A Digital Data Architecture and KPI-Driven Decision Support System for Heavy-Haul Railway Freight: Strategic Implications for Uzbekistan

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Abstract: Railway freight systems are increasingly required to improve performance under conditions of growing demand and limited infrastructure expansion. In this context, railway operators face a practical managerial challenge: whether to increase capacity by expanding the wagon fleet or by optimizing existing assets. This paper addresses this issue through a KPI-based business analytics framework integrated into a multi-layered digital data architecture. The study develops a rule-based Decision Support System (DSS) designed to transform raw technical parameters into strategic results. The research utilizes a digital analytical engine to process wagon specifications and real-time infrastructure data, programmatically enforcing safety filters for dynamic interaction between rolling stock and track [1]. The results demonstrate that systems prioritizing higher axle loads - measured in ton-force per axle (tf) - achieve superior asset utilization and long-term performance compared to simple fleet expansion, which often leads to marginal gains and higher costs. The findings conclude that axle load optimization (25-27 tf) supported by a digital DSS, is the most sustainable strategy for capacity growth. The practical significance lies in providing a data-driven roadmap for managerial decision-making and the digital transformation of the railway sector in Uzbekistan.

1 INTRODUCTION

Central Asia lies at the heart of the ancient Silk Road routes, where unlocking the potential of railway transport is vital for regional economic development and removing logistical bottlenecks. A critical factor in railway efficiency is the load-carrying capacity of freight wagons, determined by permissible axle load. Many leading railway systems have adopted heavy-duty rolling stock strategies to reduce unit transportation costs and improve the utilization of infrastructure and assets [1].

Effective heavy-haul development requires a systematic approach, integrating improvements in track structure, train control, and monitoring technologies. Heavy-haul development also requires particular attention to railway track infrastructure because increasing axle loads directly affect infrastructure requirements and operational constraints [2]. While these systems are well-studied from an engineering perspective, modern decision-making requires an integrated evaluation of their operational and economic impacts through measurable performance indicators [3].

Accordingly, this study adopts a KPI-based business analytics approach combined with a Digital Data Architecture and a Decision Support System (DSS) framework. A system of key performance indicators-including freight density, wagon productivity, and infrastructure capacity utilization-is integrated into an analytical modeling environment to examine the relationship between axle load policies and railway performance. Building on previous research, this paper aims to develop a comprehensive digital framework to support strategic decision-making and identify practical implications for improving railway freight transport in Uzbekistan.

The framework facilitates the transition from manual statistical evaluation to an automated digital analytical engine capable of processing heterogeneous data streams. A multi-layered data architecture enables the programmatic enforcement of safety constraints and real-time monitoring of rolling stock-track interaction [4], [5]. The digital environment serves as an intelligent platform for precision simulation modeling and verification of various development scenarios.

2 RESEARCH DESIGN AND METHODOLOGY

The purpose of this study is to evaluate heavy-haul freight operations through a KPI-based business analytics lens, specifically focusing on the optimization of rolling stock and its impact on operational efficiency. The research assesses the correlation between increased axle load and key performance indicators within a digitized decision-making framework.

The study integrates analytical and comparative methods to ensure a robust evaluation. Laboratory observation was employed to systematize international datasets, providing a unified basis for benchmarking Uzbekistan's railway performance. Furthermore, abstract-logical analysis was applied to identify cause-and-effect relationships between axle load policies and operational throughput. Specifically, laboratory observation consisted of systematically compiling and cross-checking published axle load, freight density, and infrastructure parameters (Table 2) for the eight benchmark railway systems from national statistical and industry sources; abstract-logical analysis was then applied to these compiled indicators to derive the KPI relationships and DSS decision rules.

These methods form an integrated business analytics framework, where KPI-driven evaluation is synthesized with rule-based decision logic. The use of structured decision-support and multi-criteria frameworks has also been demonstrated in railway infrastructure planning applications [6]. By transforming technical parameters into measurable economic outcomes, this framework provides the methodological foundation for the Digital Data Architecture and strategic management in railway freight transport.

