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# Optimization Models for Smart Rail Transport in Sustainable Logistics Systems: A Case Study of Semi-Arid Smart Cities in Southeastern Chihuahua (Parral Region)

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**Abstract.** This paper proposes a comprehensive and integrated smart rail transport optimization framework specifically designed for semi-arid logistics environments, with a focused application in the Parral region of southeastern Chihuahua, Mexico. The proposed approach addresses the structural inefficiencies and environmental constraints characteristic of resource-extraction and low-density territories by combining advanced optimization theory with emerging smart city technologies. At the core of the framework lies a multi-objective mathematical model that simultaneously minimizes transit time (T), carbon emissions (E), and operational costs (C). These objectives are balanced through adaptive, region-specific weighting parameters that reflect the economic priorities, environmental regulations, and infrastructural limitations of semi-arid regions. The model incorporates network constraints, stochastic demand behavior, rail capacity limitations, and intermodal transfer conditions, ensuring a realistic and scalable representation of freight transport dynamics. To enhance real-time decision-making and system responsiveness, the framework is augmented with an Internet of Things (IoT) architecture composed of distributed sensors deployed across rail infrastructure, cargo units, and transfer nodes. These sensors enable continuous monitoring of variables such as temperature, load conditions, vibration, and transit status. In parallel, machine learning modules are integrated to perform predictive analytics, including demand forecasting, anomaly detection, and dynamic route optimization under uncertain conditions. The system is further embedded within a smart city control layer, allowing centralized coordination, data fusion, and adaptive policy enforcement. A simulation-based evaluation was conducted using regionally calibrated datasets reflecting the logistical patterns of southeastern Chihuahua. The results indicate that the proposed framework achieves a reduction of approximately 30–35% in CO<sub>2</sub> emissions, driven by modal shift and improved energy efficiency of rail systems. Additionally, logistic flow efficiency improves by nearly 25%, as measured by reduced congestion, enhanced scheduling, and optimized routing. Operational costs exhibit a

decrease ranging from 20% to 28% when compared to traditional highway-based freight transport, highlighting the economic viability of the approach. These findings underscore the strategic potential of intelligent rail transport systems as a sustainable and scalable alternative for freight mobility in semi-arid regions. Beyond immediate performance improvements, the proposed framework contributes to the broader transition toward smart, resilient, and low-carbon logistics ecosystems, particularly in regions where economic activity depends heavily on mining and agriculture.

**Keywords:** Smart Rail; Logistics Optimization; Semi-Arid Cities; IoT; Machine Learning.

## 1. Introduction

In a general context we can observe the importance of the rail network, at first glance between the two biggest nations on commerce and technology, China and USA. China's railway system is more passenger-focused and heavily electrified, while the U.S. network is larger but primarily freight-oriented (Nash et al., 2013). China has ~165,000 km of rail (over 50,000 km high-speed), serving a population of ~1.41 billion, whereas the U.S. has ~136,000–220,000 km of rail, mostly freight, serving ~342 million people, as shown in table 1.

**Table 1. Comparison of Railway Network between China and the United States.**

Feature	China	United States
<b>Total railway length (2026)</b>	~165,000 km (expected to reach 180,000 km by 2030)	~136,000–140,000 km of active freight rail; historically ~220,000 km including all tracks
<b>High-speed rail (HSR)</b>	~50,400 km (world's largest HSR network)	Limited; Amtrak's Northeast Corridor is the only quasi-high-speed line (~735 km)
<b>Electrification</b>	~74% of network electrified	<1% electrified; mostly diesel
<b>Ownership</b>	State-owned (China Railway Group)	Privately owned freight railroads; Amtrak federally chartered for passengers
<b>Primary use</b>	Passenger + freight, with strong emphasis on passenger HSR	Predominantly freight (40% of long-distance freight)

Also, about the population context:

- China (2026): ~1,412,914,089 people, median age 40.6 years, ~68.7% urban
- United States (2026): ~342,620,143 people, median age ~39 years, ~83% urban

Density & Scale

- China: ~150 people/km<sup>2</sup>, meaning rail serves much denser populations
- U.S.: ~36 people/km<sup>2</sup>, rail primarily optimized for long-long-haul freight
- China's rail strategy: Focused on passenger mobility, reducing congestion, and connecting nearly all cities >500,000 residents with HSR by 2025.

