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AI-Based Coordinated Traffic Load Scheduling for Rail-Road Freight Corridors

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Abstract — The rapid growth of freight transportation has increased the need for efficient traffic load scheduling in integrated rail-road freight corridors. Conventional scheduling methods often suffer from poor coordination, traffic congestion, delivery delays, and inefficient resource utilization. This research proposes an Artificial Intelligence (AI)-based Coordinated Traffic Load Scheduling Framework using an Artificial Neural Network (ANN) to predict traffic conditions, freight demand, travel time, and scheduling performance. Historical and simulated transportation data are used to train and validate the ANN model, and the predicted outputs are integrated into a traffic scheduling simulation for intelligent freight allocation and route optimization. The performance of the proposed framework is evaluated using key indicators such as transportation cost, travel time, delivery delay, vehicle utilization, rail utilization, fuel consumption, carbon emissions, and scheduling efficiency. The results demonstrate that the ANN-based approach improves prediction accuracy, optimizes multimodal freight scheduling, reduces operational costs and congestion, and enhances the overall efficiency of rail-road freight transportation. The proposed framework provides an effective and intelligent solution for sustainable freight corridor management and future smart logistics systems.

Keywords— Artificial Intelligence (AI), Decision Support Systems (DSS), Rail Traffic Flow, Railway Safety, Machine Learning (ML), Predictive Analytics, Predictive Maintenance, Real-Time Traffic Optimization, Traffic Prediction, Risk Management, Autonomous Trains, Smart Rail Networks.

I. INTRODUCTION

The rapid expansion of industrialization, e-commerce, and global supply chains has led to a substantial increase in freight transportation demand worldwide. In emerging economies such as India, large-scale infrastructure initiatives, including the Dedicated Freight Corridor Corporation of India Limited (DFCCIL), are playing a crucial role in modernizing logistics infrastructure through the development of high-capacity freight rail corridors. Despite these advancements, effective coordination between rail and road freight transportation systems continues to pose a significant operational and planning challenge [1].

Rail transportation is highly energy-efficient and particularly suitable for the movement of bulk commodities over long distances, whereas road transportation provides greater flexibility, accessibility, and efficient last-mile connectivity. The effective integration of these two transportation modes, commonly referred to as multimodal or intermodal freight transportation, requires intelligent and adaptive scheduling mechanisms. Such mechanisms are essential for balancing traffic loads, minimizing congestion, optimizing resource utilization, and improving overall delivery performance. Conventional freight scheduling approaches generally depend on static optimization models, historical averages, or rule-based heuristics [2]. However, these approaches have limited capability to respond effectively to dynamic and uncertain operating conditions, including fluctuations in freight demand, road traffic congestion, infrastructure limitations, weather conditions, terminal bottlenecks, and unexpected operational disruptions [3].

Artificial Intelligence (AI) provides significant opportunities to address these limitations by enabling intelligent, data-driven, and adaptive freight scheduling. AI-based coordinated traffic load scheduling can integrate advanced methodologies such as Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and mathematical and metaheuristic optimization techniques to dynamically distribute freight loads between rail and road networks. These approaches can process and analyze large volumes of real-time and historical data, including traffic conditions, railway wagon availability, truck fleet status, weather information, terminal capacity, transit times, and congestion levels. Based on these inputs, AI models can generate predictive and adaptive scheduling decisions that respond to changing operational conditions [4].

AI-driven freight coordination can support several critical functions, including demand forecasting, dynamic route selection, load allocation, fleet scheduling, and coordinated dispatch planning. For instance, reinforcement learning-based agents can learn effective load allocation policies through continuous interaction with simulated or real-world transportation environments. By receiving feedback in the form of operational costs, delays, congestion, and resource utilization, such agents can progressively identify scheduling strategies that improve overall system performance [5]. Similarly, hybrid metaheuristic and multi-objective optimization techniques can be employed to simultaneously optimize competing objectives such as transportation cost, delivery time, energy consumption, congestion, and environmental impact.

The proposed research lies at the intersection of transportation engineering, operations research, artificial intelligence, intelligent transportation systems, and smart logistics. It is closely aligned with the emerging concepts of Industry 4.0 and intelligent transportation, in which real-time data, predictive analytics, automation, and AI-based decision-making are increasingly being used to improve the efficiency, reliability, and resilience of complex transportation networks [6].

