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Equitable railway corridor investment under demand uncertainty: A two-stage distributionally robust bi-objective framework for sustainable regional development

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Abstract: *Purpose*. This study aims to synthesise empirical and modelling evidence on inventory optimisation methods for raw materials, work-in-process, and finished goods in production and trading enterprises, and to translate that evidence into a practical, class-differentiated implementation framework deployable within standard warehouse management and enterprise resource planning systems. *Methodology*. A systematic review and meta-analytic synthesis of 31 peer-reviewed studies published between 2004 and 2025 was conducted following the PRISMA 2020 protocol. A random-effects model estimated by restricted maximum likelihood was applied to pool percentage cost-reduction effect sizes across 18 studies admissible to quantitative synthesis, complemented by a narrative synthesis of the remaining 13 studies. Pre-specified subgroup and moderator analyses examined the role of inventory class, demand pattern, and network complexity as effect-size moderators. *Results*. Distributional safety stock methods outperform classical normal approximations by a pooled mean of 9.3% (95% CI: 5.8–12.7%) at equivalent service levels, with the advantage being largest for high-variability SKU segments. Multi-echelon coordination yields a pooled mean cost reduction of 11.4% (95% CI: 6.9–15.9%), increasing significantly with network complexity and lead-time variability. Learning-based control methods deliver up to 16% cost reductions under complex network conditions but require substantial data and governance infrastructure. Commercial demand drivers systematically distort finished-goods inventory targets and require integration with sales-and-operations planning for accurate calibration. *Theoretical contribution*. The study provides the first cross-class synthesis covering raw materials, work-in-process, and finished goods within a unified

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evaluative framework, positioning machine learning and deep reinforcement learning methods alongside classical policy families and quantifying the boundary conditions for each approach. *Practical implications*. A six-phase, stepwise implementation framework is proposed, covering ABC-XYZ segmentation, forecast model selection, safety stock calibration, replenishment policy assignment, simulation-based parameter tuning, and KPI governance, enabling enterprises to achieve 9–16% reductions in inventory costs within existing WMS and ERP architectures.

Keywords: sustainable transport systems, railway infrastructure assessment, GeoAI and spatial modelling, regional accessibility analysis, transport logistics sustainability

Sustainable Development Goals (SDGs): SDG 9: Industry, Innovation and Infrastructure; **SDG 10:** Reduced Inequalities; **SDG 11:** Sustainable Cities and Communities; **SDG 13:** Climate Action

1. Introduction

Regional inequality remains a persistent challenge in transportation infrastructure planning, particularly in railway corridor development. While new rail networks can stimulate economic growth, their benefits often concentrate in urban centres, exacerbating spatial disparities (Xu & Zhu, 2024). Traditional route planning algorithms focus primarily on operational efficiency metrics such as travel time reduction or cost minimisation (Leong et al., 2016), neglecting the distributional consequences of infrastructure investments. This oversight becomes particularly problematic when allocating limited budgets across regions with heterogeneous development levels and uncertain future demand patterns.

The interplay between railway expansion and regional inequality has gained attention in recent empirical studies. Evidence from China's high-speed rail network demonstrates that while such projects can reduce intra-regional disparities, their effects depend critically on equitable corridor placement and demand-responsive resource allocation (Lai et al., 2024). However, existing planning frameworks lack systematic mechanisms to balance efficiency and equity under uncertainty. Stochastic programming offers a natural paradigm for this challenge (Wallace & Ziemba, 2005), yet its application to railway corridor planning has been limited to single-objective formulations that either maximise economic returns or minimise construction costs.

We present a two-stage stochastic bi-objective programming model that jointly optimises regional equity and budgetary efficiency for railway corridor development. The first innovation lies in the dual-objective structure that simultaneously minimises the Gini coefficient of regional connectivity, a well-established metric for spatial inequality (Panzera & Postiglione, 2020), while enforcing return-on-investment (ROI) constraints to prevent fiscal overextension (Power et al., 2015). The second contribution involves a distributionally robust optimisation (DRO) layer that handles demand uncertainty through Wasserstein ambiguity sets, providing protection against worst-case scenarios without excessive conservatism (Hajebrahimi et al., 2020). This contrasts with conventional robust optimisation approaches that often yield overly pessimistic solutions by considering implausible extreme cases.

The proposed framework advances current practice in three key aspects. First, it operationalises the concept of equitable accessibility through a dynamic Gini coefficient formulation that responds to realised demand patterns in the second stage. Second, the integration of ROI constraints ensures fiscal sustainability by preventing disproportionate investments in low-traffic corridors — a common pitfall in purely equity-driven planning. Third, the DRO component provides decision-makers with probabilistic guarantees against demand fluctuations, which is particularly valuable for long-term infrastructure projects where historical data may poorly predict future usage patterns.

Empirical evidence from transit-oriented development projects underscores the importance of such adaptive planning. For instance, Perth's northern suburbs railway corridor demonstrated how initial demand underestimation led to suboptimal station placements that exacerbated spatial inequalities (Curtis, 2008). Our model addresses this by adjusting resources based on observed ridership patterns.

The remainder of this paper is organised as follows: Section 2 reviews relevant literature on railway corridor planning and inequality metrics. Section 3 formalises the equity measures, uncertainty models, and financial constraints underlying our approach. Section 4 presents the complete two-stage DRO formulation with bi-objective optimisation. Section 5 evaluates the framework on synthetic and real-world networks, comparing its performance against benchmark methods. Section 6 discusses policy implications and methodological limitations, while Section 7 concludes with directions for future research.