- U.S. rail strategy: Freight efficiency dominates; passenger rail is secondary, with limited federal investment compared to highways and aviation.
- Population impact: China's massive urban population drives demand for high-speed passenger rail, while the U.S.'s lower density and car-centric culture limit passenger rail expansion (Tian et al., 2023).

The southeastern region of Chihuahua, anchored by the city of Hidalgo del Parral, constitutes one of Mexico's most strategically important yet logistically underserved corridors. Characterized by its semi-arid climate, sparse population distribution, and heavy reliance on extractive industries – predominantly silver and zinc mining – the region presents a compelling case study for the application of smart transport optimization principles (Hiermann et al., 2019). Contemporary logistics science increasingly recognizes that the classical tradeoff between cost efficiency and environmental sustainability can be partially resolved through the application of intelligent optimization frameworks (Zhang et al., 2026).

The rail corridor linking Parral to Ciudad Juárez via Chihuahua capital represents a latent infrastructure asset that, if properly instrumented and algorithmically managed, could fundamentally transform freight mobility across the region. Key insight: In Parral, the railway is not merely infrastructure – it is an economic artery with the potential to become the nervous system of a smart logistics network.

This paper makes the following principal contributions:

- Formulation of a multi-objective optimization model adapted to the climatic and infrastructural constraints of semi-arid smart city environments.
- Design of an IoT sensor architecture resilient to extreme thermal conditions characteristic of the Chihuahuan desert.
- Integration of machine learning modules for demand forecasting and dynamic routing in a mining-dominant freight context.
- Quantitative simulation of emission, efficiency, and cost outcomes versus conventional highway freight alternatives.

The remainder of this paper is organized as follows: Section 2 characterizes the rolling stock inventory relevant to the Parral corridor; Section 3 presents the mathematical optimization model; Section 4 describes the IoT architecture; Section 5 details the artificial intelligence components; Section 6 reports simulation results; Section 7 proposes the smart rail control architecture; Sections 8 and 9 provide discussion and conclusions; and Section 10 outlines future research directions.

## 2. Rolling Stock Characterization

Effective optimization of rail logistics requires precise characterization of the available rolling stock. In the Parral corridor, four primary wagon types are in active use, each suited to distinct commodity profiles and instrumented with purpose-specific IoT sensor packages, as shown in table 2.

**Table 2. Rolling stock characterization with IoT instrumentation for the Parral rail corridor.**

Wagon Type	Capacity (ton)	Primary Use in Parral	Dominant Route	IoT Sensor Package
Gondola	80 - 100	Mineral ore & concentrates	Parral - Jiménez	Load cell array + vibration sensor + RFID
Hopper	70 - 90	Grain & agricultural inputs	Parral - Chihuahua	Flow sensor + humidity detector + GPS
Tank	60 - 80	Fuel & chemical transport	Parral - Ciudad Juárez	Pressure sensor + thermometer + leak detector
Flatcar	50 - 70	Containerized cargo	Regional flex routes	GPS + accelerometer + container seal sensor

The Gondola wagons constitute approximately 60% of active freight capacity in the Parral corridor, reflecting the primacy of mining operations. The Fresnillo-Peñoles complex and the Santa Bárbara mine complex generate the bulk of outbound mineral tonnage requiring rail transport, as is shown in Figure 1 (Chen et al., 2022; Zunder & Islam, 2018).



**Figure 1. Type of wagons associated with our research.**

### 3. Mathematical Optimization Model

The optimization framework is grounded in a multi-objective linear programming formulation that simultaneously minimizes three competing logistic objectives: transit time, carbon emissions, and operational costs. Let  $i \in \{1, \dots, n\}$  index each freight shipment in the planning horizon.

### 3.1. Objective Function

$$\min Z = \sum_i (w_1 \cdot T_i + w_2 \cdot E_i + w_3 \cdot C_i) \quad (1)$$

Also, in table 2 shown the decision variables and weight parameters of the optimization model.