2.1 KPI Framework for Business Analytics Evaluation

A structured system of Key Business Performance Indicators (KPIs) forms the core analytical layer of this study. These metrics do more than just describe operations; they serve as digital variables that feed directly into the Analytical Modeling Framework. By converting technical rail parameters into managerially significant data, the system maintains analytical consistency across different networks and operating conditions [7].

In this architecture, KPIs function as the primary decision variables for the rule-based Decision Support System (DSS). For instance, freight density tracks the intensity of infrastructure utilization, while wagon productivity and train mass utilization reveal how efficiently assets perform under network constraints. Table 1 defines these indicators as specific data inputs for the automated decision logic.

Table 1: Data specification for the analytical modeling framework.

KPI	Business / DSS Interpretation
Axle load	Core strategic parameter determining freight capacity and heavy-haul potential
Railway length	Base indicator for normalization and international comparison
Gross freight turnover	Reflects overall transport output and market scale
Freight density	Measures intensity of infrastructure utilization
Average train mass	Indicates efficiency of train formation and axle load utilization
Number of wagons per train	Reflects operational strategy (long/heavy trains vs. fleet expansion)
Wagon productivity	Measures efficiency of rolling stock utilization
Train mass utilization	Indicates effectiveness of asset use under infrastructure constraints
Infrastructure capacity utilization	Shows ability to increase volumes without network expansion
Normative operational speed	Key operational constraint in DSS decision logic
Dynamic linear track load	Primary safety constraint governing axle load feasibility
Wagon load utilization coefficient	Indicates whether axle load increase produces real efficiency gains

This data structure transforms infrastructure management from passive reporting to proactive modeling. By treating axle load and dynamic impact as binding constraints, the model defines safety thresholds as wagon capacity increases and enables simulation of future operational scenarios, including the transition from 23.5 tf to 25-27 tf. Thus, technical parameters become transparent instruments for substantiating heavy-haul investment decisions in Uzbekistan's railway network [8].

3 BUSINESS ANALYTICS APPROACH

The research applies a comparative KPI-based framework integrated into a digital decision-support environment. This approach consists of the following computational components:

1) International benchmarking: comparative analysis of heavy-haul systems to quantify the impact of different axle load regimes.
2) KPI sensitivity analysis: Assessment of infrastructure utilization and train mass optimization using freight density and axle load as key output variables.
3) DSS evaluation: Scenario-based modeling of increased wagon capacity subject to dynamic track impact and investment feasibility.
4) Data grouping and normalization: Algorithmic classification of railway systems by axle load level to ensure comparability of datasets.

3.1 International Comparison of Heavy Haul Railway Systems

An international comparison of heavy-haul railway systems was conducted using a KPI-based business analytics approach to assess the impact of axle load on freight efficiency.

A key metric in this analysis is the average freight density, which was calculated using the following formula:

$$\bar{f} = \frac{\sum Pl_{year}}{L_{exp}}, \tag{1}$$

where: $\sum Pl_{year}$-annual freight turnover on a given railway section (million t-km), and L_{exp} represents the operational length of the railway section [3].

International experience demonstrates that axle load is not merely a technical parameter but a controllable managerial variable within DSS.

The cross-country dataset includes railway length, gross freight turnover, average train mass, number of wagons per train, and calculated freight density indicators (Table 2).

In countries such as Australia, Brazil, Canada, and the USA, axle loads reach 30-40 tf, whereas in Russia, China, and India, they remain at approximately 25 tf. Empirical evidence shows that even a moderate increase to 25 tf leads to a significant rise in operational efficiency and freight density. These values are used to calibrate the predictive modules of the Analytical Modeling Framework for Uzbekistan's specific infrastructure [8], [9].