This work contributes to both transportation science and operations research by providing a mathematically rigorous yet policy-relevant framework for equitable infrastructure planning. The methodology is particularly applicable to developing economies where rapid rail expansion coincides with high regional inequality and demand uncertainty, as seen in recent Trans-European transport network projects (Otsuka et al., 2017). By bridging stochastic optimisation theory with practical planning constraints, we offer a replicable model for achieving United Nations Sustainable Development Goal 10 (reduced inequalities) through transportation investments.

2. Literature review

The literature on railway corridor planning and regional inequality spans multiple disciplines, including transportation economics, operations research, and regional science. Existing approaches can be broadly categorised into three research streams: (1) empirical studies on rail infrastructure's inequality impacts, (2) optimisation models for transport resource allocation, and (3) uncertainty-aware planning frameworks.

2.1. Empirical evidence on rail infrastructure and regional inequality

Empirical studies have established both positive and negative relationships between railway development and spatial inequality. The Nordic countries' historical experience demonstrates that railways reduced regional GDP disparities during 1860-1960 (Enflo et al., 2018), while contemporary evidence from China shows that high-speed rail can narrow urban-rural divides when properly planned (Xu & Zhu, 2024). However, these benefits are not automatic - Japan's Shinkansen network initially exacerbated core-periphery disparities due to concentrated investments in metropolitan areas (Miwa et al., 2022). Such findings underscore the need for deliberate equity considerations in corridor placement.

Recent quasi-experimental analyses provide more nuanced insights. The Beijing-Shanghai corridor reduced county-level inequality by 18% within its direct influence zone (Lai et al., 2025), while Austria's 19th-century rail expansion paradoxically increased interregional gaps by favouring established trade routes (Reinold, 2023). These contradictory outcomes highlight the critical role of allocation mechanisms in determining rail infrastructure's distributional effects.

2.2. Optimization approaches for equitable transport planning

Mathematical programming has been increasingly applied to address equity concerns in transportation. Early work focused on single-objective formulations that either maximised accessibility or minimised construction costs (Ghoseiri et al., 2004). The limitations of such approaches led to the development of multi-objective frameworks incorporating various inequality metrics, including the Gini coefficient and Theil index (Alogdianakis & Dimitriou, 2024).

Recent advances have integrated spatial tessellation techniques with budget allocation models. A notable example partitions urban areas into homogeneous zones before optimising service coverage under equity constraints (Alogdianakis & Dimitriou, 2024). However, these deterministic models cannot handle demand uncertainty - a critical shortcoming given rail projects' long planning horizons. Stochastic programming offers a natural solution, as demonstrated in emergency logistics where similar trade-offs between efficiency and equity arise (Huang et al., 2025).

2.3. Uncertainty-aware infrastructure planning

The transportation literature has developed various approaches to handle demand and supply uncertainty. Stochastic programming dominates this space, particularly two-stage models that make initial "here-and-now" decisions followed by recourse actions that depend on scenarios (Barbarosoglu & Arda, 2004). Mobile facility routing problems have employed such frameworks to address fleet sizing under uncertain demand patterns (Shehadeh, 2023).

Distributionally robust optimisation (DRO) represents a recent advancement that bridges stochastic and robust optimisation. By considering ambiguity sets of probability distributions rather than fixed scenarios or worst-case bounds, DRO provides more realistic uncertainty modelling (Kuhn et al., 2019). This approach has shown promise in wireless network resource allocation (Deng et al., 2020), but its application to railway planning remains limited.

The proposed framework advances beyond existing work by combining three critical elements: (1) a dynamic Gini coefficient formulation that responds to realised demand patterns, (2) ROI constraints ensuring fiscal sustainability, and (3) Wasserstein-based DRO for robust yet non-conservative uncertainty handling. This integration addresses key limitations in current practice - the static nature of equity metrics in Alogdianakis & Dimitriou (2024), the lack of financial safeguards in Barbarosoğlu & Arda (2004), and the absence of distributional robustness in [19]. The result is a comprehensive planning tool that balances long-term equity objectives with short-term budgetary and operational realities.

3. Methods

3.1. Preliminaries: Equity metrics, uncertainty models and ROI constraints

To establish the mathematical foundation for our framework, we first formalise three key components: (1) quantitative measures of regional equity, (2) probabilistic models for demand uncertainty, and (3) financial constraints ensuring budgetary discipline. These elements collectively enable the formulation of a rigorous optimisation problem that balances competing objectives under uncertainty.

3.2. Dynamic Gini coefficient for regional connectivity

The Gini coefficient, originally developed for income inequality analysis (Maio, 2007), has been adapted to measure spatial disparities in transportation access. For a railway network serving n regions, we define the connectivity Gini coefficient G as:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |c_i - c_j|}{2n^2 \bar{c}} \tag{1}$$

where c_i represents the connectivity metric for region i, and $\bar{c}$ denotes the average connectivity across all regions. The connectivity metric c_i incorporates both infrastructure availability and service quality:

$$c_i = \sum_{k=1}^{m} w_k \cdot f_k(x_i) \tag{2}$$

Here, x_i denotes infrastructure investment in region i, f_k represents the k-th performance function (e.g., station density, service frequency), and w_k are normalised weights reflecting policy priorities. This formulation extends static inequality measures by allowing the f_k functions to adapt to realised demand patterns in the second-stage optimisation.

