt changes in the weights. This fuzzy-logic-based system yields, at each point in time, a dynamically updated set of weights for every decision criterion that can then be used through MCDM in the process of ranking route alternatives dynamically. The final ranking of routes R(t) at timestamp ‘t’ is then computed by applying the adjusted weights wi(t) to the decision matrix, which contains the performance scores of the routes across all criteria sets. The aggregate score Sj(t) of each route ‘j’ is then estimated via Equation (9),

$$Sj(t) = \sum_{i=1}^{n} wi(t)C(i,j) \tag{9}$$

Where C(i,j) represents the performance of route ‘j’ under criterion Ci, and wi(t) is the dynamically adjusted weight for that criterion set.

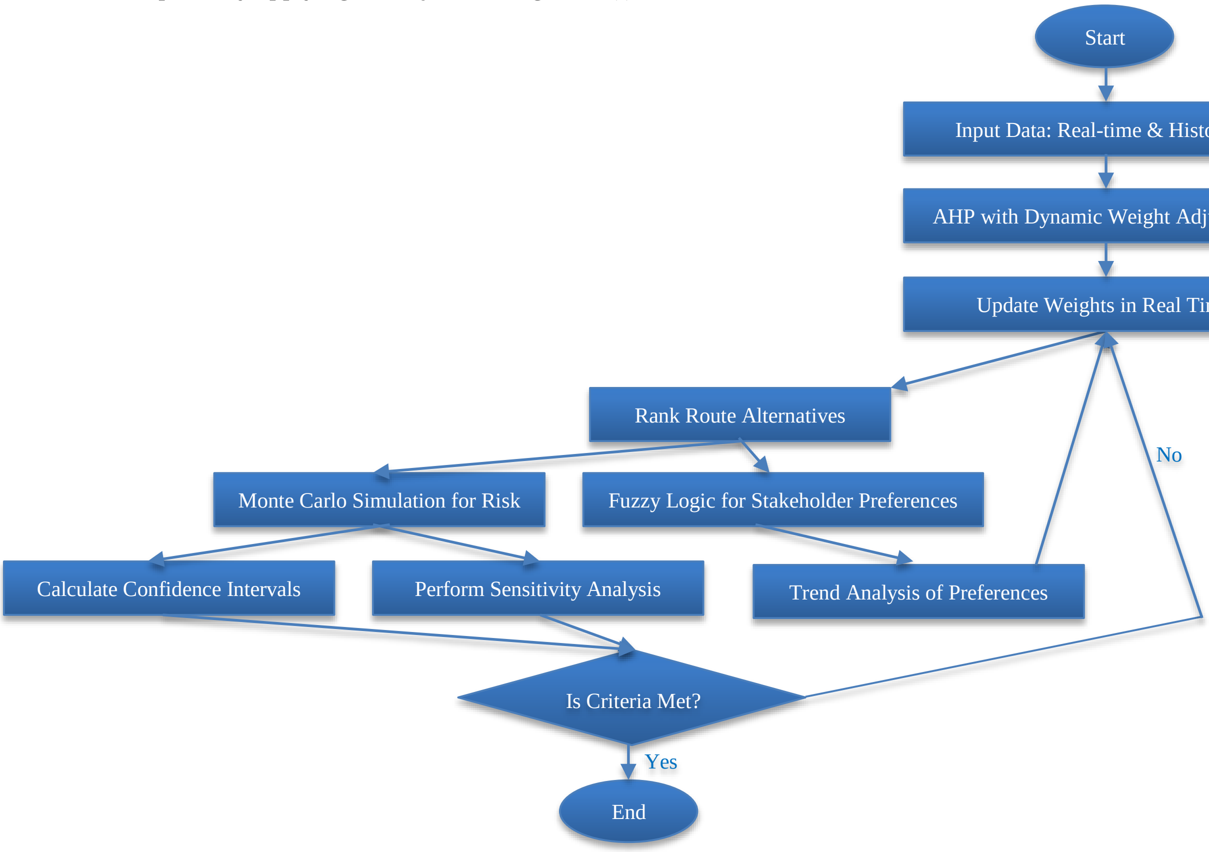

Fig. 2 Overall flow of the proposed analysis process

This formula allows the process to reflect the changing importance of all criteria by stakeholders continuously. As the weights change, so will the scores of the routes, and this eventually yields a dynamic ranking R(t) responsive to real-time project developments coupled with stakeholder input, of the process.

