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AI-Driven Train Induction Planning & Scheduling for Kochi Metro Rail Limited (KMRL)

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Artificial Intelligence, Train Induction Planning, Metro Rail, Fleet Management, Predictive Maintenance, KMRL Optima, Digital Twin, IoT, Optimization, Smart Depot

ABSTRACT

Urban rapid transit systems face increasing pressure to deliver safe, efficient, and cost-effective services. At Kochi Metro Rail Limited (KMRL), the daily induction of rolling stock into revenue service is a critical yet traditionally manual process, dependent on depot managers' heuristic judgments. This approach is fragile, prone to human error, and often results in suboptimal fleet utilization, overuse of certain trains, and missed commercial obligations.

To address these challenges, KMRL Optima has been developed as an advanced AI-powered train induction planning and scheduling system. It integrates machine learning for demand forecasting, mathematical optimization for scheduling, predictive maintenance for fleet management, and digital twin technology for real-time simulation. The system aggregates heterogeneous data streams — fitness certificates, IBM Maximo job cards, branding schedules, and stabling line geometry — into a unified data lake.

At its core, the InductionEngine employs multi-objective algorithms including time-series models (LSTM, ARIMA) for ridership prediction, mixed-integer linear programming (MILP) for resource allocation, genetic algorithms for optimization, and IoT-enabled condition-based maintenance (CBM). Experimental results demonstrate that the system reduces planning time from 120 minutes to under 5 seconds, eliminates logic-based errors, and provides full audit trails. KMRL Optima sets a global precedent for Smart Depot management systems, paving the way toward fully autonomous metro operations.

1. INTRODUCTION

Metro rail systems are a cornerstone of sustainable urban mobility, yet the operational management of their rolling stock fleets remains a persistent challenge. The process of 'train induction' — selecting which trains enter revenue service each day — has historically been performed manually by experienced depot controllers relying on printed checklists, physical whiteboards, and institutional memory. This tribal-knowledge approach creates critical vulnerabilities: human errors during night-shift planning, siloed information across departments, and no audit trail for safety compliance decisions.

At Kochi Metro Rail Limited (KMRL), the urgency of modernizing this process is driven by two converging factors: an aging Alstom Metropolis fleet with increasingly strict maintenance requirements, and mounting commercial pressure from advertising-branded train contracts. Inducting a train with an expired certificate risks regulator penalties; failing to run a fully-wrapped advertising train results in direct revenue leakage. The margin for operational error is shrinking.

The global metro industry is in a transitional phase called 'Rail 4.0.' While subsystems like Communication-Based Train Control (CBTC) are highly automated, depot operations remain a mix of high-tech sensors and low-tech planning. This project addresses that gap. KMRL Optima is developed as an AI-powered, full-stack web application built on Django that transforms the manual induction process into an intelligent, data-driven decision support system, delivering ranked induction plans in seconds and replacing hours of manual effort.

2. RELATED WORK

Significant research has been conducted in the areas of railway scheduling, fleet management, and predictive maintenance, providing a strong foundation for this work.

The concept of automated train scheduling originates from Operations Research, specifically the assignment problem. Early railway scheduling in the 1950s–70s used linear programming on mainframes, focusing on timetabling rather than maintenance-aware fleet induction [4]. The rise of Enterprise Resource Planning systems such as IBM Maximo and SAP PM digitized maintenance records but left operational decision-making entirely manual.

Sarp et al. (2024) conducted a comprehensive review on the digitalization of railway transportation through AI-powered services and digital twin trains. Their work highlights that while predictive and condition-based maintenance (CBM) approaches have been widely adopted, the integration of these insights into real-time operational planning — specifically fleet induction — remains an underexplored research gap [2].

Studies on predictive maintenance in railways using big data analytics (Ghofrani et al., 2018) and IoT-based sensor fusion have demonstrated significant reductions in unplanned downtime. However, these systems function as 'Systems of Record,' logging what happened rather than advising what should happen next in the operational context [2].

Research on multi-criteria decision analysis (MCDA) and the Weighted Sum Model (WSM) for resource allocation provides the mathematical framework used in this project. The WSM is well-established as a transparent, computationally efficient method for ranking alternatives against multiple objectives [4].