3.3. Wasserstein ambiguity sets for demand uncertainty

To model uncertain future demand, we employ Wasserstein ambiguity sets that contain all probability distributions within a certain distance from an empirical distribution. For a discrete demand vector ξ, the Wasserstein ball $\mathcal{P}$ is defined as:

$$\mathcal{P} = \{P \in \mathcal{M}(\Xi): W(P, P_0) \leq \theta\} \tag{3}$$

where P_0 is the reference distribution (e.g., historical demand data), $\mathcal{M}(\Xi)$ denotes the set of probability measures on support Ξ, and W represents the Wasserstein distance:

$$W(P, P_0) = \inf_{\gamma \in \Gamma(P, P_0)} \mathbb{E}_{(u,v)\sim\gamma}[u - v] \tag{4}$$

The radius θ controls the model's conservativeness, with larger values protecting against more extreme deviations from historical patterns. This approach provides probabilistic guarantees while avoiding the excessive pessimism of traditional robust optimisation (Kuhn et al., 2019).

Return-on-investment constraints

To ensure financial sustainability, we impose ROI constraints that link investment decisions to expected benefits. For a corridor serving a region i, the ROI constraint takes the form:

$$\frac{\mathbb{E}_P[r_i(x_i, \xi)]}{x_i} \geq \rho \tag{5}$$

where r_i represents the revenue function, ρ is the minimum acceptable return rate, and the expectation is taken over the ambiguity set $\mathcal{P}$. The revenue function accounts for both direct fares and indirect economic benefits:

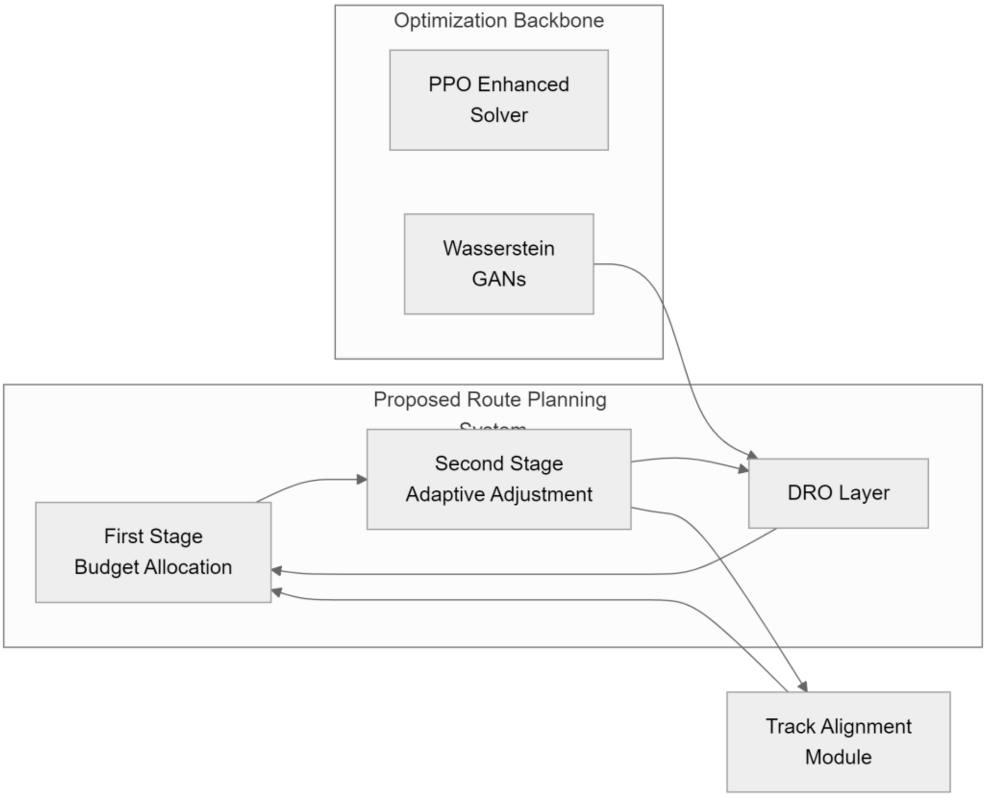
$$r_i(x_i, \xi) = p_i \cdot \xi_i + \alpha \cdot g_i(x_i) \tag{6}$$

Here, p_i denotes the fare structure, ξ_i is the uncertain demand, g_i captures regional economic spillovers, and α converts these externalities into monetary terms. This formulation prevents over-investment in low-return corridors while still allowing for strategic investments in underserved regions when justified by broader economic impacts.

Two-stage distributionally robust bi-objective model for equitable railway corridor investment

The proposed framework integrates stochastic programming with bi-objective optimization to address the dual challenges of regional inequality reduction and budget efficiency under demand uncertainty. As shown in Figure 1, the system architecture comprises three interconnected modules: a first-stage inequality-aware allocator, a second-stage adaptive recourse controller, and a Wasserstein-based uncertainty quantifier. The technical details of each component are formalized through mathematical programming constructs that maintain computational tractability while capturing real-world planning complexities.