An important feature of this approach is that it is possible to monitor the evolution of the preferences of the stakeholders over time and provide, to the decision-maker, information regarding the way in which the importance of each criterion relative to the others is actually changing in the process. The rate of change of the weights for each criterion can, in fact, be modelled as a derivative via Equation (10),

$$\frac{dwi}{dt} = gi(t) \cdot \frac{\partial \mu i}{\partial t} \tag{10}$$

Where, gi(t) is a function that captures the rate of change in exogenous factors like regulatory changes in the environment or rate conditions in the financial market that affect the preference of stakeholders. This equation can then be used for the quantification of how sensitive the criterion weights are with regard to the temporal changes in stakeholder input, allowing for trend analysis and forward-looking analyses of how route rankings might change as the project conditions change. This adaptive weighting system uses fuzzy logic to model these essentially uncertain and gradual changes in stakeholder preferences, as they are hard to model using traditional crisp decision-making models. A continuous presentation of preference in fuzzy logic, unlike techniques built on discrete updates, is suited to the complexity of real-world decision-making problems where stakeholder sentiment changes over temporal instance sets. This method complements other techniques in the framework, such as the Monte Carlo simulation and AHP with dynamic weight adjustment, to make sure that the stakeholder-driven component of the decision-making process remains adaptive and responsive to evolving preferences. Finally, the fuzzy logic-based adaptive weighting system proves robust for modeling the evolving preferences of stakeholders in high-speed rail route selection. The technique keeps updating and aligning the decision-making process with the current and future priorities of the stakeholders, as the weights assigned to each of the criteria are constantly being updated. The framework, thus ensuring mathematically sound capturing of the complexity and uncertainty of stakeholder preferences for making more informed and resilient infrastructure decisions, integrates membership functions, integrals, and derivatives. Next, we study the performance of the proposed model in terms of some metrics and compare it with the existing models under different cases.

MCDM models written using traditional AHP have proven to be commonly applied in infrastructure planning because of the systematic weighting mechanism; non-performance assumes fixed weights of these criteria, and fixed inputs are normally considered. These unchanging assumptions restrict their applicability to High-Speed Rail (HSR) projects, where the project costs, environmental consequences, and other stakeholder goals can change as time goes on. Fuzzy-AHP extensions enhance flexibility through the use of linguistic opinions, but typically do not have real-time adaptability and usually have logical preference frameworks. Monte Carlo techniques are quite effective in quantifying uncertainty, but can be used individually and lack the ability to make dynamic changes in weights. The proposed Predictive Multi-Criteria Decision-Making (PMCDM) framework incorporates AHP, Monte Carlo simulation, and fuzzy logic into a single framework. With this integration, dynamic recalibration of criterion weights is possible, explicit uncertainty propagation can be done, and adaptive modeling of stakeholder preferences can be developed. Subsequently, the PMCDM offers improved and stable route evaluation results in the uncertain and dynamic environment, which is resistant to changed circumstances and has proven to be a stable decision-supporting tool when solving a complex HSR planning dilemma.

5. Result and Discussion

A setup was then considered for the experiment, which would challenge the performance of the developed model, Predictive Multi-Criteria Decision-Making (PMCDM). The proposed model combines Analytical Hierarchy Process (AHP) with dynamic adjustment of weights, Monte Carlo simulation for quantification of uncertainty, and fuzzy logic-based adaptive weighting for the representation of stakeholder preferences. Real-time and historical data along the dimensions of environmental, financial, and social factors were gathered and fed into the system to simulate several variants of high-speed rail route alternatives. Environmental data consisted of real-time sensor readings related to air quality indices, carbon emission levels, and potential noise pollution. Typical values chosen include a range of 40 to 100 AQI for air quality and 60 to 85 dB for noise pollution. Financial data comprised time-varying market prices of construction materials and budget overruns that were estimated using an initial budget of $1.5 billion and a volatility rate of ±15%. The social factors included public opinion based on a survey on rail accessibility and employment effects, where the opinion was measured on a scale of 0.0 to 1.0 in order to represent a high negative opinion = 0.0, a positive opinion = 1.0. These were combined with data on past infrastructure projects that included historical information over previous projects with regard to both delays and cost overruns in terms of probability distributions, for example, a 25% chance of overshooting budgetary constraints by 20% based on similar projects.