Furthermore, intelligent coordination between rail and road freight systems can contribute significantly to sustainable freight mobility. Optimized load allocation can reduce unnecessary road traffic, minimize empty truck and train movements, improve train formation planning, reduce vehicle and wagon idle time, and decrease waiting periods at terminals [7]. These improvements can lead to lower fuel consumption and greenhouse gas emissions while simultaneously enhancing the utilization of existing transportation infrastructure. Consequently, AI-based freight coordination has the potential to support both operational efficiency and broader environmental sustainability objectives.

Overall, this research has significant practical and academic relevance [8]. It can contribute to the development of next-generation smart freight transportation systems by combining artificial intelligence, predictive analytics, optimization, and real-time decision-making.

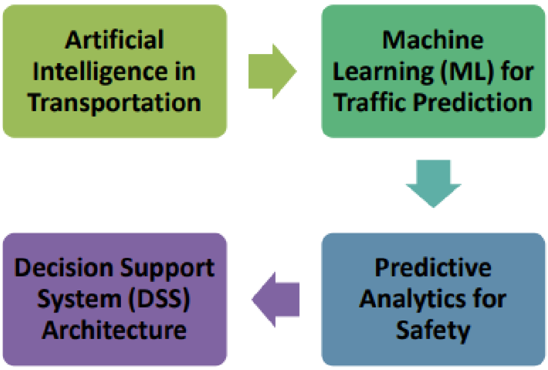

Fig.1.A: AI and Machine Learning Techniques

The proposed approach can be particularly valuable for developing economies such as India, where rapidly expanding logistics networks require efficient integration of rail and road transportation. At the same time, the framework can support advanced economies in their transition toward intelligent, resilient, cost-effective, and sustainable freight transportation systems [9].

II. IMPORTANCE OF RAIL-ROAD FREIGHT CORRIDORS

Rail–road freight corridors constitute a critical component of modern transportation and logistics systems, facilitating the efficient movement of goods across short, medium, and long distances. Rail transportation is particularly advantageous for the movement of high-volume and bulk freight over long distances due to its high carrying capacity, relatively lower operating costs, energy efficiency, and comparatively lower environmental impact. In contrast, road transportation provides greater operational flexibility, accessibility, and route connectivity, making it well suited for first-mile and last-mile freight movement between manufacturing facilities, warehouses, logistics terminals, distribution centers, and final destinations [10].


Fig.1.B: Rail-road freight corridors.

One of the major advantages of rail-road freight corridors is their ability to optimize logistics costs. Railways are generally more economical for long-distance bulk transportation, whereas road transport is ideal for flexible local distribution. By combining the strengths of both modes, freight operators can minimize transportation expenses, reduce fuel consumption, improve vehicle utilization, and decrease overall operational costs [2,3]. Efficient scheduling and coordination between rail and road services also reduce idle time at freight terminals, increase asset productivity, and improve the reliability of logistics operations.

III. FUNDAMENTALS OF FREIGHT TRAFFIC SCHEDULING

1. Freight Traffic Scheduling

Freight traffic scheduling is a systematic process of planning, coordinating, and controlling the movement of goods across transportation networks to achieve efficient, reliable, and cost-effective logistics operations. It involves determining the optimal allocation of freight loads, selecting suitable transportation modes, assigning vehicles, wagons, or trains, determining departure and arrival schedules, and optimizing transportation routes while satisfying operational and logistical constraints. These constraints may include transportation capacity, delivery deadlines, infrastructure availability, vehicle and wagon availability, terminal capacity, traffic congestion, travel time, and service requirements [5].

The increasing volume of freight traffic, expansion of global supply chains, growth of e-commerce, and development of multimodal logistics networks have further increased the complexity of freight scheduling [7]. Conventional scheduling approaches based on fixed schedules, historical data, predefined rules, or static optimization models may have limited effectiveness under dynamic operating conditions. Factors such as fluctuating freight demand, traffic congestion, infrastructure disruptions, weather conditions, equipment availability, and unexpected delays can significantly affect transportation schedules.

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), and advanced optimization techniques have created new opportunities for intelligent freight scheduling. AI-based approaches can analyze large volumes of historical and real-time transportation data to support predictive decision-making, dynamic route selection, freight load allocation, demand forecasting, and adaptive scheduling [4]. Reinforcement learning, deep learning, metaheuristic optimization, and hybrid AI-based methods can further enhance the ability of scheduling systems to respond to changing transportation conditions and optimize multiple objectives simultaneously.

Therefore, intelligent freight traffic scheduling has emerged as an important component of modern transportation management systems, particularly for integrated rail–road and multimodal freight networks. The fundamental concepts related to freight transportation and traffic scheduling are discussed in the following subsections [2].