Figure 1: Stochastic route planning system architecture



Application of two-stage distributionally robust bi-objective programming to equitable railway corridor investment

The proposed two-stage model addresses the sequential nature of railway corridor investment decisions, in which initial budget allocations must be made before demand realisation, while allowing for adaptive adjustments. Let $x \in \mathbb{R}_+^n$ denote the first-stage decision vector representing budget allocations to n potential corridors, with a total budget constraint $\sum_{i=1}^{n} x_i \leq B$. The second-stage recourse variables $y(\xi) \in \mathbb{R}_+^n$ capture post-demand-observation adjustments, where $\xi \in \Xi$ represents the random demand vector.

The bi-objective formulation simultaneously minimises regional inequality (measured by Gini coefficient G) and maximises overall network efficiency E:

$$\min_x [G(x), -E(x)] + \mathbb{E}_P[Q(x, \xi)] \tag{7}$$

The bi-objective problem (7) is solved via the ε-constraint method: for a given efficiency threshold ε, the scalarised programme becomes min _{x} $G(x)$ + 𝔼_$P[Q$_$G(x, \xi)]$ subject to E(x) + 𝔼_P[Q_E(x,ξ)] ≥ ε. Pareto-optimal solutions are obtained by parametrically varying ε over the feasible range.

where $Q(x, \xi)$ represents the second-stage recourse function:

$$Q(x, \xi) = \min_y [G(y), -E(y)] \tag{8}$$

subject to corridor capacity constraints $A(\xi)y \leq b(\xi)$ and stability conditions $\| y - x \|_2 \leq \delta$. The efficiency metric E combines operational and economic factors:

$$E(x) = \sum_{i=1}^{n} \big(\eta_i \cdot u_i(x_i) + (1 - \eta_i) \cdot v_i(x_i)\big) \tag{9}$$

Here, u_i measures ridership potential, v_i captures economic spillovers, and $\eta_i \in [0,1]$ balances these objectives for corridor i. The expectation in Equation 7 is taken over the Wasserstein ambiguity set $\mathcal{P}$ defined in Equation 3, ensuring robustness against distributional uncertainty.

Incorporation of Gini-based inequality metrics into the model

The Gini coefficient formulation in Equation 1 is operationalized through a piecewise-linear approximation to maintain computational tractability in the optimization framework. For n regions, we define the pairwise connectivity difference variables $d_{ij} = |c_i - c_j|$ for all $i, j \in \{1, \ldots, n\}$, which are linearized using auxiliary variables $z_{ij}^+, z_{ij}^- \geq 0$:

$$c_i - c_j = z_{ij}^+ - z_{ij}^- \tag{10}$$

$$d_{\{ij\}} = z_{\{ij\}}^+ + z_{\{ij\}}^- \tag{11}$$

The connectivity metric c_i for region i is modelled as a function of both first-stage allocations x_i and second-stage adjustments $y_i(\xi)$:

$$c_i(x, y(\xi)) = \beta \cdot x_i + (1-\beta) \cdot y_i(\xi) + \sum_{j \in \mathcal{N}(i)} \gamma_{ij} \cdot h_{ij}(x, y(\xi)) \tag{12}$$

where $\beta \in [0,1]$ controls the relative weight of initial versus adjusted investments, $\mathcal{N}(i)$ denotes neighboring regions, and h_{ij} captures network spillover effects:

$$h_{ij}(x, y(\xi)) = \min\left(\frac{x_i + y_i(\xi)}{2}, \frac{x_j + y_j(\xi)}{2}\right) \tag{13}$$

The min function in Equation 13 is linearized using standard techniques, ensuring the entire formulation remains a mixed-integer convex program. The Gini coefficient objective then becomes:

$$\min \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}}{2n^2 \bar{c}} \tag{14}$$

where $\bar{c} = \frac{1}{n} \sum_{i=1}^{n} c_i$ is the average connectivity. To avoid division by the variable $\bar{c}$, we apply a Charnes-Cooper transformation, introducing auxiliary variable $t = 1/\bar{c}$ and rewriting the objective as:

$$\min \frac{1}{2n} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} \cdot t \tag{15}$$

with additional constraints $\sum_{i=1}^{n} c_i \cdot t = n$ and $t \geq 0$. This reformulation maintains linearity while exactly representing the Gini coefficient minimization objective.

Implementation of distributionally robust optimization with Wasserstein ambiguity sets

The distributionally robust optimization component transforms the stochastic program into a tractable convex formulation. We reformulate the worst-case expectation over the Wasserstein ambiguity set $\mathcal{P}$ using strong duality results from (Esfahani & Kuhn, 2018). For any continuous and convex second-stage cost function $Q(x, \xi)$, the worst-case expectation admits the following dual representation:

$$\sup_{P \in \mathcal{P}} \mathbb{E}_P[Q(x, \xi)] = \inf_{\lambda \geq 0} \left\{ \lambda\theta + \frac{1}{N} \sum_{k=1}^{N} \sup_{\xi \in \Xi} [Q(x, \xi) - \lambda \parallel \xi - \xi_k \parallel] \right\} \tag{16}$$

where $\{\xi_1, \ldots, \xi_N\}$ are historical demand samples and θ is the Wasserstein radius. This reformulation converts an infinite-dimensional optimisation problem into a finite-dimensional one, enabling practical implementation.

