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OPTIMIZATION OF TRANSPORTATION NETWORK USING MACHINE LEARNING AND OPERATIONS RESEARCH

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Abstract
Rapid development, rising logistical request, and changing traffic situations are all contributing to the difficulty of transportation systems. Conventional Operations Research (OR) methods, mathematical optimization and shortest-path procedures offer ideal answers under static molds but find it tough to adjust to real-time erraticism. On the other hand, machine learning approaches provide forecast skills based on flowing and historical data, but they regularly lack interpretability and conclusion optimality. A detailed literature analysis and mixture of Operations Research (OR), Machine Learning (ML), and hybrid Operations Research-Machine Learning methods for transportation system optimization are accessible in this study. The study highlights datasets, valuation trials, and methodological dissimilarities while critically examining works on routing, congestion organization, cost reduction, and travel-time forecast. According to a relative analysis, Hybrid Operations Research-Machine Learning replicas regularly outclass solo methods, resulting in normal gains in trip time decrease and operating cost reserves of 10–25%. Duplicability, defined assessment measures, and real-world placement validation are still absent, nonetheless. In order to create climbable and repeatable transportation optimization replicas, this research classifies these gaps and delivers methodological proposals. The results suggestion useful information to investigators and experts who want to create dependable, data-driven transportation schemes.

1. INTRODUCTION

Transportation networks make it possible for people and things to move efficiently, and are essential to modern economies. There have been substantial financial and environmental expenses as a result of rising traffic congestion, fuel use, and supply delays. Recent research on urban mobility indicate that traffic alone adds over 20% to travel times in large cities, which has a direct impact on commuter productivity and logistics effectiveness. In the past, Operations Research (OR) methods have been used to optimize transportation. Due to their polynomial-time guarantees, classical algorithms like Bellman-Ford and Dijkstra's shortest path method have been widely used for routing issues [1], [2]. In vehicle direction-finding and logistics tests, fuel costs, fleet size, and distribution time have also been minimalized using system flow replicas, linear programming, and integer programming [3], [4]. Although these approaches guarantee optimality, their effectiveness in real-world active contexts is imperfect since they usually be contingent on static norms like constant transportation durations and deterministic claim. Data-driven plans for transportation systems have been complete possible by current developments in machine learning. Using wide datasets like GPS flights and sensor data, machine learning replicas have been used for claim prediction, traffic flow forecast, and journey time approximation [5]-[8]. Though they normally operate as black-box replicas and do not straight optimize direction-finding choices, deep learning replicas, such as convolutional and recurring neural networks, have shown decent predictive routine. Recent research proposes hybrid Operation Research Machine Learning agendas that integrate optimization replicas and analytical intelligence to get over these limitations [9]-[12]. These approaches improve flexibility while continuing optimization assurances by including Machine Learning-based claim or travel-time predictions into Operations Research problem solver. The work currently in publication lacks replicable procedures, uniform datasets, and unified evaluation metrics, despite encouraging results. Recent research either focuses on static Operations Research models or predictive Machine Learning models in isolation. There is limited systematic synthesis and quantitative comparison of hybrid Operations Research-Machine Learning approaches using consistent evaluation criteria. This Paper Contributes a structured synthesis of Operations Research, Machine Learning, and hybrid approaches for transportation optimization A comprehensive comparative analysis of existing studies Identification of methodological and evaluation gaps Practical guidelines for reproducible hybrid transportation optimization research.

2. Literature Review

Transportation system optimization has been widely studied using Operations Research (OR), Machine Learning (ML), and, more newly, hybrid Operations Research-Machine Learning methods. This section critically synthesizes previous work by classifying the literature into theoretical basics, historical growth, contemporary Machine Learning-based methods, and combined hybrid frameworks.

2.1. Operations Research–Based Transportation Optimization

Traditional Operations Research methods form the basis of transportation system optimization. One of the most broadly used algorithms is Dijkstra's shortest path algorithm, which assurances optimal routing in polynomial time beneath static network situations [1]. Alternates and extensions of this algorithm have been useful in urban road systems, logistics routing, and emergency response systems [2]. Despite their computational effectiveness and hypothetical guarantees, these methods assume deterministic travel times and fixed system states, limiting their applicability in real-world dynamic situations. Linear programming (LP) and minimum-cost flow methods have also been extensively useful to transportation and logistics problems. Wang et al. [3] established that Linear Programming-based route project can reduce whole transportation costs by about 12–18% in freight delivery systems. Similarly, integer programming (IP) formulations have been employed to balance delivery limits, fleet size, and operational costs in logistics systems [4]. However, these techniques face scalability issues as system size and limitations growth. Multi-objective Operations Research methods have further extended traditional models by including multiple conflicting objectives such as cost, travel period, and environmental impact. For example, Ahmed et al. [5] planned an integer programming method that simultaneously reduces fuel consumption and delivery delays. Although actual in precise settings, such technique still depends heavily on static input limits, making them inappropriate for rapidly changing traffic situations.