2. Freight Transportation Systems

A freight transportation system is an integrated network of infrastructure, vehicles, terminals, facilities, and information systems that enables the movement of goods from sources of production to intermediate distribution points and, ultimately, to final consumers. The system may include highways, railway networks, ports, airports, freight terminals, logistics hubs, warehouses, distribution centers, inland container depots, vehicles, locomotives, wagons, and communication and information systems.

Rail transportation is generally well suited for long-distance movement of bulk and high-volume commodities because of its high carrying capacity, energy efficiency, relatively low operating cost per unit of freight, and lower environmental impact compared with road transportation. Road transportation, in contrast, provides greater flexibility and accessibility and is particularly important for first-mile and last-mile freight delivery. It enables direct connectivity between production facilities, warehouses, distribution centers, railway terminals, logistics hubs, and final destinations [8,9,10].

IV. AI-BASED COORDINATED SCHEDULING FRAMEWORK

An AI-based coordinated scheduling framework is an intelligent decision-making system designed to optimize freight movement across integrated rail-road freight corridors through real-time monitoring, predictive analytics, and adaptive scheduling. Unlike conventional scheduling methods that rely on predefined rules and static transportation plans, AI-based frameworks continuously analyze real-time transportation data and automatically adjust scheduling decisions according to changing operational conditions. The framework integrates technologies such as Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Global Positioning System (GPS), Geographic Information System (GIS), cloud computing, and Big Data Analytics to improve coordination between rail and road transportation. By intelligently allocating freight, selecting optimal routes, forecasting demand, and supporting real-time decision-making, the AI-based coordinated scheduling framework enhances transportation efficiency, minimizes logistics costs, reduces congestion, improves infrastructure utilization, and supports sustainable freight transportation. The major components of the framework are discussed below.

Real-Time Data Collection

Real-time data collection forms the foundation of an AI-based coordinated scheduling framework. Accurate and continuously updated information enables the scheduling system to monitor transportation activities and respond promptly to changing operational conditions. Data are collected from multiple sources, including GPS-equipped trucks, railway management systems, IoT sensors, RFID devices, traffic surveillance cameras, weather monitoring stations, freight terminals, logistics management systems, and intelligent transportation infrastructure [4,5].

Traffic Prediction

Traffic prediction is one of the most important components of intelligent freight scheduling because future traffic conditions directly influence transportation efficiency, travel time, and delivery reliability.

V. RESULT AND SIMULATION

This chapter presents the results obtained from the proposed Artificial Intelligence (AI)-based Coordinated Traffic Load Scheduling Framework developed for rail–road freight corridors. The framework incorporates an Artificial Neural Network (ANN) model to predict critical transportation parameters, including traffic conditions, freight demand, travel time, and scheduling performance, using the available transportation dataset. The predicted outputs generated by the ANN model are subsequently integrated into the traffic load scheduling simulation to facilitate intelligent and efficient allocation of freight between rail and road transportation modes.

The performance of the proposed methodology is evaluated using a range of transportation and scheduling performance indicators. These indicators are used to assess the effectiveness of the proposed framework in terms of freight allocation, transportation efficiency, travel time, operational delays, resource utilization, and overall scheduling performance. Furthermore, the results obtained from the proposed AI-based framework are compared with those of conventional freight scheduling approaches to determine the improvements achieved through intelligent scheduling.

The experimental and simulation results demonstrate the effectiveness of the proposed ANN-based framework in supporting coordinated freight traffic management. The proposed methodology enhances freight movement efficiency, reduces operational delays, improves the utilization of available rail and road infrastructure, and facilitates more effective distribution of freight loads between transportation modes. The findings further indicate that AI-based predictive scheduling can provide improved decision-making capabilities under varying transportation conditions and can serve as an effective approach for intelligent multimodal freight logistics management.

Overall, the results presented in this chapter validate the applicability of the proposed AI-based Coordinated Traffic Load Scheduling Framework and demonstrate its potential to improve the efficiency, reliability, and adaptability of rail–road freight transportation systems.