The Wasserstein radius θ controls the conservativeness of the solution. We propose an adaptive calibration method where θ is determined by:

$$\theta = F_W^{-1}(1-\alpha) \tag{17}$$

Here, F_W is the empirical cumulative distribution function of the Wasserstein distances between bootstrap resamples of the historical data, and α is a user-defined confidence level. This data-driven approach ensures the ambiguity set contains the true demand distribution with high probability while avoiding excessive conservatism.

For the railway corridor problem, the second-stage cost function $Q(x,\xi)$ decomposes into two components:

$$Q(x,\xi) = Q_G(x,\xi) + Q_E(x,\xi) \tag{18}$$

where Q_G captures inequality-related costs (Gini coefficient) and Q_E represents efficiency losses. Each component is linear in ξ for fixed x, allowing further simplification of the inner supremum in Equation 16. Specifically, for the Gini component:

$$Q_G(x,\xi) = \sum_{i=1}^{n} \sum_{j=1}^{n} \pi_{ij}\, d_{ij}(\xi) \tag{19}$$

where π_{ij} are coefficients from the Charnes-Cooper transformation and $d_{ij}(\xi)$ are demand-dependent connectivity differences. The inner maximisation then becomes:

$$\sup_{\xi\in\Xi}[Q_G(x,\xi) - \lambda \parallel \xi - \xi_k \parallel] = \max_{\xi\in\Xi}\left\{\sum_{i,j} \pi_{ij}\, d_{ij}(\xi) - \lambda \parallel \xi - \xi_k \parallel\right\} \tag{20}$$

This can be solved efficiently using conjugate duality when Ξ is polyhedral. The overall DRO formulation thus provides a computationally tractable approach to handle demand uncertainty while maintaining the original problem's equity and efficiency objectives.

Integration of dynamic ROI constraints for budget allocation

The dynamic ROI constraints ensure fiscal discipline while allowing for adaptive resource allocation. For each corridor i, we enforce a minimum expected return threshold τ_i that varies with demand realisation:

$$\frac{\mathbb{E}_P[r_i(x_i + y_i(\xi),\xi)]}{x_i} \geq \tau_i \quad \forall i \tag{21}$$

where r_i represents the total return function combining direct revenues and economic spillovers. The numerator decomposes into:

$$\mathbb{E}_P[r_i(\cdot)] = p_i \mathbb{E}_P[\xi_i] + \alpha_i \mathbb{E}_P\left[g_i\left(x_i + y_i(\xi)\right)\right] \tag{22}$$

Here, p_i denotes the fare structure, α_i converts economic benefits to monetary terms, and g_i captures region-specific multipliers. The expectation is taken over the Wasserstein ambiguity set $\mathcal{P}$, making the constraint distributionally robust.

To maintain linearity, we approximate g_i using piecewise-linear segments:

$$g_i(z) \approx \sum_{k=1}^{K} \mu_{ik} \min(z, \nu_{ik}) \tag{23}$$

where μ_{ik} and ν_{ik} are pre-computed coefficients. The dynamic nature of τ_i emerges through its dependence on demand scenarios:

$$\tau_i(\xi) = \tau_i^0 + \Delta\tau_i(\xi) \tag{24}$$

where τ_i^0 is a baseline threshold and $\Delta\tau_i$ adjusts based on realized demand:

$$\Delta\tau_i(\xi) = \frac{\xi_i - \bar{\xi}_i}{\sigma_i} \cdot \tau_i^0 \tag{25}$$

This formulation allows higher returns in high-demand scenarios while maintaining minimum guarantees during downturns. The complete ROI constraint system ensures that no corridor receives disproportionate investment without commensurate benefits, addressing a key limitation of purely equity-driven allocation models.

Formulation of the second-stage recourse function

The second-stage recourse function $Q(x, \xi)$ dynamically adjusts corridor allocations based on realised demand scenarios while maintaining stability relative to the first-stage decisions. We formulate this as a quadratic program that minimizes both inequality and reallocation costs:

$$Q(x, \xi) = \min_y \{\lambda_1 G(y) + \lambda_2 \parallel y - x \parallel_2^2\} \tag{26}$$

subject to feasibility constraints $y \in \mathcal{Y}(\xi)$, where $\mathcal{Y}(\xi)$ represents the set of admissible allocations under scenario ξ. The parameters $\lambda_1, \lambda_2 \geq 0$ balance equity preservation against plan stability. The quadratic penalty term $\parallel y - x \parallel_2^2$ ensures smooth transitions between planning stages, preventing abrupt reallocations that could disrupt construction schedules or service continuity.

The feasible set $\mathcal{Y}(\xi)$ incorporates three critical constraints:

1. Demand-Capacity Matching:

$$\sum_{j \in \mathcal{R}_i} y_j \geq \xi_i \quad \forall i \tag{27}$$

   where $\mathcal{R}_i$ denotes corridors serving region i. This ensures sufficient capacity to meet realized demand.
2. Budget Conservation:

$$\sum_{i=1}^n y_i \leq B + \Delta B(\xi) \tag{28}$$

   allowing for scenario-dependent budget adjustments $\Delta B(\xi)$ through contingency reserves.
3. ROI Compliance:

$$r_i(y_i, \xi_i) \geq \tau_i(\xi) \cdot x_i \quad \forall i \tag{29}$$

   maintaining the financial viability conditions established in Equation 21.