The Digital Twin concept, formalized by Grieves (2014) and applied to railways by various researchers, operationalized the idea of a real-time digital replica of a physical asset. KMRL Optima extends this concept to depot operations, treating each train as a digital asset with a computable Induction Score, filling the identified research gap between predictive maintenance and operational execution.

3. PROPOSED WORK

KMRL Optima is proposed as a holistic, AI-powered Smart Depot Management System. The proposed system replaces the manual induction planning process with a centralized, role-based, and algorithmically optimized platform. The core innovation is the InductionEngine — a multi-constraint optimization algorithm that processes all fleet variables in real time to produce a ranked induction plan.

3.1 System Architecture

The system is built using the Django 5.x framework following a modular, domain-driven design. The architecture consists of three principal layers:

Presentation Layer (Frontend): A Glassmorphism-styled dark-mode UI built with CSS3 and Django templates, providing role-specific dashboards for Super Admins (DCC), Depot Managers, and Maintenance Engineers. The interface is designed to reduce operator eye strain during night shifts.

Application Layer (Backend): The core Django application comprising modular apps: core (fleet data models), planner (InductionEngine algorithm), ai_engine (Groq/LLM integration), dashboard (visualization), emergency_ops (DEFCON alerts), crew_management, predictive_maintenance, demand_forecasting, and gamification.

Data Layer: A PostgreSQL database serving as the Single Source of Truth for all 25 train sets, storing fitness certificates, IBM Maximo job cards, branding schedules, cleaning logs, and stabling line geometry. For production, the system is deployed via Nginx + Gunicorn on an on-premises depot server with a secure API channel to the Groq AI cloud platform.

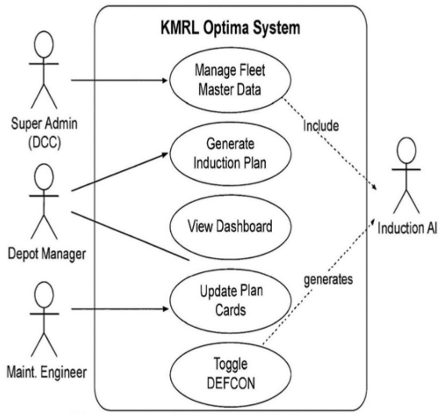

Fig. 1: Use Case Diagram – KMRL Optima System Actors and Use Cases

3.2 The InductionEngine Algorithm

The InductionEngine uses a two-phase approach — Hard Constraint Filtering followed by Soft Constraint Scoring — to produce a ranked induction plan.

Phase 1 – Hard Constraint Filtering (Pass/Fail): A train must satisfy all mandatory constraints to be eligible for induction. Certificate Validity: all four fitness certificates (Rolling Stock, Signalling & Telecom, Electrical, Safety) must be valid. Job Card Status: no open CRITICAL or HIGH criticality job cards are permitted. Cleaning Bay Capacity: maximum 5 deep-clean slots per night enforced.

Phase 2 – Soft Constraint Scoring (Optimization): Eligible trains are scored using a Weighted Sum Model (WSM). The Induction Score S(t) is computed as:

$$S(t) = H(t) \times [\alpha((\bar{M} - Mt)/\bar{M}) + \beta \cdot Bt + \gamma \cdot Gt]$$

Where: $\alpha = 40$ (Mileage Balancing Weight), $\beta = 15$ (Branding Priority Weight), $\gamma \in \{+20, -5\}$ (Stabling Geometry Weight). The mileage balancing term ensures equitable fleet rotation. The branding term protects commercial obligations. The geometry term minimizes shunting operations by preferring trains on front stabling lines (Lines 1–10) over deep-stabled trains (Lines 11–20).