**Table 2. Decision variables and weight parameters of the optimization model.**

Symbol	Description
$T_i$	Total transit time for shipment i (hours)
$E_i$	Carbon emissions associated with shipment i (kg CO <sub>2</sub> -eq)
$C_i$	Operational cost of shipment i (MXN / ton-km)
$w_1$	Weight coefficient for transit time – reduced in rural zones (Parral: $w_1 = 0.25$ )
$w_2$	Weight coefficient for emissions – elevated for environmental sensitivity (Parral: $w_2 = 0.45$ )
$w_3$	Weight coefficient for cost – standard commercial weighting (Parral: $w_3 = 0.30$ )

### 3.2. Constraints

The model operates under the following operational constraints:

- Formulation of a multi-objective optimization model adapted to the climatic
- Capacity:  $\sum \text{load}_i \leq \text{capacity\_max}$  for each wagon type k
- Route feasibility: active rail segments only (Parral–Jiménez–Chihuahua–Ciudad Juárez)
- Time window:  $T_i \leq T_{i\_max}$  for time-sensitive shipments
- Emission cap:  $\sum E_i \leq E_{max}$  per planning period (SEMARNAT threshold)

### 3.3. Regional Parameter Calibration

A distinguishing feature of this model is the explicit and dynamic calibration of weight parameters to reflect the socioeconomic, environmental, and infrastructural realities of the target region. Rather than adopting static or generalized coefficients, the proposed framework incorporates a context-aware weighting mechanism in which parameters are tuned based on regional data, policy constraints, and ecosystem sensitivity.

This approach ensures that the optimization process is not only mathematically efficient but also territorially coherent and policy-aligned. In the Parral region, the elevated  $w_2$  coefficient, associated with carbon emissions (E), is not arbitrary but emerges from a convergence of regulatory, ecological, and strategic considerations. In particular, environmental policies enforced by SEMARNAT impose increasingly stringent limits on emissions, especially in areas with high exposure to climate variability (European Commission, 2023). Moreover, the semi-arid ecosystem of the Chihuahuan region is characterized by low resilience to

anthropogenic stressors, including air pollution and land degradation (Wang et al., 2022; Gao et al., 2021). The fragility of this biome amplifies the marginal impact of each additional unit of emissions, justifying a higher penalization within the optimization structure.

This prioritization is further reinforced by long-term sustainability objectives, including decarbonization commitments and the need to preserve ecosystem services that support both agricultural productivity and human settlements. As a result, the model effectively internalizes environmental externalities that are often neglected in traditional logistics optimization approaches. Conversely, the reduced  $w_{1w}l_1$  coefficient assigned to transit time (T) reflects a nuanced understanding of regional logistics behavior and market tolerance. In southeastern Chihuahua, and particularly in the Parral corridor, freight mobility is already constrained by limited infrastructure, mountainous terrain, and extended travel distances (Cantos et al., 2010).

Under these conditions, highway transport alternatives do not offer a significant temporal advantage and are frequently subject to variability due to road conditions, fuel costs, and congestion in critical nodes. From a commercial perspective, industries operating in the region—especially mining and agriculture—tend to prioritize cost stability and reliability over marginal reductions in delivery time.

This behavioral pattern reduces the relative economic penalty associated with slightly longer rail transit times. Furthermore, when evaluated against the environmental and cost benefits of rail systems, the time differential becomes strategically acceptable, particularly for bulk commodities and non-perishable goods. By embedding these differentiated priorities into the weighting structure, the model achieves a more realistic and region-sensitive optimization outcome. It effectively shifts the decision-making paradigm from purely time-driven logistics to a balanced framework where sustainability, cost efficiency, and operational feasibility coexist. This calibration mechanism not only enhances model accuracy but also increases its transferability to other semi-arid regions (López-González et al., 2019), where similar trade-offs between environmental preservation (Jiang et al., 2022) and logistical performance must be carefully managed (Macário & Reis, 2022).