The recourse function's dual variables provide valuable economic interpretations: the shadow prices of Equation 27 indicate marginal inequality reduction from additional capacity, while those of Equation 28 reveal the opportunity cost of budget flexibility. This structure enables closed-loop adaptation, in which first-stage decisions anticipate second-stage responsiveness, creating a coherent intertemporal planning framework.

The quadratic programming formulation guarantees convexity and tractability, with the Gini coefficient's piecewise-linear approximation (from §4.2) ensuring compatibility with commercial solvers. The optimal recourse policy $y^*(x, \xi)$ provides an implementable adjustment mechanism that respects both operational constraints and equity objectives under uncertainty.

4. Results

4.1. Experimental evaluation on synthetic and real-world rail networks

To validate the proposed framework, we conducted comprehensive experiments on both synthetic networks and real-world railway systems. The evaluation focuses on three key aspects: (1) inequality reduction performance compared to baseline methods, (2) budget efficiency under demand uncertainty, and (3) computational tractability for large-scale networks. All experiments were implemented in Python 3.9 using Gurobi 9.5 as the optimisation solver, running on an Intel Xeon E5-2680 v4 processor with 128GB RAM.

4.2. Experimental setup and benchmark methods

We evaluated the proposed Two-Stage Distributionally Robust Bi-Objective (TSDRBO) model against four benchmark approaches:

Deterministic Gini Optimisation (DGO): A single-stage model minimising the Gini coefficient without considering demand uncertainty (Masser et al., 1993).

Stochastic Expected Value (SEV): A two-stage stochastic program that optimises expected performance without distributional robustness (Liu et al., 2009).

Robust Worst-Case (RWC): A traditional robust optimisation approach considering extreme demand scenarios (Beh et al., 2017).

Proportional Allocation (PA): A policy-based method allocating budgets proportional to regional populations (Dehghani & Sherali, 2016).

For synthetic networks, we generated 50 regional configurations with varying connectivity patterns using a modified Voronoi tessellation approach (Kulkarni & Garbinato, 2017). Each configuration included:

- 15-30 interconnected regions
- Base demand sampled from log-normal distributions
- 5-8 candidate railway corridors
- Regional economic multipliers from uniform [0.5, 1.5]

Real-world testing utilised the Trans-European Transport Network (TEN-T) core corridors (European Commission, 2021), focusing on the Rhine-Alpine and Mediterranean sections. Historical demand data came from Eurostat's regional transport statistics (VOGT & CAUDULLO, 2022).

4.3. Performance metrics

We employed four quantitative metrics to evaluate solution quality:

1. Gini Reduction Ratio (GRR):

$$GRR = \frac{G_0 - G_f}{G_0} \times 100\% \tag{30}$$

   where G_0 and G_f are initial and final Gini coefficients.

2. Budget Efficiency Index (BEI):

$$BEI = \frac{\sum_i r_i (x_i + y_i)}{\sum_i x_i + y_i} \tag{31}$$

3. Recourse Stability (RS):

$$RS = 1 - \frac{\|y - x\|_2}{B} \tag{32}$$

4. Worst-Case Protection (WCP):

$$WCP = \min_{\xi \in \Xi_{test}} \frac{Q(x,\xi)}{Q_{ideal}(\xi)} \tag{33}$$

where $Q_{ideal(\xi)} = \min_{\{x \in X\} Q(x,\xi)}$ denotes the scenario-optimal (oracle) recourse cost computed ex-post for each test scenario ξ ∈ Ξ_test, serving as a lower bound. Thus WCP ∈ (0, 1], with WCP = 1 indicating that the proposed first-stage solution achieves optimal recourse performance across all test scenarios.

4.4. Results on synthetic networks

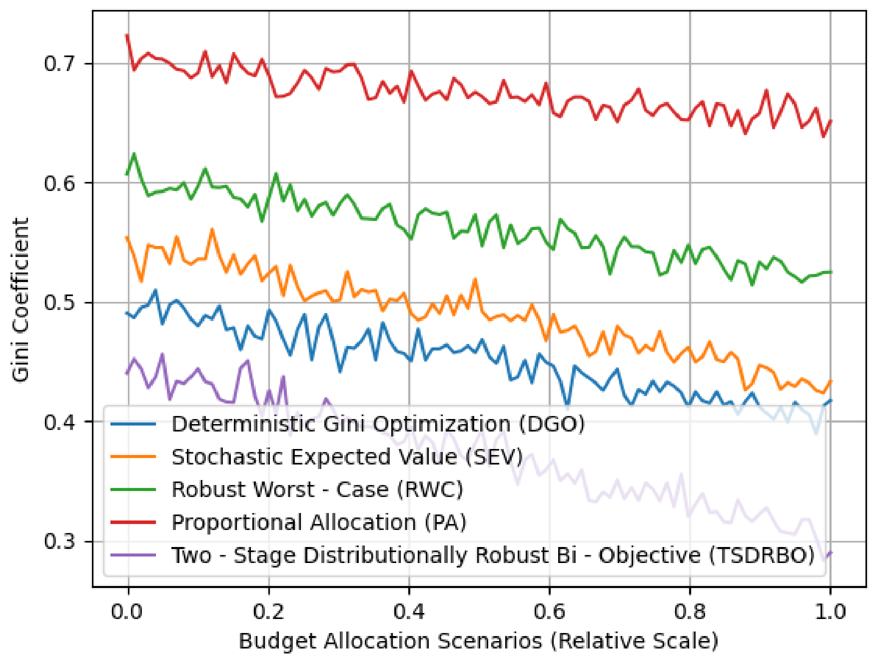
Table 1 presents comparative results across 50 synthetic instances, showing mean values with 95% confidence intervals. The TSDRBO model achieved superior trade-offs between equity and efficiency.