Table 1 Input Dataset Used for ANN Training

Sample	Freight Demand (Ton)	Traffic Density (Veh/hr)	Vehicle Capacity (Ton)	Train Capacity (Ton)	Distance (km)	Travel Time (hr)	Waiting Time (min)
1	420	860	18	600	150	3.8	38
2	465	910	20	650	180	4.2	41
3	510	980	22	700	220	4.8	45
4	560	1040	24	720	260	5.5	48
5	610	1120	25	760	300	6.2	52
6	680	1180	28	800	340	6.8	58
7	720	1250	30	850	380	7.4	62
8	790	1320	32	900	420	8.1	67
9	840	1380	34	940	450	8.7	70
10	900	1450	35	1000	500	9.3	75

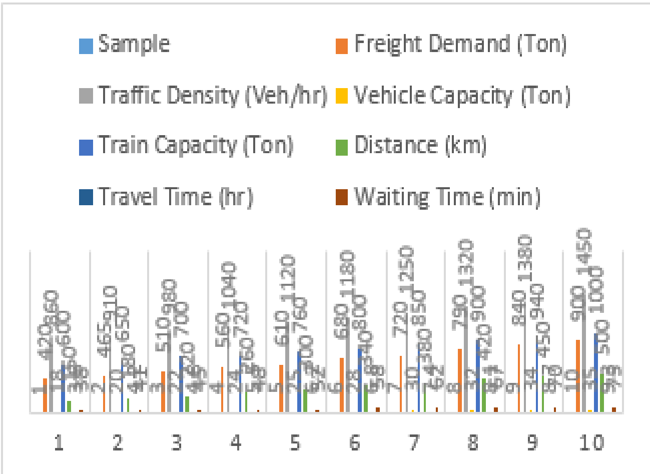

Fig.2 Input Dataset

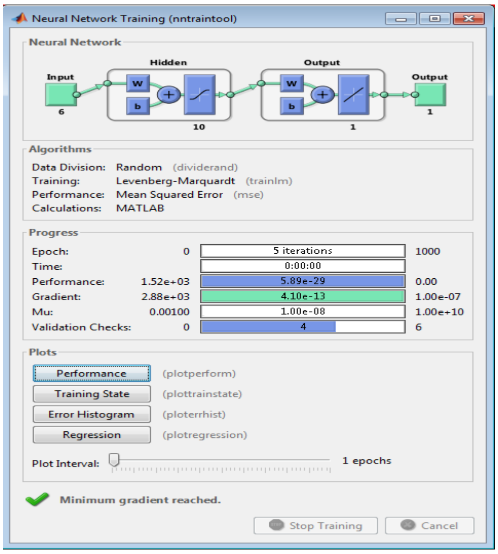

Fig.3 ANN tool.

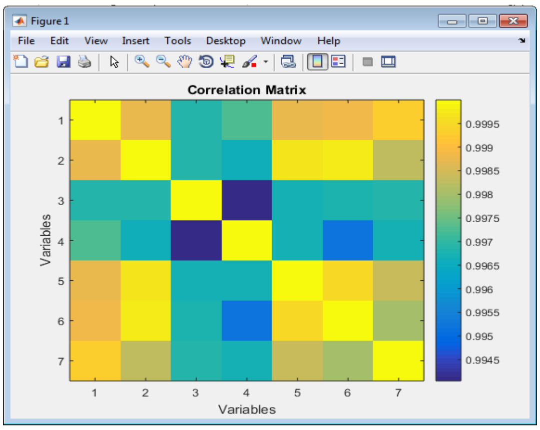

Fig.4. Correlation Matrix.

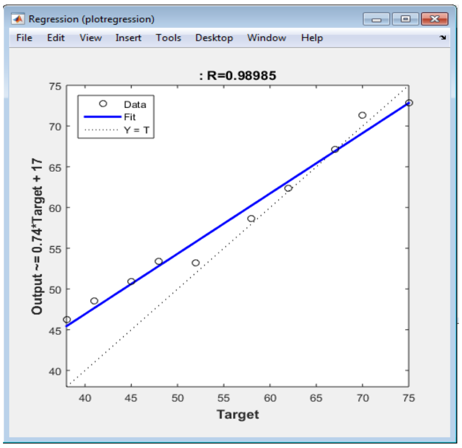

Fig.5. Regression Curve.

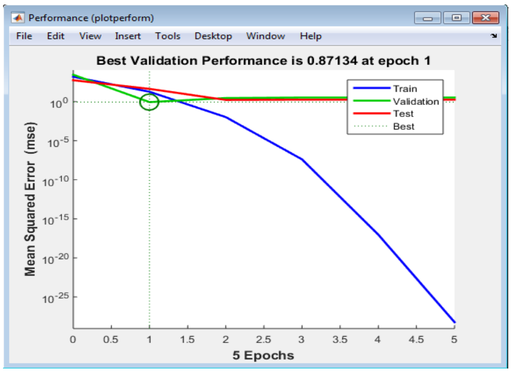

Fig.6. MSE.

