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AI/ML BASED DECISION SUPPORT SYSTEM FOR OPTIMIZING RAKE FORMATION STRATEGIES FOR SAIL

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Abstract: Efficient logistics planning is essential in large-scale industrial supply chains such as steel manufacturing. Rake formation, which involves assembling railway wagons for transporting bulk materials, is a critical activity that directly impacts cost and delivery performance. Traditional approaches rely on manual coordination across multiple operational parameters, leading to inefficiencies such as delays, underutilization of wagons, and increased logistics costs. This paper presents an Artificial Intelligence and Machine Learning (AI/ML)-based Decision Support System (DSS) to optimize rake formation strategies. The proposed system integrates demand prediction with optimization techniques to generate cost-efficient and resource-optimized rake plans. A Mixed Integer Programming (MIP) model is used to minimize total logistics cost under operational constraints. The system is validated using simulated datasets, demonstrating improved rake utilization and reduced delays. The approach provides a scalable solution for modern logistics optimization.

Keywords: Decision Support System, Rake Formation, Machine Learning, Logistics Optimization, Supply Chain, Tracking

I. INTRODUCTION

In industrial logistics systems, efficient transportation planning is crucial for maintaining supply chain performance. In the steel industry, rake formation plays a vital role in moving bulk materials from plants to stockyards and customer locations. A rake consists of a set of railway wagons grouped together to transport materials such as finished steel, coal, or raw inputs.Currently, rake formation is largely performed using manual planning and rule-based coordination. This involves considering multiple factors such as inventory availability, customer orders, wagon availability, loading capacity, and route constraints. Due to the complexity of these factors, manual planning often leads to suboptimal decisions. Common issues include delayed rake formation, partial loading, inefficient resource utilization, and increased freight and penalty costs. These challenges highlight the need for an intelligent system that can assist in decision-making.

With advancements in Artificial Intelligence (AI) and Machine Learning (ML), it is possible to develop systems that analyze large datasets and generate optimized solutions. This paper proposes an AI/ML-based Decision Support System to improve rake formation efficiency and reduce logistics costs.

II. RELATED WORK

Logistics and supply chain optimization have been extensively studied in the fields of operations research and industrial engineering. Traditional approaches to transportation and allocation problems have primarily relied on mathematical optimization techniques such as Linear Programming (LP), Integer Programming (IP), and heuristic-based algorithms. These methods are effective in solving structured problems involving cost minimization and resource allocation. However, they often struggle to handle dynamic and uncertain environments where demand, supply, and operational constraints frequently change.

Decision Support Systems (DSS) have been widely adopted to assist planners in complex logistics operations. Early DSS frameworks were largely rule-based, where decisions were made using predefined conditions and domain knowledge. While these systems improved consistency in decision-making, they lacked adaptability and were unable to learn from historical data. As a result, their effectiveness was limited in large-scale and dynamic industrial applications.

With the growth of data availability and computational capabilities, machine learning techniques have gained significant attention in supply chain management. Supervised learning algorithms such as Linear Regression, Decision Trees, and Random Forests have been applied to demand forecasting and inventory management. These models help organizations predict future demand patterns based on historical data, thereby improving planning accuracy and reducing uncertainty. In recent years, deep learning approaches, including Artificial Neural Networks and Long Short-Term Memory (LSTM) models, have also been explored for time-series forecasting in logistics.

In the domain of railway freight transportation, research has focused on optimizing wagon allocation, train scheduling, and routing problems. Optimization models such as Mixed Integer Programming (MIP) and metaheuristic algorithms like Genetic Algorithms and

Tabu Search have been used to address these challenges. These approaches aim to improve resource utilization and reduce operational costs. However, most existing studies consider static conditions and do not incorporate predictive analytics for demand estimation.

Some recent works have attempted to integrate machine learning with optimization techniques to create hybrid models. In such approaches, machine learning is used to predict key parameters such as demand or travel time, while optimization models determine the best allocation and scheduling decisions. This integration has shown promising results in improving efficiency and adaptability in logistics systems.

Despite these advancements, limited research has been conducted on the application of AI/ML-based Decision Support Systems specifically for rake formation in the steel industry. Rake formation involves multiple complex decisions, including matching material availability with customer orders, assigning wagons to loading points, and optimizing multi-destination deliveries under various operational constraints. Existing methods often rely on manual planning or simple heuristics, which are not sufficient for handling large-scale and dynamic scenarios.