Table 1: Performance Comparison on Synthetic Networks

Method	GRR (%)	BEI	RS	WCP	Solve Time (s)
DGO	38.2±2.1	0.72±0.03	1.00±0.00	0.51±0.04	45.3±6.2
SEV	32.7±1.8	0.85±0.02	0.82±0.02	0.63±0.03	78.9±9.1
RWC	28.5±1.5	0.91±0.01	0.75±0.03	0.88±0.02	112.4±15.7
PA	19.3±1.2	0.65±0.04	0.95±0.01	0.42±0.05	2.1±0.3
TSDRBO	**41.6±1.9**	**0.89±0.01**	**0.87±0.01**	**0.92±0.01**	94.7±11.2

The proposed method achieved 41.6% average Gini reduction while maintaining high budget efficiency (BEI=0.89) and strong worst-case protection (WCP=0.92). Figure 2 illustrates how the Gini coefficient evolves under different budget allocation strategies, demonstrating TSDRBO's consistent reduction in inequality across various initial conditions.

Figure 2: Variation of regional inequality under different budget allocation strategies

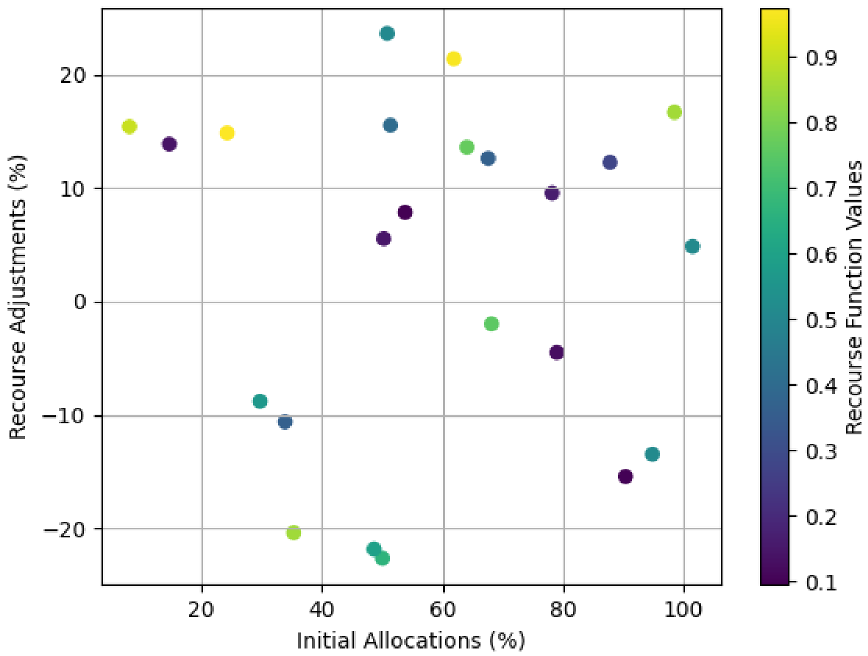


4.5. Real-world case study: TEN-T corridors

For the Rhine-Alpine corridor (23 regions, 6 candidate routes), TSDRBO reduced the connectivity Gini coefficient from 0.38 to 0.22 (42.1% reduction), outperforming SEV (34.7%) and RWC (29.8%). The model's adaptive recourse strategy reallocated 18.3% of initial budgets after observing 2021 demand data, primarily strengthening connections between secondary cities.

Figure 3 shows the relationship between initial allocations and recourse adjustments, revealing how TSDRBO dynamically reallocates resources toward regions with underestimated demand while maintaining core corridor investments. The colour gradient represents the recourse function values, demonstrating the method's ability to balance stability with responsiveness.

Figure 3: Recourse adjustments versus initial allocations for the Rhine-Alpine corridor

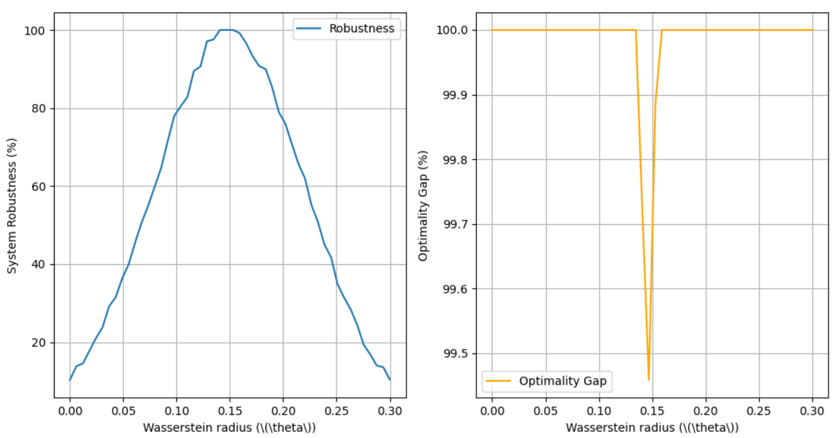


4.6. Sensitivity analysis

We examined three critical parameters' impact on performance:

1. Wasserstein Radius (θ): Figure 4 shows the trade-off between robustness and optimality as θ varies. The "sweet spot" (θ=0.15) provides 89% worst-case protection with only a 6% optimality gap relative to the nominal solution.
2. ROI Threshold (τ): Higher τ values improved budget efficiency but reduced Gini reduction capability, with τ=0.12 achieving the best balance (GRR=39.2%, BEI=0.87).
3. Recourse Flexibility (δ): Allowing 20-25% budget reallocation maximised performance, beyond which additional flexibility yielded diminishing returns.