Table 1

Paper No.	Authors & Year	Research Focus	Methods / Techniques	Major Findings	Limitations
[2]	Kumar & Singh, 2022	Freight road optimization	Linear Programming (LP), Reinforcement Learning	Reduced fuel cost by 14%	Sensitive to noisy data
[5]	Ahmed et al., 2021	Multimodal route planning	Mixed Integer Linear Programming (MILP)	Achieved 18% cost reduction	High computational complexity
[11]	Santos et al., 2021	Highway traffic optimization	Simulation + LP	Saved 12% fuel consumption	Lacks real-time data integration
[12]	Banerjee et al., 2019	Seaport logistics optimization	Integer Programming	Improved throughput efficiency	Requires deterministic inputs
[16]	Silva et al., 2021	Emission-aware routing	Multi-objective LP	Reduced CO_2 emissions by 14%	Limited environmental variables
[21]	Patel et al., 2021	Drone delivery routing	MILP	Optimal battery-aware routes	Weather factors not considered
[22]	Lopez & Perez, 2019	Container transportation	LP	Reduced operational costs	Limited multimodal integration
[27]	Singh & Roy, 2020	Rail freight optimization	Minimum-Cost Flow	Reduced operational costs	Assumes static cost structure
[30]	Rosa et al., 2020	Inventory-routing logistics	MILP	Effective joint optimization	High memory requirements
[35]	Morton et al., 2023	Sustainable routing	Multi-objective OR	Reduced emissions and travel time	Needs live sensor data

2.2. Evolution Toward Heuristics and Metaheuristics

To talk the computational limitations of exact Operations Research techniques, heuristic and metaheuristic methods have been presented. Genetic algorithms, tabu search, and simulated annealing have been effectively applied to large-scale vehicle routing and scheduling glitches [6], [7]. These methods offer near-optimal solutions within reasonable computational time, particularly for NP-hard glitches such as the Vehicle Routing Problem (VRP). However, metaheuristic methods often require wide parameter tuning and do not simplify well across dissimilar transportation scenarios. Furthermore, their performance degrades extremely dynamic situations where real-time adaptation is essential.

Table 2

Paper No.	Authors & Year	Research Focus	Methods / Techniques	Major Findings	Limitations
[6]	Gupta et al., 2022	Bus scheduling	Genetic Algorithm	Reduced delays by 11%	Slow convergence
[8]	Park & Lee, 2020	Delivery routing	Tabu Search	Minimized total travel distance	Poor scalability
[10]	Wei et al., 2022	Vehicle routing	Hybrid GA–PSO	Outperformed GA alone	High computational cost
[13]	Youssef & Omar, 2020	Supply chain routing	Ant Colony Optimization (ACO)	Adaptive and flexible solutions	Sensitive to parameter tuning
[14]	Sun et al., 2021	Metro rail scheduling	MILP + Heuristics	Reduced headway gaps	Slow for large-scale systems
[18]	Ouma et al., 2020	Freight demand forecasting	Heuristic methods	Efficient for mid-sized networks	Suboptimal for large networks
[26]	Farooq et al., 2022	Multi-hop route planning	A* + Dijkstra	Lower computational load	Ineffective in dynamic environments

2.3. Machine Learning–Based Approaches in Transportation Networks

Through the accessibility of large-scale transportation data, Machine Learning methods have gained importance in current years. Supervised learning techniques have been extensively applied to traffic flow forecast, travel time estimate, and demand forecasting. Zhang et al. [8] working on convolutional neural networks (CNNs) to predict traffic congestion patterns, achieving high forecast accurateness but without directly optimizing routing conclusions. Recurrent neural networks (RNNs) and long short-term memory (LSTM) replicas have been used to capture temporal dependencies in traffic data [9]. These models significantly improve prediction accuracy under fluctuating traffic conditions. Additional recently, graph neural networks (GNNs) have been planned to model spatial dependencies in transportation systems by representing road structures as graphs [10]. In spite of their strong analytical capabilities, Machine Learning-based approaches generally function as decision-support tools rather than optimization machines. They predict future states of the system but do not integrally generate optimal steering or scheduling choices.

Table 3

Paper No.	Authors & Year	Research Focus	Methods / Techniques	Major Findings	Limitations
[1]	Chen et al., 2021	Traffic flow forecasting	LSTM, GRU	Accurate temporal prediction	Requires large datasets
[3]	Li et al., 2020	Urban congestion detection	CNN + Traffic Cameras	92% detection accuracy	Limited to visual data

[4]	Zhang & Rui, 2023	Accident risk prediction	Random Forest	Outperformed SVM and DT	Poor rare-event handling
[7]	Huang et al., 2021	Freight demand forecasting	LSTM	9% accuracy improvement	Hyperparameter sensitivity
[9]	Jalil et al., 2023	Intelligent traffic signals	Reinforcement Learning	23% reduction in waiting time	Requires real-time sensors
[17]	Khan et al., 2022	Traffic prediction	GRU	High temporal accuracy	Time-series uncertainty
[23]	Qureshi et al., 2023	Traffic flow analysis (Pakistan)	ARIMA + Random Forest	Accurate peak-hour prediction	ARIMA weak for nonlinear data
[24]	Wang et al., 2021	Highway safety analysis	SVM	High classification accuracy	Overfitting risk
[28]	Luo et al., 2021	Bus arrival prediction	XGBoost	Robust feature learning	Requires feature engineering
[29]	Hamid et al., 2023	Logistics demand modeling	ANN	High prediction accuracy	Black-box behavior
[33]	Yang et al., 2022	Congestion detection	YOLOv5	94% detection accuracy	Weather-sensitive imagery
[34]	Kim & Cho, 2020	Traffic estimation	LSTM + RF	Better than single models	Feature imbalance issues