3.2 Key DSS Indicator: Permissible Dynamic Linear Track Load

According to the permissible track impact standards, direct limitations on wheel-rail contact forces are not explicitly defined. Instead, the standard regulates the maximum allowable dynamic linear load transmitted from a group of axles of a single bogie to the railway track. This indicator serves as a key constraint within the proposed Decision Support System (DSS) and is expressed as:

$$q = \frac{nP_0(1+K_{do})}{l+2{,}2} \le [g_{din}], \tag{2}$$

where:

- n - number of axles in the group;
- P_0 - vertical static load transmitted from wheelsets to the rails; K_{do} - dynamic coefficient, defined as the ratio of the dynamic component of oscillations to the static load (determined based on experimental and analytical studies); Typical values of Kdo, obtained from field dynamometer measurements, range from approximately 0.15-0.25 for standard freight wagons (axle load up to 23.5 tf) to 0.20-0.35 for heavy-haul wagons with axle loads of 25-27 tf, depending on suspension design, speed, and track condition. l - bogie wheelbase;
- [g_{din}] - permissible dynamic linear load on the track, equal to 168 kN/m [10], [11].

The inequality indicates that, when increasing axle load, compliance with the permissible dynamic linear load can be ensured through two alternative mechanisms: reducing the dynamic coefficient K_{do} or increasing the bogie wheelbase l.

Based on this condition, the admissible range of the dynamic coefficient for wagons with increased axle load can be defined as:

$$K_{do} \le \frac{[g_{din}](l+2{,}2)}{nP_0} - 1. \tag{3}$$

Similarly, the requirement for the bogie wheelbase is formulated as:

$$l \le \frac{nP_0(1+K_{do})}{[g_{din}]} - 2{,}2. \tag{4}$$

These inequalities define design requirements for wagons with increased axle loads, including suspension stiffness and optimal bogie wheelbase. Since the dynamic coefficient and axle load are inversely related, higher dynamic coefficients limit axle load growth; for 25 t it must remain within 0.3-0.4, and for 27 t within 0.2-0.3.

Table 2: International dataset for KPI-based business analytics.

Country	Axle load (tf per axle)	Railway length (km)	Annual freight turnover (million t-km)	Average train mass (thousand tons)	Number of wagons per train	Average freight density (tons per km)
Australia	40	33 000	448 000	34	236	3719,4
Brazil	32,5	30 000	400 000	25,5	206	3653,0
Canada	32,5	49 000	450 000	13,2	110	2516,1
China	25	155 000	3 580 000	20	200	6327,9
India	25	68 000	1 100 000	5,06	58	4431,9
Russia	25	85 500	2 600 000	6,3	70	8331,3
USA	32,5	220 000	2 800 000	16,46	120	3486,9
Sweden	30	14 000	21 950	8,52	68	1,567.9
South Africa	30	20 000	300	41	342	15,000
Uzbekistan	23,5	7 400	28	3	60	3,783.8

Equation (3) expresses the upper bound on the dynamic coefficient Kdo for a given bogie wheelbase l, while (4), obtained by algebraically rearranging (2) for l, expresses the equivalent lower bound on the bogie wheelbase for a given Kdo; the two inequalities are therefore two representations of the same permissible-load constraint and either may be used depending on which design parameter (Kdo or l) is being solved for. These recommended ranges of Kdo apply under normative operating conditions, i.e., train speeds up to 80-90 km/h on track in satisfactory (class 1-2) condition with standard rail profile; higher speeds or degraded track condition require re-evaluation using (2)-(4).

Within the DSS framework, the permissible dynamic linear load functions as a key decision indicator, ensuring infrastructure safety while enabling systematic evaluation of enhanced wagon designs.

3.3 A Rule-Based Decision Support System for Evaluating Increased Wagon Axle Loads

The problem of increasing wagon axle load under conditions of limited infrastructure capacity is addressed through the development of a rule-based Decision Support System (DSS). The decision-support algorithm is formulated taking into account the analytical constraints on permissible dynamic linear track load defined by relationships (2) - (4) and is designed to reflect the actual operational, technical, and economic logic of wagon operation with a new technical solution. Computational-intelligence-based decision support systems have demonstrated the value of converting complex technical parameters into structured operational decisions [12]. At the strategic management level, AI-driven decision support can also improve the consistency and transparency of complex business decisions [13].

If speed constraints are satisfied, the algorithm assesses the wagon load utilization coefficient. When the coefficient does not exceed unity, increasing axle load does not lead to growth in net linear load and is therefore considered inefficient. In such cases, the DSS redirects the decision process toward alternative technical solutions, including transition to enlarged wagon dimensions, use of articulated wagons, or modernization of loading and unloading equipment, aimed at increasing freight mass per unit length of train [14], [15].