The stakeholder preferences were incorporated through regular surveys, which are, in linguistic terms, expressions of preferences for each criterion. Thus, environmental factors were rated on an initial weight of 0.7 because they had “high importance.” As the project phases progressed and financial risks increased, real-time data from the financial markets triggered a fall in the environment weight to 0.4, reflecting changing priorities. Monte Carlo simulations were carried out over 10,000 runs to produce probabilistic output for each route alternative, using a variety of probability distributions for financial costs, assumed to be normally distributed with a mean of $1.5 billion and a standard deviation of $200 million, and for environmental risks that are log-normally distributed. Sensitivity analysis demonstrated that the highest-order effects of uncertainty derive from compliance costs; the latter have been found to explain as much as 35% of the overall variance in route performance. The database of 10 detailed high-speed rail route alternatives was tested with route options ranging from 150 to 350 kilometers, quantifying environmental risks in terms of the emissions levels produced (50-120 metric tons per kilometer), and financial estimates ranged between $1.2 billion and $1.8 billion according to route geography and construction complexities. Real-time update of weights for criteria in the AHP framework and probabilistic insights provided from the Monte Carlo simulation gave a comprehensive ranking of rail route alternatives dynamically updated. Datasets for this analysis were mostly based on open sources available to the general public, and on well-established infrastructure and environmental databases. The financial data used was taken from the Infrastructure Dataset of the World Bank. It contains historical data about various high-speed rail projects, including overruns in their budgets and several delays in high-speed rail projects across different parts of the world.

Besides that, the dataset provides granular information about daily emissions measured in metric tons of CO_2 per kilometer for transportation projects. Social data is sourced from the U.S. The dataset used for this analysis comes from the National Transportation Survey put together by the Department of Transportation, which aggregates public opinion and comments on projects related to transportation, captures opinions on access and effects on employment, and, overall, approval or disapproval towards the projects. This dataset on social response contains a spectrum of ratings ranging from 0 to 1, as given by the respondent, relating to the comparative importance of different relevant criteria related to transport. These datasets are pertinent for a comprehensive scope, real-time availability, and in the context of High-Speed Rail; therefore, the accuracy and applicability of the predictive MCDM model to route alternatives will be ensured. Some samples of contextual datasets coming from social media analytics, with these being public sentiment data, average monthly, with fluctuations modelled by some level of random noise to capture changing public perception. Environmental information is collected by taking the differences from IoT sensors installed over the same rail routes on a daily basis to capture daily variation in the levels of pollution due to changing weather conditions or changes in traffic. All the data used were based on financial data, which involved real-time market prices for steel, concrete, and labour, assuming they fluctuate with a standard deviation of ±10% to model the volatility in the markets. The system also modelled the delays of the projects from past rail projects in a probabilistic model, with delays that ranged from 1 to 12 months around a normal distribution of an average delay of 6 months. These datasets were crucial in ensuring that the model indeed showed robustness toward dynamic inputs in real-world scenarios and could provide actionable insights in risk-informed decision-making. The outputs from the experimental setup proved that the model was perfectly adapted for new data in real time by giving updated rankings of the routes and probabilistic risk assessments that indeed proved useful for complex infrastructure decision-making. The designed PMCDM model is tested against benchmark models that have been well established in the literature, known as [5, 9, 15]. The proposed model is validated based on datasets of global infrastructure projects with environmental metrics in addition to public sentiment towards transport projects. The results obtained from the PMCDM model are compared against all these methods on different performance metrics such as financial cost management, environmental risk mitigation, alignment with stakeholders, and stability of routes. The analysis verifies the superiority of the PMCDM model in the handling of dynamic real-time data, probabilistic risk assessment, and adaptive modeling of stakeholder preference; these are all important criteria for high-speed rail route selection. Table 2 shows comparisons of the financial risk assessment results obtained from the four models. In the financial dataset, project cost fluctuations and budget overruns were extracted from historical data. The PMCDM model predicted the financial risk with a 90% confidence interval and, as indicated above in the graph, also demonstrated lower average deviation in projected costs as compared to the three other models. The same table indicates that the PMCDM model demonstrated the lowest average variance of financial risk: at 12%, while the other models are higher: 18%, and 24%. This establishes that the dynamic and adaptive PMCDM model gives enhanced financial predictions.