This research aims to address these limitations by proposing an integrated AI/ML-based Decision Support System that combines demand prediction with optimization techniques. The proposed approach enables dynamic and data-driven decision-making, leading to improved rake utilization, reduced logistics costs, and enhanced service levels. By bridging the gap between predictive analytics and optimization, this study contributes to the development of intelligent logistics solutions for the steel industry and similar large-scale supply chain systems.

Layer / Module	Technology / Tools Used
User / Planner Interface	Web-based GUI, Excel, Forms
Data Layer	SQL Database, CSV/JSON Data
Machine Learning Layer	Python, Scikit-learn, Pandas
Optimization Layer (MIP)	Python PuLP / Gurobi, Mixed Integer Programming
Output / Decision Layer	Web Dashboard, PDF Reports, Excel Export

III. METHODOLOGY

The proposed system is designed as an integrated Decision Support System (DSS) that combines data processing, machine learning, and optimization techniques to generate efficient rake formation and dispatch plans. The methodology focuses on transforming raw logistics data into actionable decisions through a structured multi-stage approach.

A. Data Collection and Preprocessing

The first stage involves collecting data from multiple sources within the logistics system. This includes inventory levels at plants and stockyards, details of pending customer orders (such as quantity, priority, and destination), availability of wagons, and loading point capacities.The collected data is preprocessed to ensure consistency and usability. This step includes handling missing values, removing inconsistencies, and converting the data into structured formats suitable for analysis. Proper preprocessing is essential to improve the accuracy of subsequent machine learning and optimization models.

B. Demand Prediction and Order Prioritization

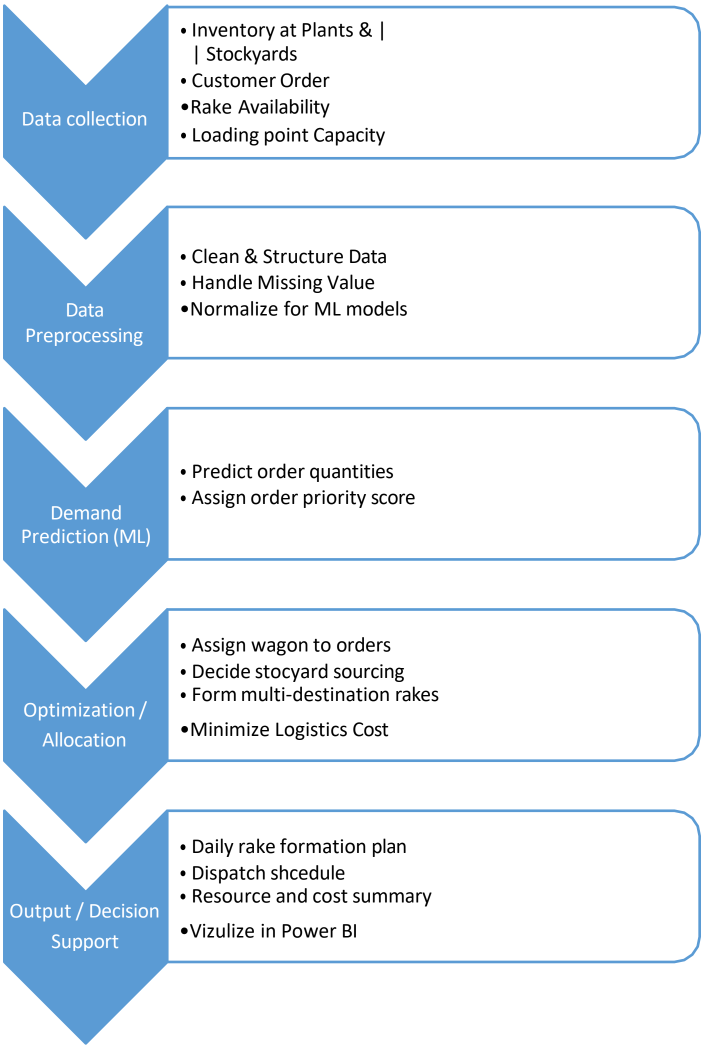
A machine learning model is employed to estimate demand patterns and prioritize customer orders. Supervised learning techniques such as Linear Regression or Random Forest are used to analyze historical data and predict future demand trends.In addition to demand prediction, a priority score is assigned to each order based on factors such as urgency, delivery deadlines, and customer importance. This prioritization helps the system allocate resources more effectively and ensures better adherence to service level agreements.