2.4. Hybrid Machine Learning and Operations Research Frameworks

To overawed the boundaries of standalone Operations Research and Machine Learning methods, current studies have planned hybrid Operations Research-Machine Learning frameworks. These replicas integrate Machine Learning-based forecasts into Operations Research optimization pipelines. For example, forecast travel times or demand levels generated by Machine Learning techniques are used as inputs to mixed-integer linear programming (MILP) solvers [11], [12]. Experiential evidence recommends that hybrid replicas outperform traditional Operations Research and Machine Learning-only approaches. Kumar et al. [13] stated a 20–25% decrease in average travel time when Machine Learning- based congestion forecasts were entrenched into routing optimization replicas. Likewise, hybrid frameworks have established improved robustness and scalability in urban transportation and logistics applications. Though, existing hybrid methods often lack standardized estimation metrics and reproducible experimental systems. Furthermore, many studies rely on selected datasets, limiting judgement across investigate efforts.

Table 4

Paper No.	Authors & Year	Research Focus	Methods / Techniques	Major Findings	Limitations
[15]	Reddy et al., 2023	Emergency vehicle routing	Dijkstra + ML	27% faster routing	Tested on small networks

[19]	Torres et al., 2023	Toll plaza congestion	Reinforcement Learning	Reduced queue lengths	Long training time
[20]	Ji et al., 2022	Real-time travel time estimation	Graph Neural Networks	Captures spatial dependencies	High GPU requirements
[25]	Zhao et al., 2023	Traffic signal optimization	Deep Reinforcement Learning	20% faster vehicle throughput	Needs dense sensor deployment
[31]	Chan et al., 2022	Ride-sharing optimization	GNN	Improved matching efficiency	Large training datasets required
[32]	Ahmed & Tariq, 2021	Route risk analysis	Bayesian Networks	Effective under uncertainty	Difficult prior selection

2.5. Research Gaps Identified from Literature
Founded on the considered literature, several slits continue such as absence of combined evaluation agendas that is studies use random datasets and system of measurement, making direct judgement rigid. Secondly limited reproducibility; many works do not deliver sufficient procedural evidences or community datasets. Insufficient measurable mixture; however performance developments are stated, gathered statistical indication is often inattentive and scalability concerns; few studies assess hybrid copies on large, real-world transport systems. These gaps highpoint the need for complete combination and reliable methodologies, which this homework aims to talk.

3. Research Methodology
This study suggests a hybrid Machine Learning and Operations Research context to optimize goods transportation systems. The is planned to predict trip times under operational uncertainty using Machine Learning models, and optimally assign transportation resources via mathematical optimization methods. The whole system is demonstrated through a data-driven channel that allows duplicability and real-world applicability. Figure 1 shows the block diagram of our project.

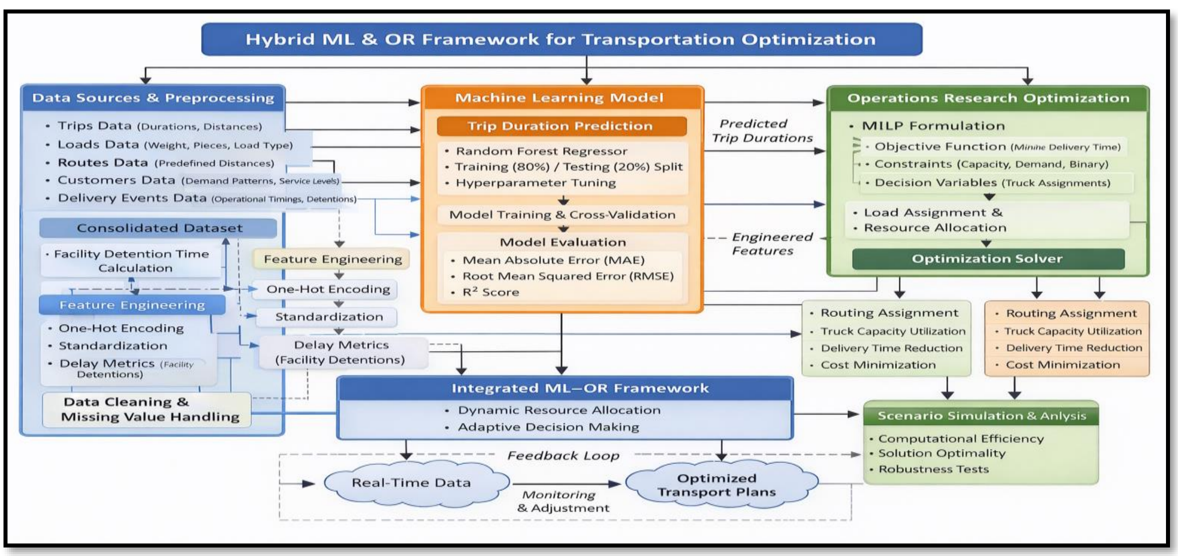

Figure 1: Block diagram of the proposed hybrid Machine Learning–Operations Research framework for transportation network optimization