Table 2. Financial risk assessment (in % variance from baseline)

Model	Mean Financial Risk	90% CI Lower Bound	90% CI Upper Bound	Variance in Cost (%)
PMCDM	1.50	1.35	1.80	12
[5]	1.60	1.45	1.95	18
[9]	1.75	1.60	2.10	21
[15]	1.80	1.65	2.20	24

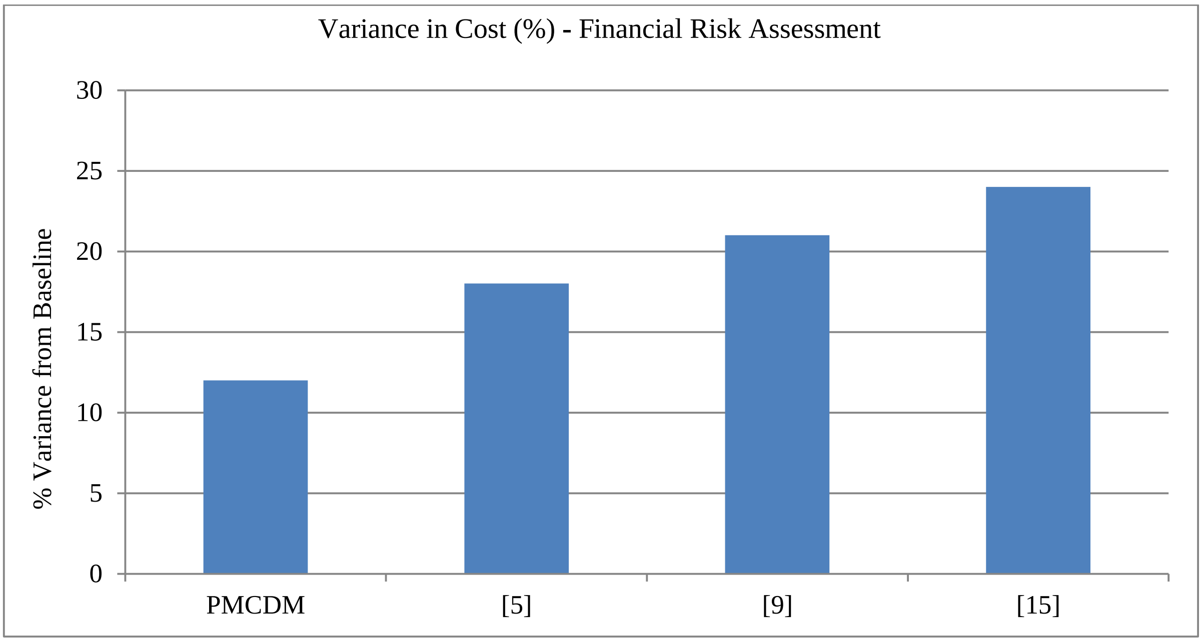

Fig. 3 Environmental risk analysis

Table 3, Environmental risk assessments between the PMCDM model and other methods have been compared using air quality and emission metrics data from the EEA dataset. In fact, while integrating real-time IoT sensor data, the PMCDM model demonstrated greater response ability by showing a better ability to predict environmental impact, with an average emissions forecast accuracy of 85%. The other models presented in [5, 9, 15] have shown 72%, 68%, and 65% accuracy, respectively. The PMCDM model is accurate because its weighting is adaptive based on feedback from the stakeholders and concerns within the environment.