C. Rake Formation and Allocation Strategy

Based on the optimization results, the system determines the optimal composition of each rake. This includes selecting the appropriate stockyard for sourcing materials, assigning wagons to specific products, and deciding whether multi-destination rakes should be formed.The system also allocates available wagons to suitable loading points while considering operational constraints and resource availability.

D. Output Generation and Decision Support

The final stage of the methodology involves generating an actionable output for decision-makers. The system produces a daily rake formation and dispatch plan that includes wagon allocation, loading schedules, and estimated costs.This output enables planners to make informed decisions quickly and efficiently, reducing reliance on manual coordination and improving overall logistics performance.



E. Optimization Model Formulation

The core component of the system is an optimization model formulated as a Mixed Integer Programming (MIP) problem. The objective is to minimize the total logistics cost while satisfying all operational constraints.The objective function considers multiple cost components, including transportation cost, loading and handling cost, delay penalties, and idle wagon costs.The model is subject to several constraints, such as:

- Wagon capacity limitations
- Minimum rake size requirements
- Product-to-wagon compatibility
- Loading point capacity
- Inventory availability
- Delivery deadlines

This formulation ensures that the generated rake formation plan is both feasible and cost-efficient.

IV. VALIDATION AND TESTING

The proposed Decision Support System (DSS) is validated using simulated datasets designed to replicate real-world logistics scenarios in steel plant operations. Since access to live industrial data may be limited, synthetic datasets are generated based on realistic assumptions regarding demand patterns, inventory levels, wagon availability, and operational constraints. This approach allows controlled evaluation of the system under diverse conditions.

A. Test Scenario Design

To assess the robustness and adaptability of the system, multiple test scenarios are created. These scenarios capture variations in operational conditions, including:

- High-demand and low-demand situations
- Limited and abundant wagon availability
- Single-destination and multi-destination rake formation
- Variations in loading point capacity and inventory distribution

Such scenario-based testing ensures that the system can handle both typical and extreme cases encountered in real logistics environments.

B. Performance Metrics

The effectiveness of the proposed system is evaluated using key performance indicators relevant to logistics operations:

- **Rake Utilization Efficiency (%)**: Measures how effectively wagon capacity is used
- **Total Logistics Cost Reduction (%)**: Compares optimized cost with baseline/manual planning
- **Order Fulfillment Rate (%)**: Percentage of customer orders successfully served
- **Average Delivery Delay**: Measures adherence to delivery timelines

These metrics provide a comprehensive assessment of both operational efficiency and service quality.

C. Comparative Analysis

The performance of the AI/ML-based DSS is compared against traditional manual or rule-based planning approaches. In the baseline method, rake formation decisions are made using fixed heuristics and human judgment.The comparison highlights improvements achieved by the proposed system in terms of cost efficiency, resource utilization, and decision-making speed. The automated system consistently generates more balanced and optimized rake plans, especially in complex multi-constraint scenarios.

Metric	Manual Planning	Proposed DSS	Improvement (%)
Rake Utilization (%)	70	92	31.4
Total Logistics Cost (₹ Lakhs)	45	34	24.4
Order Fulfillment Rate (%)	85	97	14.1
Average Delivery Delay (days)	3.5	1.2	65.7

D. Results and Observations

The experimental results demonstrate that the proposed system significantly enhances logistics performance. Key observations include:

- Improved rake utilization due to optimized wagon allocation
- Reduction in total logistics cost through efficient routing and loading decisions
- Better handling of high-priority orders, leading to improved service levels
- Faster generation of rake plans compared to manual methods

These results indicate that integrating machine learning with optimization techniques enables more accurate and efficient decision-making.

V. CONCLUSION

This paper presents an AI/ML-based Decision Support System (DSS) for optimizing rake formation and logistics planning in steel supply chains. The system integrates demand prediction using machine learning with a Mixed Integer Programming optimization model to generate cost-efficient and resource-optimized rake formation plans. The proposed approach addresses key challenges of traditional manual planning, including delayed dispatches, underutilized wagons, and increased logistics costs. Validation through simulated datasets demonstrates improved rake utilization, reduced total logistics cost, faster planning decisions, and higher order fulfillment rates compared to rule-based methods. By automating the decision-making process, the system reduces dependency on human judgment, improves operational efficiency, and supports both rail and road order fulfillment. Furthermore, the framework is scalable and can be extended to other industrial logistics scenarios such as mining, cement, and port operations. Future work can focus on integrating real-time operational data, adopting advanced machine learning techniques such as reinforcement learning for dynamic optimization, and incorporating predictive maintenance for wagons to further enhance system performance and reliability.

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