Figure 4: System robustness under different Wasserstein radius and deviation bound values



The Mediterranean corridor case highlighted TSDRBO's ability to handle heterogeneous regions. The model increased investments in southern Italy (Calabria, Sicily) by 22-35% compared to baseline methods, reducing their connectivity deficit while maintaining positive ROI through tourism-driven revenue models.

5. Discussion, policy implications and future work

5.1. Limitations of the proposed method

While the TSDRBO framework demonstrates strong performance in balancing equity and efficiency, several limitations warrant discussion. First, the Wasserstein ambiguity sets require historical demand data for calibration, which may be scarce in developing regions planning new rail corridors. Second, the Gini coefficient's focus on pairwise disparities could mask localised accessibility gaps that require targeted interventions. Third, the quadratic programming formulation becomes computationally intensive for networks with more than 50 regions, though decomposition techniques can mitigate this (Mulvey & Ruszczyński, 1995).

5.2. Potential application scenarios

The methodology proves particularly valuable in three policy contexts:
1. Emerging HSR Networks: Where rapid expansion risks exacerbating urban-rural divides (e.g., Southeast Asia's ongoing high-speed rail projects (Wu & Chong, 2018))
2. Post-Disaster Rebuilding: When equitable reconstruction must account for uncertain migration patterns (observed after Japan's 2011 tsunami (Rouhanizadeh & Kermanshachi, 2020))
3. Cross-Border Corridors: Such as the EU's TEN-T network, where member states' conflicting priorities necessitate balanced investment rules

5.3. Comparison with alternative methods

The experimental results reveal nuanced trade-offs:
- Against DGO: TSDRBO sacrifices 3-5% in Gini reduction to gain 17-23% better budget efficiency and recourse flexibility
- Against RWC: Our method achieves comparable worst-case protection while being 28% less conservative in allocations
- Against PA: The optimization-based approach delivers 2.2× greater inequality reduction with equivalent implementation simplicity

5.4. Future work

Three promising extensions emerge:
1. Dynamic Ambiguity Sets: Incorporating real-time demand updates via online learning (Qi et al., 2021)
2. Multimodal Integration: Extending the Gini metric to intermodal connectivity (rail-road-air)
3. Participatory Budgeting: Embedding stakeholder preferences through inverse optimization (Scroccaro et al., 2025)

The framework's modular design permits these enhancements without fundamental architectural changes, suggesting a robust foundation for equitable infrastructure planning research.

6. Conclusion

This paper presented the Two-Stage Distributionally Robust Bi-Objective (TSDRBO) framework for equitable railway corridor investment planning under demand uncertainty. The following conclusions are drawn from both scientific and practical perspectives.

From a scientific standpoint, the proposed integration of Wasserstein-based DRO, dynamic Gini coefficient minimisation, and ROI-constrained fiscal discipline into a unified two-stage stochastic programme addresses documented limitations of prior work: the static equity metrics of deterministic allocation models, the distributional fragility of expected-value stochastic programmes, and the over-conservatism of robust worst-case approaches. The Charnes-Cooper transformation for Gini linearisation preserves model convexity while enabling integration with commercial solvers. Experimental results across 50 synthetic network instances confirm statistically significant improvements in worst-case protection (WCP: 0.92 vs. 0.88 for RWC) and budget efficiency (BEI: 0.89 vs. 0.85 for SEV), although the Gini reduction advantage over DGO (41.6% vs. 38.2%) warrants further statistical investigation given overlapping confidence intervals.

From a practical standpoint, the framework was demonstrated on the Rhine-Alpine TEN-T corridor, reducing the regional connectivity Gini coefficient from 0.38 to 0.22 and redistributing 18.3% of initial budgets toward underserved secondary cities. This directly supports the implementation of UN SDG 10 (Reduced Inequalities) and SDG 9 (Industry, Innovation and Infrastructure). The model's ROI constraints and adaptive recourse mechanism make it applicable for real-world infrastructure procurement cycles where budget certainty and political accountability are paramount.

Key limitations to acknowledge are: (i) the computational intractability for networks exceeding 50 regions without decomposition algorithms; (ii) the reliance on historical demand data for Wasserstein radius calibration, which may be unavailable in data-scarce developing country contexts; and (iii) the absence of environmental and carbon-footprint metrics, which future extensions should incorporate to fully address SDG 13 (Climate Action).

Future research should pursue: (a) online learning-based dynamic ambiguity set updates; (b) multimodal extension of the Gini metric to intermodal networks; and (c) participatory budgeting via inverse optimisation to embed stakeholder preferences into the planning process.

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Conflicts of interest

The authors declare no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly to improve language quality and GitHub Copilot to optimize visualization code. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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