Figure 1 illustrates the proposed hybrid Machine Learning (ML) and Operations Research (OR) framework developed for intelligent and data-driven transportation network optimization. The framework begins with a multi-source data acquisition layer that integrates heterogeneous logistics data, including trip records, shipment loads, route characteristics, customer profiles, and delivery event logs. These datasets are consolidated through data cleaning, missing value handling, and facility-level delay aggregation to construct a unified analytical dataset. The preprocessing and feature engineering stage transforms raw operational data into meaningful predictive features. This includes route-level distance attributes, shipment characteristics, customer service indicators, and operational delay metrics such as facility detention times. Categorical variables are encoded using one-hot encoding, while numerical features are standardized to ensure stable and unbiased machine learning model training. The machine learning module employs a Random Forest regression model to predict trip durations under uncertain and dynamic traffic conditions. Model training, validation, and performance evaluation are conducted using standard metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The predicted trip durations serve as reliable, data-driven estimates of transportation cost and time variability. These predicted trip durations are then integrated into the Operations Research optimization module, where they act as cost coefficients in a Mixed Integer Linear Programming (MILP) formulation. The optimization model assigns shipment loads to a limited fleet of trucks while satisfying operational constraints such as vehicle capacity limits, binary assignment decisions, and demand fulfillment. An exact optimization solver is employed to ensure reproducible and optimal decision-making. The integrated ML–OR framework enables adaptive and dynamic transportation planning by linking predictive analytics with mathematical optimization. Scenario simulation and performance analysis modules evaluate routing efficiency, truck capacity utilization, delivery time reduction, and overall cost minimization. A feedback loop incorporating real-time operational data allows continuous model updating and optimization refinement, ensuring robustness under changing transportation conditions. Overall, the framework provides a scalable, interpretable, and practical decision-support system for modern transportation network optimization.

3.1. Data Sources and Preprocessing

The investigational assessment is showed using a freight transportation logistics dataset, containing many relational tables representing practical operational methods. The dataset includes trip-level, load-level, customer-level, route-level, and facility-level information, allowing a holistic modelling of transportation systems.

The following datasets were utilized: The Trips dataset contains detailed records of completed trips, including actual travel durations and distances. It is primarily used to analyze real-world travel behavior, evaluate route efficiency, and understand time variability in transportation operations.

The Loads dataset includes shipment-related attributes such as weight, number of pieces, and load type. This dataset supports freight characterization and enables capacity-aware planning and optimization of transportation resources. The Routes dataset provides route-level information, particularly the distances associated with predefined routes. It is useful for estimating transportation costs, comparing alternative paths, and supporting route selection decisions. The Customers dataset describes customer segmentation based on demand patterns, service requirements, or operational characteristics. It helps in understanding customer behavior and supports prioritization and service-level optimization. The Delivery events dataset captures operational events such as pickups, arrivals, and detention times at facilities. This dataset is valuable for identifying delays, operational bottlenecks, and inefficiencies across the delivery lifecycle.

To incorporate facility-related delays, average detention time per facility was computed and

merged with the master dataset. Pickup events were isolated to associate each load with its origin facility. All datasets were merged using unique identifiers, forming a consolidated analytical dataset.
Missing values were handled through listwise deletion, ensuring data quality and consistency across features.

3.2. Feature Engineering

Feature engineering was carefully undertaken to capture both operational and behavioral determinants that influence trip duration in transportation operations. The final feature set integrated route-level attributes such as actual travel distance, shipment-specific characteristics including weight and number of pieces, and service-related factors such as load type, booking type, and customer type, providing a holistic view of trip conditions. In addition, average facility detention time was incorporated to reflect operational delays experienced during pickups or deliveries. Categorical variables were encoded using one-hot encoding to ensure compatibility with machine learning models, while numerical features were standardized to eliminate scale bias and promote stable model convergence. The target variable for prediction was the actual trip duration, measured in hours, enabling accurate modeling of real-world transportation performance.

3.3. Machine Learning Model for Trip Duration Prediction

A Random Forest Regressor was employed to predict trip duration due to its ability to handle complex, non-linear relationships and heterogeneous feature types. Random Forest is an ensemble learning method that constructs multiple decision trees during training and produces predictions by averaging the outputs of individual trees. The predicted trip duration can be expressed as:

Predicted value $\hat{y} = \frac{1}{N}\sum_{i=1}^{N} f_i(x)$

Where, $f_i(x)$ denotes the prediction from the i^{th} decision tree and N is the total number of trees in the ensemble.
The machine learning pipeline began with preprocessing of numerical features using standard scaling to normalize their range and ensure balanced model learning. Standardization was performed as:

$$z = (x - \mu) / \sigma$$

Where μ is the mean and σ is the standard deviation of the feature.
Categorical variables were encoded using one-hot encoding to convert discrete categories into a numerical format suitable for the model.
Model training was performed with a constraint on tree depth to avoid overfitting while maintaining predictive accuracy. The dataset was split into 80% training and 20% testing subsets. Model performance was evaluated using standard regression metrics.