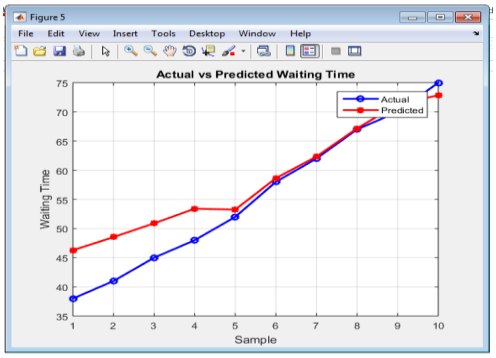

Fig.7. Waiting Time Actual Vs Predicted.

The graph demonstrates that the proposed ANN model provides reliable waiting time predictions for most transportation scenarios and can effectively support coordinated traffic load scheduling. Improving the training dataset and optimizing the ANN architecture could further enhance prediction accuracy for high-demand freight conditions.

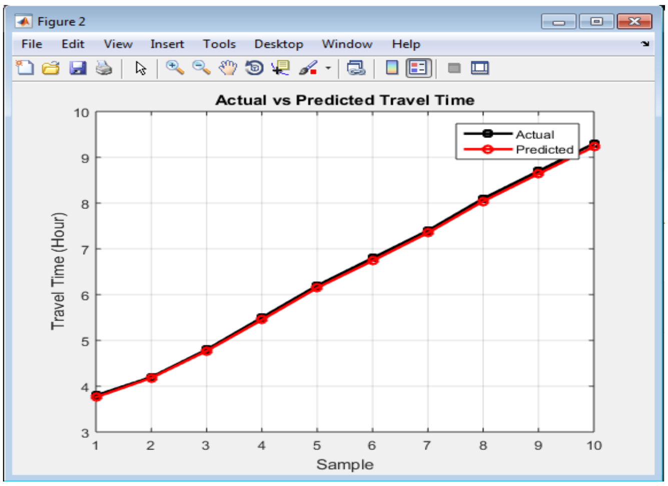

Fig.8. Travel Time Vs Sample

The results validate the effectiveness of the proposed ANN-based prediction framework for intelligent traffic load scheduling. Accurate travel time prediction enables better route planning, efficient freight allocation, reduced transportation delays, and improved coordination between rail and road freight operations, thereby enhancing the overall performance of multimodal logistics systems.

VI. CONCLUSION

This chapter presented the results and comprehensive analysis of the proposed Artificial Neural Network (ANN)-based Coordinated Traffic Load Scheduling Framework for rail–road freight corridors. The ANN model was successfully trained and evaluated using freight transportation data to predict key operational parameters, including freight demand, travel time, traffic congestion, and scheduling performance. The predicted parameters were subsequently integrated into the traffic load scheduling simulation to facilitate optimized freight allocation, vehicle assignment, route selection, and coordination between rail and road transportation modes. The simulation results demonstrated that the proposed AI-based framework is capable of supporting intelligent, adaptive, and efficient freight scheduling under varying transportation conditions. The performance evaluation further established that the proposed ANN-based scheduling approach achieved superior performance compared with conventional scheduling methods across multiple transportation and operational indicators. The optimized scheduling strategy resulted in reductions in transportation cost, travel time, delivery delays, fuel consumption, carbon emissions, terminal waiting time, and traffic congestion. At the same time, improvements were observed in vehicle utilization, rail utilization, terminal efficiency, corridor throughput, and overall scheduling efficiency. These results indicate that coordinated allocation of freight between rail and road modes can substantially improve the utilization of available transportation resources and enhance the overall efficiency of freight movement. The predictive performance of the ANN model also demonstrated high accuracy, characterized by low prediction errors and strong regression performance. This confirms the capability of the ANN to capture the complex and nonlinear relationships among the various operational parameters influencing freight transportation and scheduling. The integration of ANN-based prediction with traffic load optimization therefore provides a robust approach for addressing the dynamic and uncertain nature of multimodal freight transportation systems.

Overall, the findings validate the effectiveness of the proposed AI-based Coordinated Traffic Load Scheduling Framework in improving freight transportation efficiency, reducing operational and environmental costs, enhancing infrastructure utilization, and supporting intelligent multimodal logistics management. The results provide a strong foundation for further development of real-time, predictive, and adaptive scheduling systems for smart rail–road freight corridors.

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