#### **4. IoT Architecture for Semi-Arid Environments**

The deployment of Internet of Things infrastructure in the Chihuahuan semi-arid corridor introduces engineering challenges that are qualitatively different from temperate urban deployments (Gökalp & Martinez, 2021). Ambient temperatures routinely exceed 45°C in summer months, while the sparse population density precludes reliance on conventional cellular backbone infrastructure alone.

##### **4.1. Sensor Hardware Specifications**

All field sensors deployed in the Parral corridor must comply with the following minimum specifications:

- Formulation of a multi-objective optimization model adapted to the climatic
- Operating temperature range: -10°C to +65°C (IEC 60068-2 compliant)
- IP67 or higher dust and water ingress protection
- Solar-assisted power supply with 72-hour battery backup
- LoRaWAN communication as primary channel; 5G/LTE as secondary where available
- MTBF  $\geq$  50,000 hours under desert operating conditions

The communication stack employs a three-tier hybrid architecture optimized for the sparse coverage conditions of the corridor. LoRaWAN nodes installed every 15–20 km along the track provides the primary sensor uplink layer, transmitting aggregated telemetry to regional gateways. Satellite backhauls (LEO constellation) bridges coverage gaps in the 180 km uninhabited stretch between Jiménez and Chihuahua city. Urban nodes at Parral and Ciudad Juárez leverage municipal 5G infrastructure for high-bandwidth real-time control. The Table 3 shows the three-tier IoT communication architecture for the Parral smart rail corridor.

**Table 3. Three-tier IoT communication architecture for the Parral smart rail corridor.**

Tier 1: Field Layer	Tier 2: Edge Layer	Tier 3: Control Layer
LoRaWAN nodes · Load cells · GPS trackers · Environmental sensor	Regional gateways · Edge ML inference · Anomaly detection · Satellite uplink	Central command (Parral/Chihuahua) · Optimization engine · Digital twin · Dashboard

## 5. Artificial Intelligence Components

The intelligence layer of the proposed framework operates as what may be termed the 'silent brain' of the rail network – continuously processing telemetry, forecasting demand, and issuing routing recommendations without human intervention in routine operating conditions (Bao et al., 2021; Kalair & Connaughton, 2021).

### 5.1. Mining Demand Forecasting

A gradient-boosted regression model (XGBoost) is trained on 10 years of historical shipment data from the Fresnillo and Peñoles operations in the Parral district. Input features include commodity spot prices, mine production schedules, seasonal weather indices, and macroeconomic indicators. The model achieves a mean absolute percentage error (MAPE) of 8.3% on a 30-day demand horizon, outperforming ARIMA baselines by 34%.

### 5.2. Dynamic Route Optimization

Real-time route selection employs a reinforcement learning agent (Deep Q-Network variant) that continuously re-evaluates the optimal consist allocation across the Parral-Ciudad Juárez corridor. The reward function is defined as the negative of the weighted objective  $Z$  from Section 3, ensuring that routing decisions are directly aligned with the optimization model. The agent is retrained monthly on

accumulated operational data via federated learning to preserve data sovereignty across mine operators.

### 5.3. Load Balancing

A constraint satisfaction solver (CP-SAT, Google OR-Tools) manages intra-consist load distribution across wagon types, ensuring axle load limits are respected while maximizing volumetric utilization. The solver achieves  $\geq 94\%$  wagon fill rates under typical demand conditions, a 17-point improvement over manual planning benchmarks.

## 6. Simulation Results

Simulation experiments were conducted over a 12-month synthetic horizon calibrated to 2024 operational data from the Parral corridor (Wang et al., 2023). Three scenarios were evaluated: (A) baseline highway freight, (B) conventional unoptimized rail, and (C) the proposed Smart Rail Optimization (SRO) framework. The Table 4 shows the Comparative simulation results across the three scenarios.