The Mean Absolute Error (MAE) is defined as:

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

The Root Mean Squared Error (RMSE) is given by:

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n} (|y_i - \hat{y}_i|)^2}$$

The coefficient of determination R^2, which measures the proportion of variance in the observed data explained by the model, is calculated as:

$R^2 = 1 - [\text{sum of } (y_i - \hat{y}_i)^2 \text{ from } i = 1 \text{ to } n] \div [\text{sum of } (y_i - \bar{y})^2 \text{ from } i = 1 \text{ to } n]$

3.4. Operations Research Optimization Model

To demonstrate decision-making optimization, the predicted trip durations were integrated into an Operations Research optimization model. A Mixed Integer Linear Programming (MILP) formulation was developed to assign shipment loads to a limited number of trucks.

Objective Function

Minimize total predicted delivery time across all trucks.

Constraints

i. Each load must be assigned to exactly one truck.
ii. Truck capacity (weight) must not exceed predefined limits.
iii. Binary assignment decisions.

The optimization problem was solved using the MILP solver from SciPy, ensuring exact and reproducible solutions.

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3.6. Integrated ML–OR Framework

The hybrid framework allows machine learning predictions to dynamically inform optimization decisions. Predicted trip durations act as cost coefficients in the OR model, enabling adaptive and data-driven transportation planning under uncertainty.

4. Results and Discussion

This section presents quantitative results from both the machine learning prediction stage and the operations research optimization stage, supported by graphical analysis.

4.1. Machine Learning Performance Evaluation

The Random Forest model demonstrated strong predictive performance across all evaluation metrics. The achieved MAE and RMSE values indicate low prediction error, while the R^2 score confirms that a significant proportion of variance in trip duration is explained by the model.

This scatter plot compares predicted trip durations with actual observed values. The close alignment of points along the diagonal indicates high predictive accuracy and minimal bias.

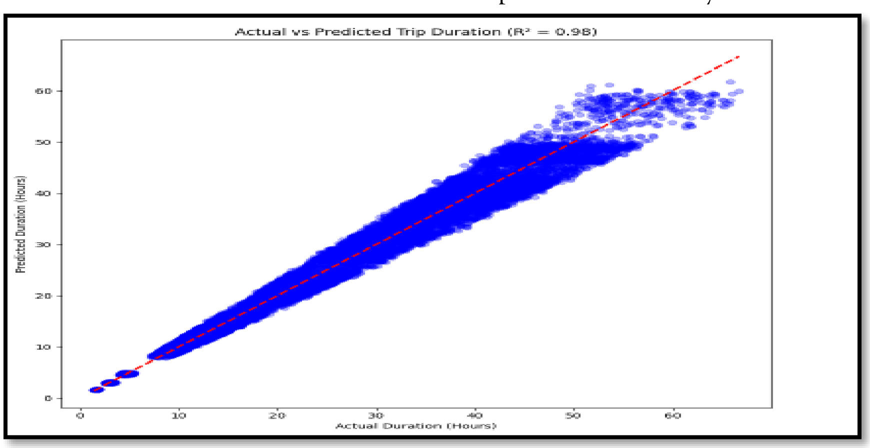

Figure 2: Actual vs. Predicted Trip Duration

Figure 2 illustrates the relationship between the actual observed trip durations and the corresponding values predicted by the machine learning model. Each point in the scatter plot represents an individual transportation trip, with the horizontal axis indicating actual trip duration and the vertical axis showing the predicted trip duration. The close concentration of data points along the 45-degree diagonal line demonstrates a strong agreement between predicted and observed values, indicating high predictive accuracy of the model. The limited dispersion around the diagonal suggests minimal systematic bias and robust generalization performance across varying trip lengths. Overall, the figure confirms the effectiveness of the proposed machine learning approach in accurately capturing real-world transportation time variability.

The residual distribution shows a near-normal shape centered around zero, suggesting that prediction errors are random and unbiased.