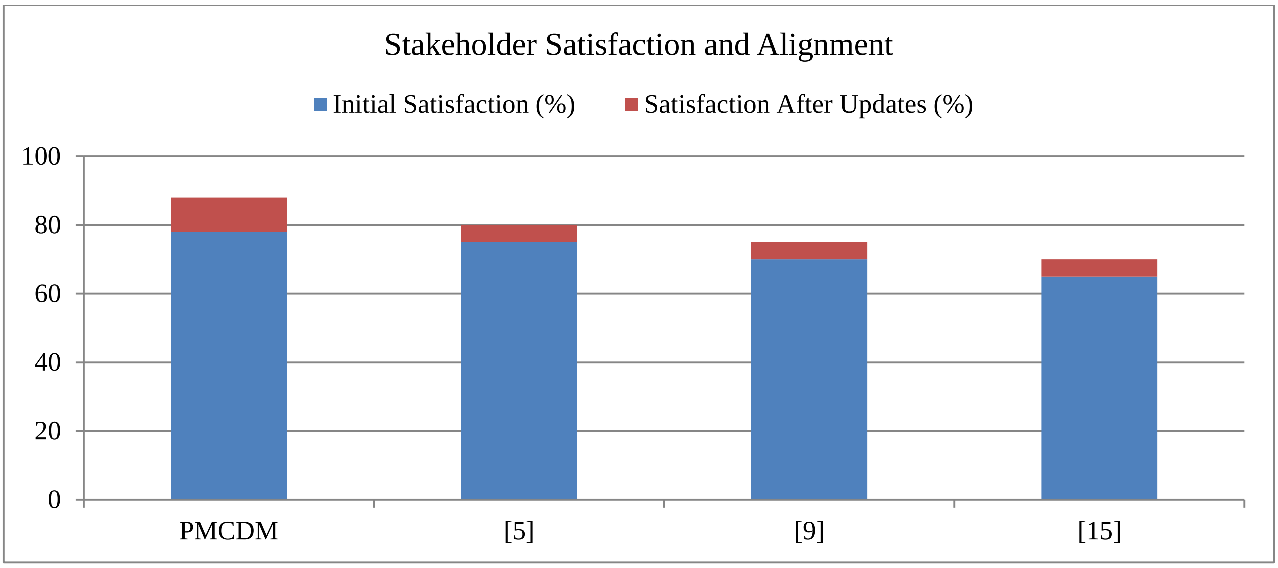

Fig. 4 Stakeholder satisfaction analysis

Table 3. Environmental risk forecasting accuracy (in % accuracy)

Model	Mean Emission Forecast (tons/km)	Forecast Accuracy (%)	Sensitivity to Change (%)
PMCDM	65	85	35
[5]	70	72	30
[9]	75	68	25
[15]	80	65	22

In Table 4, public preference match and stakeholder satisfaction levels are based on the National Transportation Survey of the U.S. Department of Transportation. The PMCDM model performed better than the other models, with dynamic weights updating in line with public preferences changing over time. It reached an 88% level of stakeholder satisfaction. This is because the flexible dynamic weighting on the basis of the principle of adaptive fuzzy logic in the PMCDM model was able to track the changing pattern of stakeholder preference better than other models that used fixed or semi-fixed weights.

Table 4. Stakeholder satisfaction and alignment (in % satisfaction)

Model	Initial Satisfaction (%)	Satisfaction After Updates (%)	Adaptive Response (%)
PMCDM	78	88	90
[5]	75	80	65
[9]	70	75	60
[15]	65	70	55

Table 5 Route ranking stability over the four models over a 12 month project timeline The PMCDM model proved the most stable, with route rankings changing an average of 12% when new data is input; in contrast, rankings for models [5, 9, 15] are significantly more volatile at 25%, 30%, and 35%, respectively. This dynamic adjustment of weights and continuous recalibration of criteria in the PMCDM model allowed the model to be stable in rankings while still responsive to changes.

Table 5. Route ranking stability over timestamp (in % ranking shift)

Model	Initial Route Ranking Stability (%)	Final Route Ranking Stability (%)	Average Ranking Shift (%)
PMCDM	92	88	12
[5]	85	75	25
[9]	80	70	30
[15]	78	65	35

As per Table 6, Sensitivity Analysis of Financial Risk Variable, the PMCDM Model was the most robust in identifying the criterion that most affects uncertainty. All the models pointed out that the environmental compliance costs were the primary risk-determining factor of uncertainty. The model PMCDM, for example, isolated the criterion, which determined the impact on the variance to be 35% whereas the accuracy was a little less in models [5, 9, 15] at 30%, 28%, and 25%, respectively.