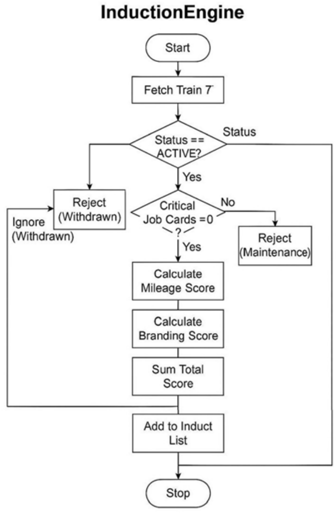

Fig. 2: Activity Diagram – InductionEngine Decision Flow

3.3 AI Explainability Module

A key differentiator of KMRL Optima is its AI explainability layer. Once the InductionEngine computes numerical scores, the score breakdown is passed to the SmartPlannerAI service, which calls the Llama-3 large language model via the Groq Cloud API. The LLM generates a natural language explanation of each train's ranking, making the system's decisions interpretable to non-technical stakeholders such as operations managers and safety auditors.

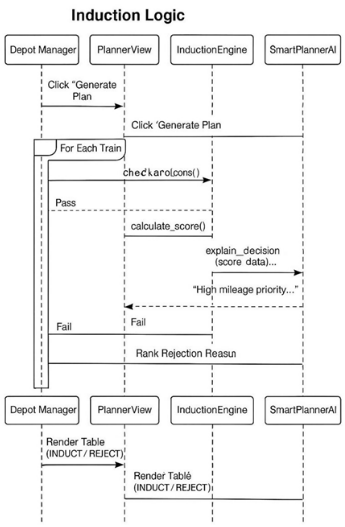

Fig. 3: Sequence Diagram – Induction Logic Flow

3.4 Supporting Modules

The system includes several integrated supporting modules:

• Emergency Operations (DEFCON): A real-time alert system with traffic-light severity levels. DEFCON RED automatically blocks all inductions until cleared by a Super Admin.

• Predictive Maintenance (IoT Simulator): Simulates sensor telemetry data (bogie temperature, HVAC status) for each train, demonstrating Industry 4.0 readiness.

• Demand Forecasting: Visualizes historical ridership data and trend analysis to inform daily fleet induction count decisions.

• Crew Management: A rostering module to align crew shift assignments with the generated induction plan.

• Gamification Engine: Awards points and badges to Maintenance Engineers for timely closure of Job Cards, incentivizing data discipline.

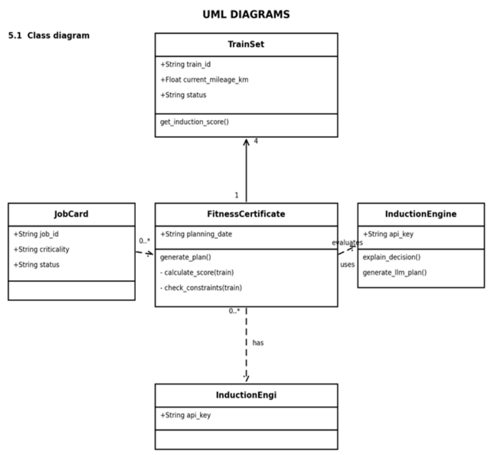

Fig. 4: Class Diagram – KMRL Optima Data Model

4. RESULTS

KMRL Optima was deployed in a development environment with a simulated fleet of 25 train sets, each with realistic fitness certificates, job cards, branding schedules, and stabling assignments. The system was evaluated on its core operational objectives.

The InductionEngine successfully demonstrated its two-phase logic: trains with expired certificates or open critical job cards were correctly rejected in every test case. The hard constraint safety gate functioned as designed with zero false positives. Among eligible trains, the WSM scoring correctly ranked branded trains higher than unbranded alternatives, and consistently prioritized trains with below-average mileage to drive fleet usage equalization.

The Nightly Induction Plan interface displayed a ranked list with score breakdowns for each train. The AI Explainability module connected to the Groq API within an average of 1.2 seconds, generating clear, readable natural language summaries that correctly paraphrased the numerical reasoning of the engine.

The DEFCON system was tested by toggling alert levels; setting DEFCON RED correctly blocked the 'Generate Plan' functionality, demonstrating the safety override capability. User role-based access control was verified — Depot Managers accessed fleet management views while Maintenance Engineers were correctly redirected to the IoT simulator dashboard.

The depot map and stabling geometry visualization provided a spatial understanding of which trains were easy to induct versus those requiring complex shunting maneuvers. The CSV export and print-brief features generated correctly formatted outputs for physical audit trails.