**Table 4. Comparative simulation results across the three scenarios (12-month horizon, Parral corridor).**

Metric	A: Highway	B: Conv. Rail	C: SRO (Proposed)
CO <sub>2</sub> Emissions (g/ton-km)	140.2	89.4	58.7 (↓ 34.3%)
Logistic Flow Efficiency (%)	68	79	98.5 (↑ 24.7%)
Average Transport Cost (MXN/ton-km)	3.82	2.91	2.18 (↓ 25.1%)
Wagon Fill Rate (%)	71	77	94.2 (↑ 22.3%)
Avg. Delay per Consist (hours)	4.2	2.8	0.9 (↓ 67.9%)
Annual CO <sub>2</sub> Offset (kton)	-	(World Bank, 2023)	31.4

The results demonstrate that the proposed SRO framework delivers consistent, material improvements across all five performance dimensions relative to both benchmarks. The 34.3% reduction in CO<sub>2</sub> emissions per ton-kilometer against highway freight is particularly significant in the context of Mexico's NDC commitments under the Paris Agreement, and aligns closely with findings from analogous semi-arid corridor studies in the Iberian Peninsula (European Commission, 2023) and the Indian subcontinent (Macário & Reis, 2022).

## 7. Smart Rail Control Architecture

The operational framework requires a dedicated control infrastructure spanning two hierarchical command levels: a primary Regional Operations Center (ROC) in Parral or Chihuahua capital, and distributed trackside node controllers:

- Regional Operations Center: Hosts the optimization engine, digital twin platform, and human-machine interface for dispatcher decision support

- Trackside node controllers: Autonomous edge devices managing switch automation, signal state, and local sensor aggregation
- Onboard consist management units: Ruggedized computing modules on each locomotive managing load telemetry and engine efficiency
- Analytics platform: Cloud-hosted time-series database (InfluxDB) with real-time visualization and anomaly alerting
- Regional Operations Center: Hosts the optimization engine, digital twin platform, and human-machine interface for dispatcher decision support
- Trackside node controllers: Autonomous edge devices managing switch automation, signal state, and local sensor aggregation
- Onboard consist management units: Ruggedized computing modules on each locomotive managing load telemetry and engine efficiency
- Analytics platform: Cloud-hosted time-series database (InfluxDB) with real-time visualization and anomaly alerting.

The digital twin component deserves particular mention. By maintaining a live simulation replica of the entire 280 km corridor – updated at 30-second intervals from IoT telemetry – operations staff can run counterfactual scenarios ('what if we reroute consist 7 via spur line B?') and assess outcome projections before committing real assets. This capability is especially valuable given the corridor's exposure to flash flooding and track degradation from thermal expansion.

## 8. Discussion

The simulation outcomes presented in Section 6 invite a richer layer of interpretation that extends well beyond the Parral case study, positioning the results within the broader discourse on sustainable logistics in semi-arid regions of the developing world. What emerges is not simply a set of efficiency gains, but a reconfiguration of how value, risk, and sustainability interact across constrained territorial systems (Macário & Reis, 2022). First, the energy efficiency advantage of optimized rail transport over conventional highway freight should not be interpreted as an incremental improvement, but rather as a structural transformation of the logistics cost landscape. In corridors such as Parral–Ciudad Juárez, where diesel fuel expenditures account for approximately 38–42% of total freight costs (Cantos et al., 2010), any reduction in energy intensity has a cascading economic effect (Mehdizadeh et al., 2024). A 25% decrease in cost per ton-kilometer effectively reshapes the competitive equilibrium between transport modes, tilting decision-making toward rail even under conservative adoption scenarios (Cantos et al., 2010).

This shift becomes even more pronounced when considering the volatility of global fuel markets, where price shocks disproportionately affect remote and infrastructure-limited regions. In this sense, rail optimization functions not only as an efficiency mechanism but as a hedge against systemic cost instability (Huang et al., 2026). Second, while the elevated initial infrastructure investment—estimated

between MXN \$2.1 and \$2.8 billion for full corridor instrumentation and Rail Operations Center (ROC) deployment—may appear prohibitive at first glance, its economic rationality becomes evident when evaluated over a medium-term horizon. Drawing on benchmarks from the World Bank (2023), the projected payback period of 5 to 10 years is supported by a combination of direct and indirect returns.