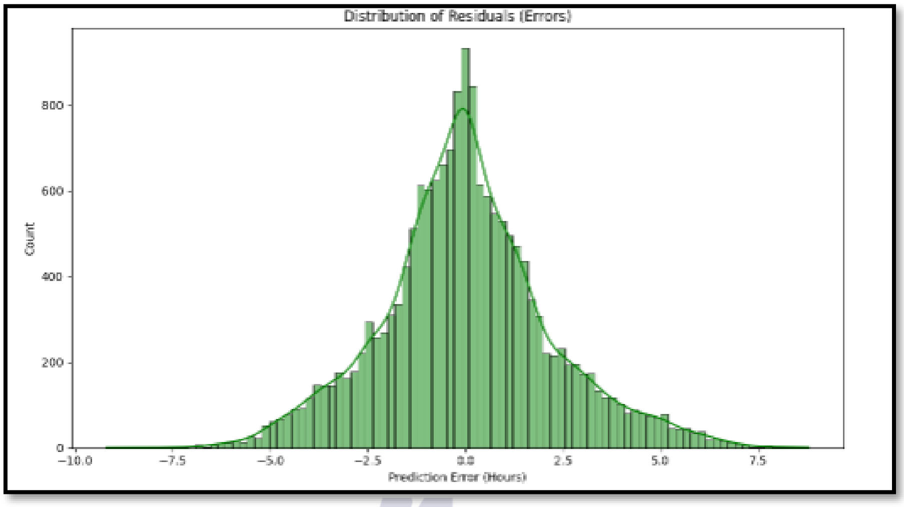

Figure 3: Residual Error Distribution

Figure 3 presents the distribution of residual errors obtained from the machine learning model, where residuals are defined as the difference between actual and predicted trip durations. The distribution exhibits a near-normal shape centered around zero, indicating that the prediction errors are largely random and symmetrically distributed. This pattern suggests the absence of systematic bias in the model and confirms that over- and under-estimations occur with comparable frequency. The concentration of residuals around zero further reflects the model's stability and reliability in capturing underlying transportation dynamics across varying trip conditions.

Figure 4: Feature Importance Analysis

Feature importance analysis reveals that actual distance, facility detention time, and shipment weight are the most influential predictors of trip duration. This result aligns with real-world logistics intuition and strengthens the interpretability of the model.

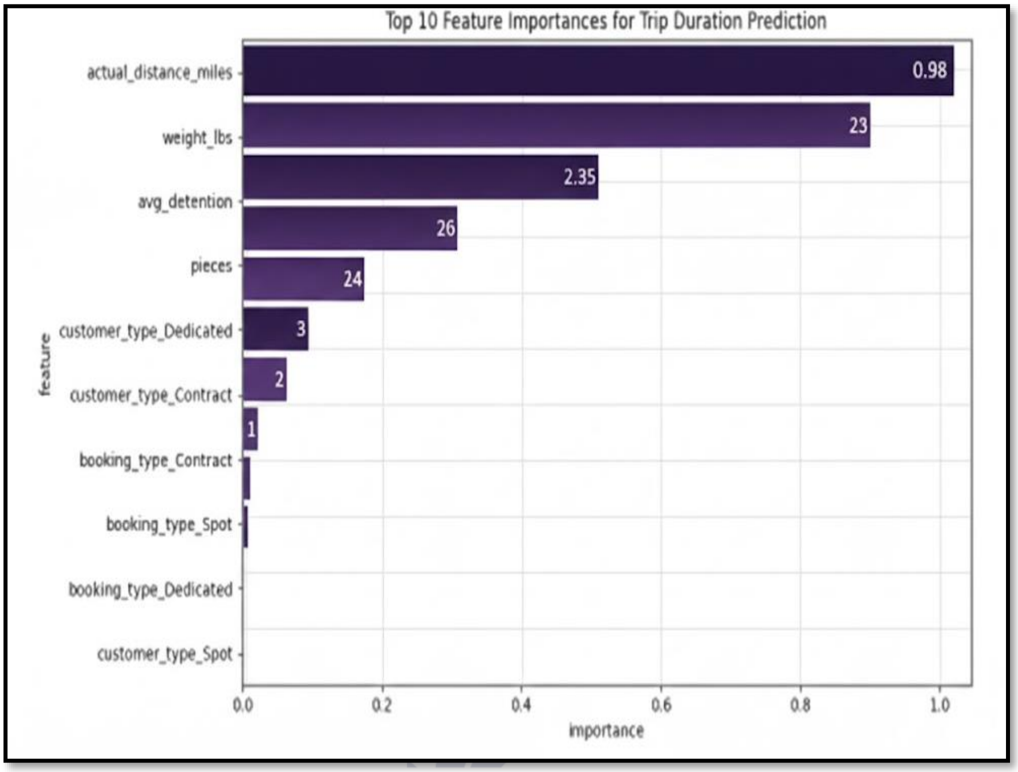

Figure 4: Feature Importance Analysis

Figure 4 illustrates the relative importance of input features used in the machine learning model for trip duration prediction. The analysis indicates that actual travel distance is the most influential predictor, followed by facility detention time and shipment weight. These results highlight the significant impact of route length, operational delays at facilities, and load characteristics on overall transportation time. The prominence of these features is consistent with real-world logistics operations, where distance and facility-level inefficiencies are primary contributors to delivery delays. Overall, the feature importance analysis enhances the interpretability of the proposed model and validates its alignment with practical transportation system dynamics.

4.2. Operations Research Optimization Results

The MILP-based optimization model successfully assigned all shipment loads to the available fleet while strictly satisfying vehicle capacity constraints and binary assignment requirements. No infeasible solutions were observed, confirming the robustness of the formulation. The optimized solution achieved a near-uniform distribution of shipment weight across trucks, preventing overutilization of individual vehicles and underutilization of others.