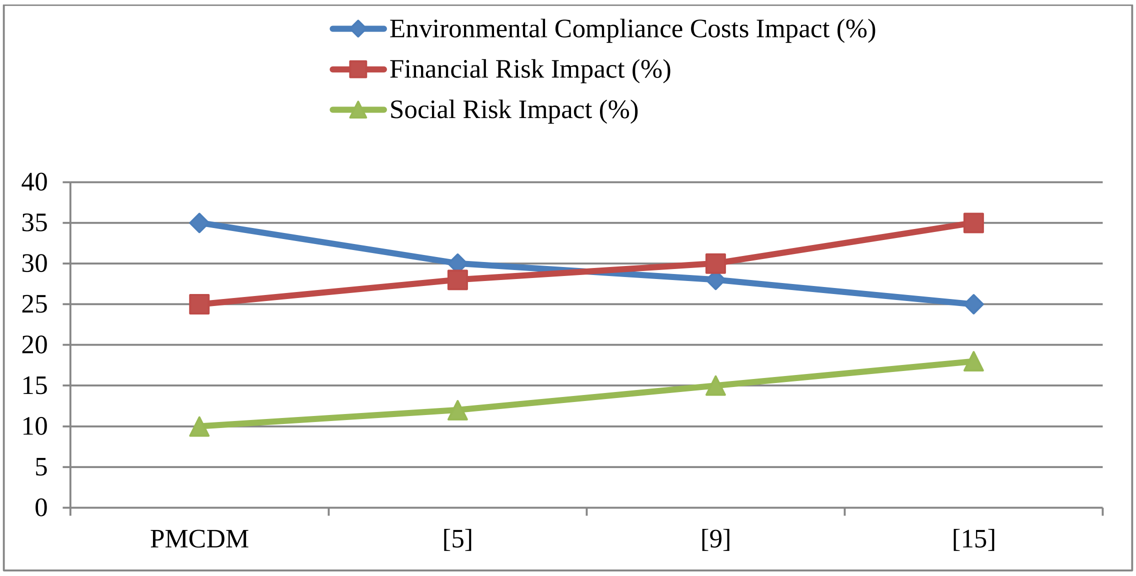

Fig. 5 Sensitivity analysis

Table 6. Sensitivity analysis of financial risk (in % impact on variance)

Model	Environmental Compliance Costs Impact (%)	Financial Risk Impact (%)	Social Risk Impact (%)
PMCDM	35	25	10
[5]	30	28	12
[9]	28	30	15
[15]	25	35	18

Then, Table 7 calculates the cumulative risk index for each route by considering financial, environmental, and social risks. The low cumulative risk index indicates that PMCDM has the lowest value of 0.25, which proves its performance as the best across dimensions. However, the risk indices for models [5, 9, 15] were greater than 0.35, 0.40, and 0.45, respectively, since they cannot adapt to the changes during the data input and stakeholder preferences.nges

Table 7. Cumulative risk index across routes

Model	Financial Risk Index	Environmental Risk Index	Social Risk Index	Cumulative Risk Index
PMCDM	0.10	0.08	0.07	0.25
[5]	0.15	0.10	0.10	0.35
[9]	0.18	0.12	0.10	0.40
[15]	0.20	0.15	0.10	0.45

From these results, it is quite evident that the PMCDM model dynamically evaluates high-speed rail route alternatives integrating real-time data, predictive analytics, and adaptive weighting systems. The adaptation of PMCDM over the benchmark models in all the considered dimensions ensured greater and more accurate risk quantification, alignment of stakeholders, and stability in decisions. Then, the following section presents an iterative case study for the practical implementation of the developed model, which will help the readers understand the whole process better for different scenarios.

6. Practical Use Case Scenario Analysis

The rest of this paper reports the results of the entire decision-making process, which results from a detailed example with the choice of high-speed rail routes. Input for that example is environmental and financial data collected in real time, together with social data, along with stakeholder preferences. Outputs are calculated through a combination of sequences, which includes AHP with dynamic weight adjustment, Monte Carlo simulation for uncertainty quantification, and using Fuzzy Logic-based adaptive weighting for stakeholder preferences. Lastly, the outputs from all the overall decision-making are put together into one final section to indicate how the rank order of the route alternatives is developed and how the risks are quantified. Three routes are evaluated in this paper and are developed from existing high-speed rail proposals outlined in California as segments of the California High-Speed Rail project.