Subsequently, the DSS evaluates the dynamic interaction between rolling stock and track. The algorithm incorporates design and operational measures for reducing dynamic impact, such as lowering the dynamic coefficient, increasing bogie wheelbase, optimizing suspension parameters, and improving the relative positioning of empty and loaded wagons, as illustrated in Figure 1.

These measures are applied to ensure the resulting dynamic linear load does not exceed the permissible threshold.

If the dynamic linear load remains above the allowable limit, the algorithm evaluates the feasibility and effectiveness of capital-intensive infrastructure measures, including gradual track reinforcement. When such investments are not economically justified, the increased axle load option is rejected due to the expected growth of residual track deformations and maintenance costs. Conversely, if compliance with permissible dynamic load is achieved without excessive capital investments, the algorithm supports the feasibility of the proposed technical solution.

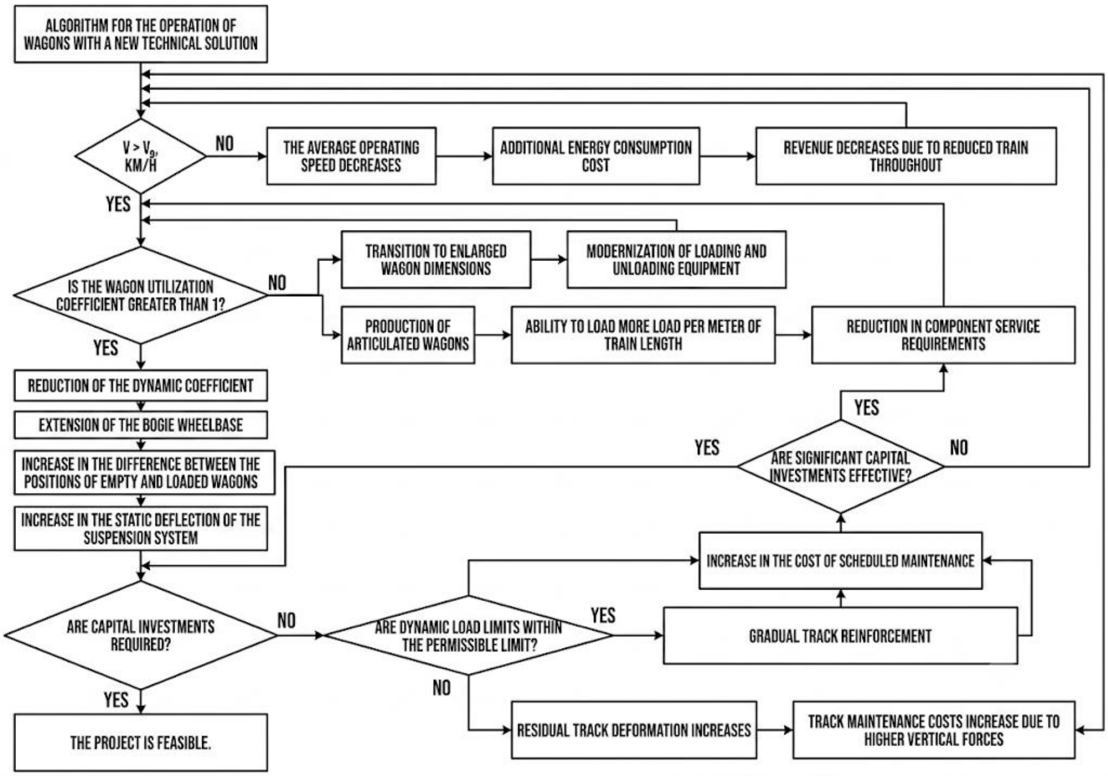

Figure 1: DSS algorithm for heavy-haul wagon operation.

4 RESULTS AND DISCUSSION: DIGITAL ARCHITECTURE AND ANALYTICAL MODELING

The primary result of this research is the development of a unified analytical modeling framework that integrates the KPI-oriented DSS algorithm into a digital decision-making environment. This architecture facilitates a transition from fragmented technical calculations to a cohesive digital ecosystem. Cross-sector studies of digital transformation further demonstrate that integrated data architectures and analytical forecasting models can improve the processing of complex operational indicators and support strategic decision-making [16], [17].