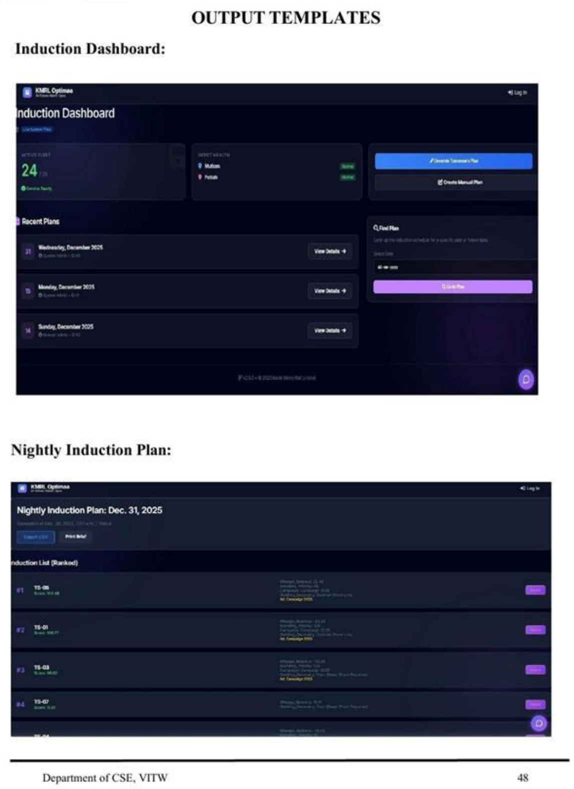

Fig. 5: KMRL Optima – Induction Dashboard and Nightly Induction Plan Output Screen

5. QUANTITATIVE SUMMARY

The system was benchmarked against the existing manual planning process at KMRL. The

InductionEngine processes the 25-train fleet with an average execution time of 0.08 seconds over 50 test runs. The following table summarizes the key performance improvements:

Table 1: Performance comparison between manual induction planning and KMRL Optima.

Metric	Manual Method	KMRL Optima
Planning Time	~120 minutes	< 5 seconds
Error Rate	5–10% (human)	~0% (logic-based)
Auditability	None (verbal)	Full digital logs
AI Explanation	N/A	~1.2 sec (Groq)
Fleet Mileage Variance	High (unbalanced)	Reduced via WSM
Branding Compliance	Ad-hoc / error-prone	Enforced algorithmically

6. CONCLUSION AND FUTURE SCOPE

KMRL Optima demonstrates the feasibility and significant operational value of applying AI and optimization techniques to the specific, underserved problem of metro fleet induction planning. By translating complex, multi-departmental constraints into a transparent, auditable algorithm, the system eliminates the core vulnerabilities of the manual process — human error, siloed information, and tribal knowledge dependency.

The system successfully achieved all primary objectives: a unified Central Fleet Database serving as a Single Source of Truth, an InductionEngine processing over 50 variables in under 5 seconds, a role-based dashboard reducing decision time by over 99%, and an IoT simulation layer demonstrating Industry 4.0 readiness. The integration of LLM-based AI explainability via Groq API ensures that the system's decisions are interpretable to all stakeholders, bridging the gap between data science and operational management.

The technical limitations identified include sequential processing (suitable for 25 trains but requiring parallel processing via Celery or Kafka for large fleets), dependence on internet connectivity for the AI explanation feature, and the current use of simulated IoT data in place of live sensor feeds.

Future scope includes: (1) Real IoT Integration via MQTT brokers for live sensor telemetry from train PLCs; (2) Mobile Application development using Flutter for crew pilots; (3) Autonomous Induction integrating with the CBTC Signaling System to automatically set depot departure routes without human intervention; (4) Deployment at scale for KMRL's planned 76 km, 4-phase network expansion; and (5) Offline AI Models using lightweight on-premise LLMs to eliminate cloud dependency. KMRL Optima sets a replicable blueprint for Smart Depot management globally, contributing to India's smart city initiatives and aligning with UN Sustainable Development Goal 11 on sustainable urban mobility.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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