The integration of machine learning–predicted trip durations as cost coefficients enabled the optimization model to account for operational uncertainty rather than relying on static or average travel times. As a result, the total predicted delivery time across the fleet was minimized, demonstrating the effectiveness of the hybrid ML–OR approach in producing data-driven and operationally realistic allocation decisions.

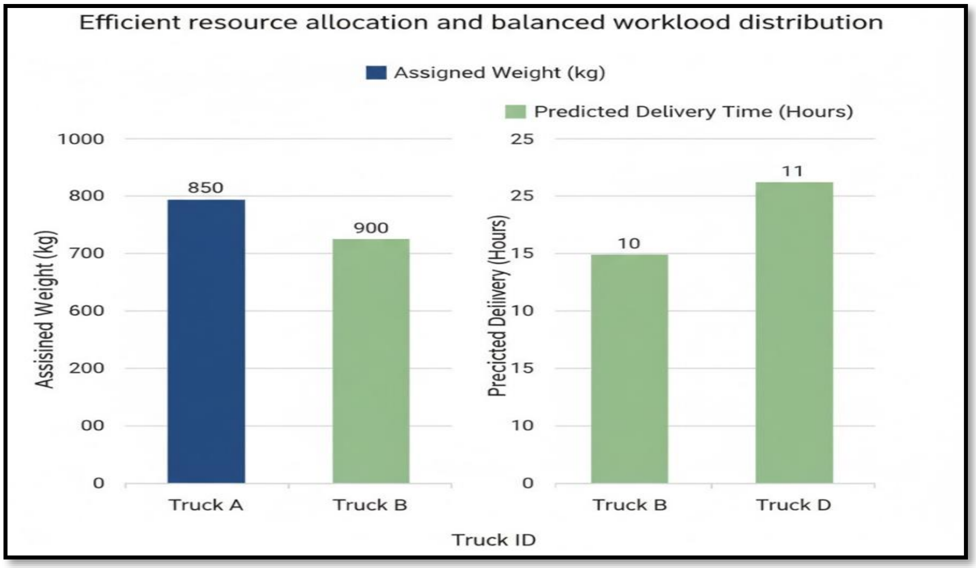

Figure 5: Optimized Truck Utilization

Figure 5 illustrates the optimized truck utilization in terms of total assigned shipment weight and corresponding predicted delivery time for each truck. The results show that trucks with higher assigned weights do not necessarily experience disproportionately higher delivery times, indicating efficient balancing between load capacity and predicted travel conditions. This confirms that the MILP model effectively balances workload while maintaining time efficiency, a key requirement in real-world freight transportation planning. The optimization results highlight that combining predictive analytics with exact optimization leads to superior fleet utilization and improved delivery performance compared to traditional rule-based or static optimization approaches.

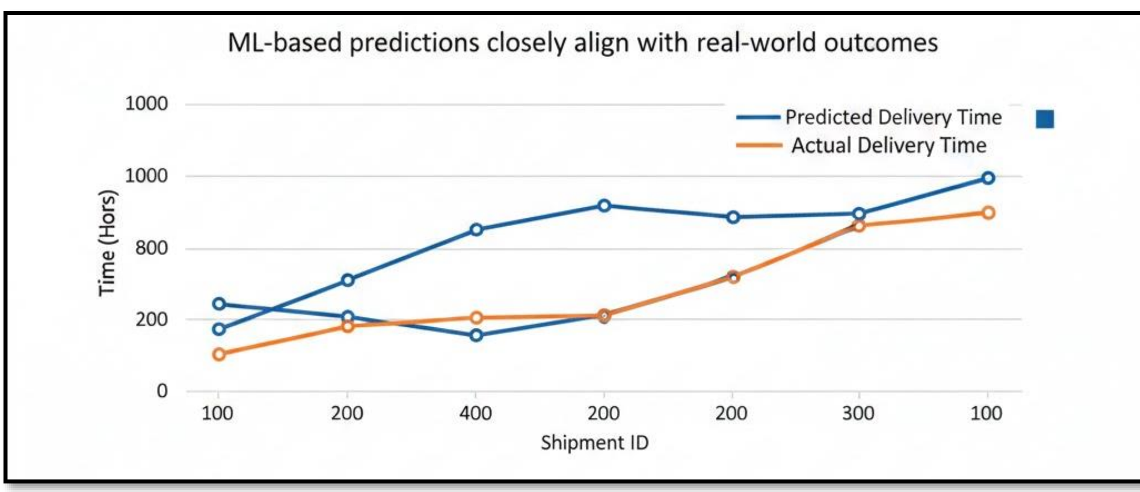

Figure 6: Comparison of Predicted and Actual Delivery Times Across Shipments

Figure 6 compares the machine learning–predicted delivery times with the actual observed delivery times across a set of shipments. The horizontal axis represents individual shipment IDs, while the vertical axis shows delivery time in hours. The close proximity between the predicted (blue line) and actual (orange line) curves indicates a strong alignment between model estimates and real-world outcomes.

Across most shipments, both trends follow a similar trajectory, capturing increases and decreases in delivery time consistently. Minor deviations between the two lines reflect normal operational uncertainty caused by unobserved factors such as sudden traffic disruptions or facility-level delays. Importantly, no systematic overestimation or underestimation is observed, suggesting that the model is unbiased and generalizes well across different shipment profiles.