4.1 Multi-layered Digital Data Architecture

The implemented architecture functions as a high-performance analytical engine, processing data through three distinct functional layers:

Data ingestion layer: the system automates the accumulation of parameters from relational SQL databases. A key result is the seamless integration of technical specifications from Table 1 (static loads, net linear load, and bogie base) with real-time infrastructure geometry and track condition data [18].

Processing layer (safety logic): this layer programmatically executes the mathematical safety filters. The central result is the real-time verification of the 168 kN/m dynamic linear load threshold. Using formula (3) as its governing logic, the system automatically flags scenarios where increased axle loads compromise infrastructure integrity.

Analytical layer (KPI Synthesis): at this stage, the framework synthesizes raw technical data into economic metrics. By integrating benchmark values from the international dataset in Table 2, the system outputs precise values for average freight density and asset utilization coefficients across various operational scenarios [18], [19].

4.2 Applied IT Implementation and Visualization Tools

The analytical results of the DSS are operationalized through a specialized technology stack designed for real-time scenario planning:

Simulation modeling (Python/R): the software environment implements the "if-then" rule-based logic of the algorithm. This allows for extensive "what-if" simulations, such as comparing the efficiency of transitioning from 23.5 tf to 25 tf or 27 tf/axle loads.

Business intelligence (BI) results: integration with platforms like Power BI or Tableau enables the visualization of KPI dynamics. The result is an interactive dashboard that allows management to immediately observe how changes in train mass or axle load impact the overall network's return on investment (ROI) [20].

Geospatial results (GIS): geographic information systems are used to map the calculated freight density, providing a visual result that identifies specific track sections where heavy-haul implementation is most viable based on current infrastructure health.

4.3 Strategic Outcomes of the DSS Integration

The integration of techno-economic indicators into the analytical model eliminates the gap between engineering constraints and market efficiency. The system ensures that every proposal for increased axle load is validated against both technical safety - specifically the 168 kN/m dynamic linear load limit and its contribution to the system's overall freight density.

The strategic value of this DSS integration is defined by two key factors. First, the transition from manual calculations to an automated rule-based engine ensures the programmatic enforcement of safety filters, effectively acting as a "digital gatekeeper" for rolling stock deployment. Second, the environment enables high-precision simulation modeling of "what-if" scenarios. This allows management to virtually test the impact of shifting from 23.5 tf to 25-27 tf per axle loads, significantly reducing financial risks and providing a clear digital roadmap for the modernization of Uzbekistan's railway sector. More broadly, transport-system modernization also requires management tools that improve the attractiveness and efficiency of transport services through informed strategic decisions [21].

5 CONCLUSIONS

This study demonstrates that railway freight efficiency is most effectively evaluated through a KPI-based business analytics and DSS-oriented approach rather than through isolated technical indicators. The developed Analytical Modeling Framework confirms that axle load is the key systemic parameter that simultaneously dictates freight density, wagon productivity, and infrastructure capacity utilization. By integrating these metrics into a unified digital architecture, the research facilitates a transition from fragmented engineering calculations to a cohesive digital ecosystem for strategic decision-making [22], [23].

The comparative KPI analysis reveals that higher axle load and train mass lead to substantially better utilization of existing railway assets, whereas fleet expansion without operational changes produces limited improvements and increases long-term costs. The DSS algorithm, by enforcing the 168 kN/m dynamic linear load threshold, provides a necessary safety filter that balances these efficiency gains with infrastructure sustainability. These findings justify axle load optimization (25-27 tf) as a superior development strategy for increasing the throughput capacity of the Uzbekistan railway network [4].

Overall, the integration of KPIs into a rule-based DSS framework provides a robust foundation for strategic management in the context of digital transformation. The proposed model enables an informed, data-driven evaluation of capacity expansion alternatives and prioritizes qualitative infrastructure upgrades. This approach ensures that the transition to heavy-haul operations is not only technically secure but also economically optimized, offering a scalable solution for enhancing railway performance in Uzbekistan and beyond.

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