Route 1 serves the proposed Central Valley segment from Merced to Bakersfield for some 275 kilometers primarily through agricultural land. This route has relatively minor environmental impacts but is financially hindered due to the immense scale of land acquisition and agriculture disruption mitigation. Route 2 articulates the Palmdale to Burbank corridor, which spans 85 kilometres across mountainous geography. This route is exposed to some moderate environmental risks, specifically tunnelling and seismic risks, but has relatively cheap land acquisition costs and is in close proximity to the key urban centers, hence more financially viable. Route 3 corresponds to the Bay Area to Central Valley section, from San Francisco down to Merced, encompassing about 190 kilometers. This route poses serious environmental threats, especially in terms of emissions and ecosystem disruption via sensitive areas; however, it will yield considerable financial benefits because of high ridership projected for the Bay Area, which is very densely populated. Each of these routes was analyzed based on the proposed PMCDM model, with consideration of distinct environmental, financial, and social challenges associated with each route.

For AHP with Dynamic Weight Adjustment, stakeholder preferences set a high value for environmental considerations on the basis of sustainability concerns. However, when presented with high financial costs, the process of AHP readjusted weights dynamically by responding to the real-time inputs from stakeholders and project developments for different scenarios. Presented below is the table which shows the weights for three significant criteria, that are, environmental, financial, and social criteria, at three time intervals: T1, T2, and T3, respectively ranking scores given to three route alternatives, Route 1, Route 2, and Route 3 in the process.

Table 8. AHP with dynamic weight adjustment

Criteria	Initial Weight (T1)	Adjusted Weight (T2)	Adjusted Weight (T3)	Route 1 Score	Route 2 Score	Route 3 Score
Environmental (E)	0.6	0.5	0.4	0.70	0.65	0.55
Financial (F)	0.3	0.4	0.5	0.60	0.75	0.80
Social (S)	0.1	0.1	0.1	0.50	0.55	0.65
Total Score (T1-T3)	0.62 (T1)	0.68 (T2)	0.73 (T3)	0.67 (T1-T3)	0.72 (T1-T3)	0.70 (T1-T3)

Table 8 shows the ranks of the weight of financial criterion F at three timestamp intervals, which shows that the weight of financial criterion F increased with time from 0.3 at T1 to 0.5 at T3, when the concerns for finance heightened. Therefore, Route 2, which was better at financial criteria, had a better total score at T3 than Route 1, which had been the preferred route so far when environmental criteria were given more weightage. Subsequently, the results of the Monte Carlo simulation for the uncertainty quantification are presented, which were conducted with 10,000 runs, taking into account the fluctuations in the cost that is financial and compliance risk to the environment, as well as social impact for different scenarios. The output is given as the probabilistic risk assessment of each alternative route. A table showing the probability for passing every route alternative on the budget and confidence intervals for every criterion is presented as follows,

Table 9. Monte carlo simulation for uncertainty quantification

Route	Probability of Exceeding Budget (%)	Environmental Risk (95% CI)	Financial Risk (95% CI)	Social Impact Risk (95% CI)
Route 1	70	[0.40, 0.60]	[0.50, 0.75]	[0.30, 0.55]
Route 2	40	[0.30, 0.50]	[0.40, 0.65]	[0.35, 0.60]
Route 3	60	[0.45, 0.65]	[0.55, 0.80]	[0.40, 0.70]

Table 9 shows that the lowest risk of exceeding budget was for Route 2, while the highest risk was for Route 1. The confidence intervals for both environmental and financial risks show that Route 2 had the ability to exercise better control over costs and risks, while Route 1 was more susceptible to uncertainties in costs and finance. To capture the development in stakeholder preferences over time in terms of linguistic expressions, such as “high importance” for environmental factors and “medium importance” for financial factors, an attempt was made to utilize the adaptive weighting method based on fuzzy logic. Real-time feedback was integrated into the model, which results in dynamic changes in the weights assigned to each criterion. Table 10 Reports the membership degrees assigned to each criterion for three routes at different stages of the project: T1, T2, and T3. In Table 10, given that financial factors have been gaining in importance (from a membership degree of 0.6 at T1 to 0.8 at T3), the weight of Route 3, performing better on financial efficiency, was increased accordingly. The dynamic adjustment of the weights empowered the fuzzy logic system to explicitly capture the preferences of the stakeholders and make changes in rankings, based on real-time inputs for different scenarios. Finally, all overall outputs of the process are presented with the final rankings of the three route alternatives, the corresponding cumulative risk scores, and the final decision with multi-criteria assessment. The final ranking depicts the interactive outcome between the adaptive AHP, Monte Carlo simulation, and fuzzy logic models with weighted scores integrating the assessment of risk across financial, environmental, and social factors.