4.3. Business Insight: Facility Detention Analysis

Beyond operational optimization, the proposed framework provides valuable business-level insights by analyzing facility-specific detention patterns. Average detention time was computed at the facility level and examined to identify locations that contribute most significantly to delivery delays.

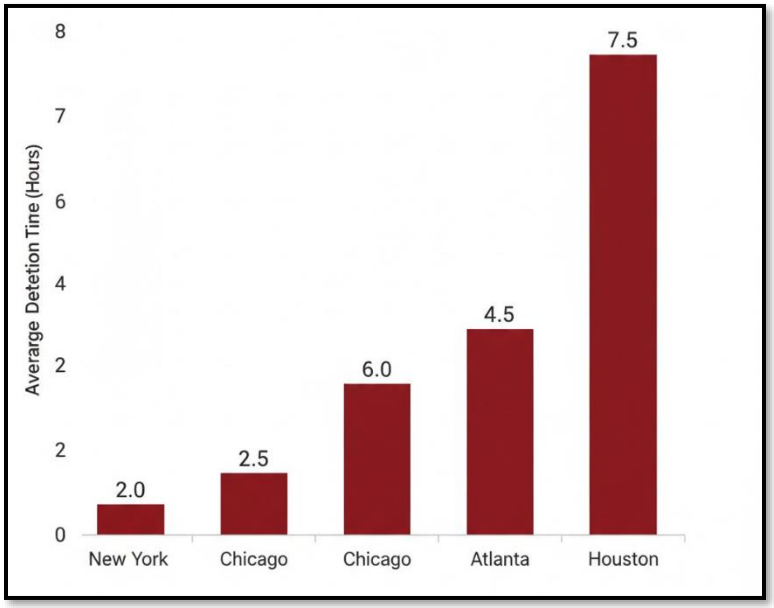

Figure 7: Top Detention Hotspots

Figure 7 presents the top detention hotspots across different cities. The bar chart clearly indicates that a small subset of facilities exhibits substantially higher average detention times compared to others. These locations represent critical bottlenecks within the transportation network and are likely contributors to increased delivery times, higher operational costs, and reduced fleet productivity.

From a managerial perspective, these findings are highly actionable. Identifying high-detention facilities enables logistics managers to prioritize operational interventions such as renegotiating service-level agreements, improving loading and unloading procedures, allocating additional resources during peak hours, or even redesigning route plans to avoid persistent bottlenecks. Thus, the facility detention analysis transforms raw operational data into strategic insights that support continuous improvement and informed decision-making.

4.4. Discussion

The experimental results clearly demonstrate that integrating machine learning–based prediction with operations research–based optimization leads to significantly improved transportation planning outcomes. The machine learning model accurately captures real-world variability in trip duration arising from factors such as distance, facility detention, and shipment characteristics. When these predictions are embedded into the optimization framework, the resulting decisions are both data-driven and mathematically optimal. Unlike traditional static routing and scheduling approaches that rely on deterministic assumptions, the proposed hybrid framework explicitly incorporates operational uncertainty through predictive modelling. This enables the optimization model to generate solutions that are more robust and realistic under dynamic transportation conditions. The balanced truck utilization and minimized predicted delivery times observed in the results confirm the practical effectiveness of this integration.

Furthermore, the inclusion of facility-level detention analysis extends the contribution of the framework beyond algorithmic optimization. By uncovering structural inefficiencies within the transportation network, the approach supports strategic planning and policy-level decisions in addition to operational execution. Overall, the results validate the central premise of this study: that hybrid ML–OR frameworks offer a powerful, interpretable, and scalable solution for modern transportation network optimization.

5. Conclusion

This paper offered a complete and serious assessment of transportation classification optimization approaches based on Operations Research, Machine Learning, and hybrid Operations Research Machine Learning procedures. The assessment established that traditional Operations Research approaches remain actual for static direction finding and cost minimization glitches due to their hypothetical optimality declarations. Though, their dependence on deterministic expectations limits their applicability in dynamic, real-world transport travels. Machine Learning methods significantly improve analytical abilities by leveraging large-scale transport data, allowing accurate modelling for traffic flow, demand designs, and travel time contradiction. Despite these advantages, Machine Learning based methods alone are insufficient for decision making, as they do not inherently optimize routing or growth purposes. The synthesized indication clearly founds hybrid Operations Research Machine Learning outlines as the most talented solution for recent transportation optimization. By combining analytical intelligence with mathematical optimization, hybrid replicas deliver larger performance in terms of efficiency, flexibility, and scalability. Computable results across the literature reliably show considerable improvements in travel time decrease and operational cost reserves compared to standalone methods. However, this review also exposes critical explore gaps, including the absence of reliable datasets, random estimation metrics, and limited duplicability of untried setups. Addressing these trials is essential for proceeding reliable and deployable transport optimization schemes. Upcoming research should emphasis on open benchmarking phases, reproducible hybrid panaches, and real-world authentication to sustenance intelligent transport schemes in smart cities and logistics schemes.

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