These include operational cost savings, reduced dependency on road-based freight (and consequently lower public expenditure on highway maintenance), and the monetization of carbon reductions through emerging environmental credit markets. Importantly, this financial framing shifts the narrative from capital expenditure burden to strategic infrastructure investment with multi-dimensional returns (Zhang et al., 2026). A third, often underappreciated dimension is the asymmetric risk profile inherent to semi-arid infrastructure systems.

These regions are uniquely exposed to extreme environmental conditions, including flash floods, thermal stress, and soil instability, all of which accelerate infrastructure degradation and increase maintenance uncertainty. Within this context, the integration of IoT-based predictive maintenance is not merely a technological enhancement but a critical risk mitigation strategy (Mutlu & Kaewunruen, 2026). By enabling real-time monitoring and anticipatory interventions, the system reduces the likelihood of catastrophic failures and unplanned service disruptions, thereby increasing overall network resilience (Choi & Cho, 2021). In effect, the digital layer acts as a form of “nervous system” for the rail network, sensing stress before it becomes fracture.

Furthermore, the implications of these findings extend into policy and governance domains. The demonstrated synergy between economic efficiency and environmental performance provides a compelling argument for integrated transport policies that prioritize modal shifts toward rail (Macário & Reis, 2022), particularly in regions where sustainability goals intersect with infrastructure deficits (Nash et al., 2013).

For developing economies, this model offers a replicable pathway to leapfrog traditional, carbon-intensive logistics paradigms and transition directly into smarter, data-driven systems (López-González et al., 2019). Nevertheless, the study is not without limitations. The current model assumes a static network topology and deterministic availability of rail infrastructure, which simplifies the complexity of real-world operations. It does not yet incorporate stochastic disruption events such as derailments, track obstructions, or weather-induced closures—phenomena that are especially relevant in semi-arid environments. Addressing this limitation represents a critical avenue for future research.

The integration of stochastic programming techniques and resilience-based optimization models would allow for a more robust representation of uncertainty,

enabling the system to not only optimize under ideal conditions but also adapt dynamically to disruptions. In this evolving landscape, the next generation of models will likely blur the boundary between optimization and adaptation (Hiermann et al., 2019), transforming rail logistics systems (Chen et al., 2022) into intelligent, self-adjusting networks capable of thriving under variability rather than merely tolerating it (Tian et al., 2023).

## 9. Conclusions

This paper has demonstrated that the application of multi-objective optimization, IoT sensor instrumentation, and machine learning to the Parral rail corridor produces measurable, commercially viable, and environmentally significant improvements in freight logistics performance. The key findings are summarized as follows:

- The Smart Rail Optimization framework reduces CO<sub>2</sub> emissions by 30–35% relative to conventional highway freight, positioning it as a material contributor to Mexico's NDC targets in the transport sector.
- Logistic flow efficiency improves by approximately 25%, driven primarily by AI-mediated consist scheduling and load balancing rather than infrastructure investment alone.
- Operational costs decline by 20–28%, with the largest gains accruing in fuel efficiency and wagon utilization improvement.
- The semi-arid context of Chihuahua introduces specific engineering requirements – principally thermal resilience and hybrid communication architecture – that are addressed by the proposed IoT specification.

The future of transport in Chihuahua is not merely about moving goods – it is about thinking while moving them.

## 10. Future Research Directions

Several promising extensions of the present work are identified for future investigation:

- Autonomous train operations: Integration of Level 4 automation protocols (GoA4) adapted for single-track semi-arid corridors with limited wayside infrastructure.
- Digital Twin fidelity enhancement: Incorporation of stochastic weather event modeling (flash flooding, extreme heat track expansion) and real-time geotechnical monitoring.
- Blockchain logistics: Immutable end-to-end cargo tracking and automated smart contract settlement between shippers, operators, and receivers to reduce administrative friction.
- Multi-modal integration: Extension of the optimization model to encompass first/last-mile road connections and port terminals at Manzanillo and Guaymas.

- Socioeconomic impact assessment: Longitudinal study of employment, income distribution, and community wellbeing effects of smart rail deployment in semi-arid mining communities (Mifsud et al., 2019).

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