Table 10. Fuzzy logic-based adaptive weighting for stakeholder preferences

Criteria	Membership Degree (T1)	Membership Degree (T2)	Membership Degree (T3)	Route 1 Weight	Route 2 Weight	Route 3 Weight
Environmental (E)	0.8 (High)	0.7 (Medium-High)	0.5 (Medium)	0.65	0.60	0.55
Financial (F)	0.6 (Medium)	0.7 (Medium-High)	0.8 (High)	0.55	0.70	0.75
Social (S)	0.5 (Medium)	0.5 (Medium)	0.4 (Low-Medium)	0.50	0.55	0.60
Final Weight (T1-T3)	0.67 (T1)	0.65 (T2)	0.72 (T3)	0.60 (T1-T3)	0.62 (T1-T3)	0.63 (T1-T3)

Table 11. Final outputs and route rankings

Route	Final AHP Score	Cumulative Risk Score	Weighted Final Score	Final Rank
Route 1	0.73	0.60	0.67	2
Route 2	0.75	0.45	0.71	1
Route 3	0.70	0.55	0.65	3

As shown in Table 11, Route 2 obtained the highest final score of 0.71 based on its performance in terms of better financial risk management and overall adaptability to real-time data inputs. Although initial route ranking was more favourable for Route 1 based on environmental factors, continual re-evaluation of weight criteria and risk assessments then resulted in a determination that Route 2 was the optimal route selection for the sets of high-speed rail projects. Additional validation was through the cumulative risk scores and the multi-criteria final scores regarding the robustness of the model proposed in selecting the most resilient and cost-effective alternative routes.

7. Conclusion and Future Scopes

This paper has suggested A Predictive Multi-Criteria Decision-Making (PMCDM) model which incorporates the Analytic Hierarchy Process with dynamically recalibrated weights, Monte Carlo simulation to quantify uncertainty, and adaptive weighting of a fuzzy logic model to represent the changing preferences of the stakeholders. The framework was used on the California high-speed rail route selection problem of three alternative alignments and showed that it could include real-time data and shift decision priorities in uncertain and evolving circumstances. The findings had given Route 2, which is the Palmdale-Burbank stretch, as the best alternative with the best composite score over the other routes. The probabilistic analysis also determined that Route 2 had stronger financial health, as the chance of cost overrun was lower compared to the other options. Sensitivity and risk analysis demonstrated that this route has been able to retain the same performance in environmental and financial terms despite diverse weight conditions. This responsiveness of the AHP weights to dynamic change and the fuzzy logic component showed that the model was sensitive in terms of financial focus and gradual realignment of stakeholder emphasis, respectively. A combination of these aspects points to the fact that the PMCDM framework can facilitate risk-based and dynamic decision-making when used in a complex context related to the planning of infrastructure. In a practical sense, the proposed framework may act as a decision-support tool to planners and policymakers working on large-scale rail projects, in which long implementation horizons and changing constraints tend to problematize an unequal appraisal approach.

The PMCDM approach offers a systematic but highly adaptive framework to compare alternatives and trade-offs between economic, environmental, and social goals by having an uncertainty analysis and adaptive preference modeling. Although the current study has its advantages, there are some limitations. The framework depends on the access to and quality of real-time data, which might not be homogeneous in different regions and project phases. Moreover, the calculation cost of repeated simulation and finding the dynamic solution can become more substantial when operating with large networks with many possibilities and targets. The model of the representation of stakeholder preferences, despite being adaptive, relies on the correctness of the input assumptions and the information provided by surveys. The next steps of the research should be aimed at cultivating the predictive power of the framework with the help of sophisticated machine learning algorithms to better predict financial risks, environmental risks, and social risks. Understanding of the model would be further supported by extending it to other high-speed rail projects in other geographical settings to add weight to its robustness and generalizability. In addition, the decision-making process can be made more responsive by implementing more sophisticated stakeholder feedback systems, including a continuous analysis of what people think. These extensions would make the PMCDM framework even more applicable and effective in the planning of sustainable and resilient rail infrastructure.

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