FLEET-LEVEL OPTIMIZATION OF TIRE ALLOCATION BASED ON A VERIFIED TIRE STATE PREDICTION FRAMEWORK

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Abstract

Tires represent a significant cost for fleets, typically ranking just behind fuel and driver wages in operating expenses. Tire retreading is a sustainable, cost-effective solution that extends tire life, reduces costs, minimizes waste, and supports the circular economy. However, the implementation of the retreading process has not been fully leveraged to realize its potential benefits for both the environment and businesses. This is largely due to conservative practices adopted by fleets to minimize downtime risks, in the absence of a comprehensive technological framework to guide the tire maintenance operations.

Truck tire casings are designed to withstand multiple retreads, allowing them to serve over long distances and extended periods, unless they are disqualified from retreading due to severe carcass damage, such as punctures, sidewall cuts, or impact breaks. Tires are mounted in various wheel positions on vehicles across a fleet and operate under a range of conditions, loads and durations throughout their life. Remaining Casing Potential (RCP) is an intuitive metric employed to assess a tire's condition at a specific point in its lifespan and determine whether it has enough structural capacity left for subsequent retreads.

Previously, the authors introduced a technological approach for monitoring tread wear and casing condition in real-time, along with methodologies for communicating a tire's status to fleet operators. A machine learning model for time-series forecasting, called the Temporal Fusion Transformer (TFT), was then implemented to predict the RCP with preliminary results presented. The optimization of tire allocation across an entire fleet of trucks, aimed at maximizing the total lifespan of a set of tires, was proposed as a potential direction for future work.

In this paper, the authors first provide an update on the latest RCP predictions obtained from the machine learning model, retrained on extended telematics data, and compare these predictions with the anticipated RCP rankings to demonstrate the performance of the developed framework. Next, the paper presents the development of a linear-constrained dynamic programming algorithm to address fleet-level optimization, minimizing the number of tires used within a prescribed mileage while making informed retreading decisions based on the tire's casing health.

Introduction and Motivation

Tires are a critical component of any fleet, yet their costs are often underestimated in terms of their impact on overall operational expenses. According to the American Transportation Research Institute (ATRI), operational costs in the trucking industry are divided into several categories, with tire-related expenses falling under equipment costs. While these tire-related costs represent about 2% of total fleet expenses [1] , as shown in Table 1, their influence on overall costs is much greater when considering the key role, they play in maintenance, vehicle downtime, and fuel consumption. Improving tire inspections procedures and optimizing tire usage can lead to substantial cost savings for fleet operators across these areas.

Insufficient maintenance practices and improper tire usage can significantly increase overall costs in fleet operations. Poor tire management can lead to more frequent and costly repairs, especially if tire condition goes unnoticed until a breakdown occurs. Furthermore, tires that are not properly inflated, for instance, lead to higher stress and rolling resistance, which results in increased tire damage and fuel consumption.

Table 1. Cost Shares based on Average Marginal Costs per Mile between 2013-2024

Fleet Costs	Average	Std.
Fuel Costs	24%	4.4%
Truck/Trailer Lease or Purchase Payments	15%	1.1%
Repair & Maintenance	9%	0.6%
Truck Insurance Premiums	4%	0.4%
Permits & Licenses	1%	0.3%
Tires	2%	0.3%
Tolls	2%	0.3%
Driver Wages	32%	2.1%
Driver Benefits	9%	1.2%
Total	100%	0.0%

According to ATRI, repair and maintenance costs account for around 9% of total operational expenses, while fuel costs make up a much larger 24%. Both cost categories are heavily influenced by the condition of the tires. In fact, tire-related failures are responsible for about 50% of unscheduled roadside events, with most of these failures beginning with slow leaks that can easily be overlooked without regular inspection. This highlights the importance of proactive tire management in reducing unforeseen costs and downtime.

Fleet management systems designed for preventive maintenance can optimize tire usage and reduce unnecessary costs. These systems can provide real-time data on tire condition, such as inflation pressure, temperature and tread depth, enabling more informed decisions about tire maintenance, tire allocation, and retreading. Regular inspections and automated alerts help prevent costly breakdowns, while also reducing repair and fuel costs. Fleets also use retreading to reduce tire costs; however, many fleets underutilize retreading due to a lack of knowledge about tires' history, current state, and future potential. By using the fleet management systems, fleet managers can reduce premature replacements and extend tire life.

The increasing availability of telematics data also presents a challenge for fleet managers. With so much data available, many operators are overwhelmed by reports and dashboards, making it difficult to make quick decisions. This overload can cause delays in addressing critical issues or lead to suboptimal decisions at the fleet level, resulting in higher costs. Advanced data analytics and predictive modeling can automate the decision-making process, reducing the burden on fleet operators, improving the efficiency of complex operations and lowering costs.

The authors previously introduced digital twin technology as the core of next-generation fleet management systems [2] and developed machine learning models trained on historical data to predict the tread depth and the Remaining Casing Potential (RCP) for casing/carcass life [3, 4]. The tread depth is predicted based on the difference between wheel and vehicle speeds. The measured RCP is an empirical metric derived from the results of endurance tests and non-invasive tire inspections conducted in Michelin's test facility. Building on this foundation, the current study validates the developed framework and focuses on fleet-level tire usage optimization through automated decision-making. The envisioned system operates in real-time, continuously monitoring and updating predictive models with new data from tire/vehicle telematics, while accounting for external drift. Fleet-level optimization, achieved via linear dynamic programming with constraints, automates decision-making and represents the key contribution of this work.

Fleet-level optimization involves advanced analysis, solving complex problems, and making numerous timely decisions—capabilities beyond what fleet managers can address manually. Automated decision-making systems process vast amounts of data, such as tire condition and vehicle usage, to predict tire life and make real-time, data-driven decisions on tire allocation, replacement, and retread timing. Aligned with circular economy principles, tire management systems exemplify the reuse, repair, and recycling of materials in the trucking industry.

Current State of the Technology Industry Uses

Tire management policies used by fleet managers cover the best practices in various areas including tire acquisition, maintenance, usage, compliance, and disposal. These policies typically define tire specifications, maintenance schedules, and safety protocols to ensure the fleet operates efficiently and safely. For many fleets, particularly smaller ones, the implementation of these policies is still largely manual. Fleet managers often rely on weekly inspections, handheld gauges, and traditional methods for monitoring tire pressure, wear, and alignment. While these manual approaches serve their purpose and accomplish the task, they are time-consuming, prone to human error, and lack real-time data that could provide more immediate insights into tire conditions.

The transition to digital tire management systems is increasingly recognized to facilitate operations and reduce costs over time [5]. These modern systems offer significant advantages, such as real-time tire monitoring, predictive maintenance alerts, and automated inventory tracking. With digital solutions, fleets can better track tire health, anticipate wear, and reduce unexpected failures, leading to fewer breakdowns and more efficient vehicle usage. However, transitioning from manual to digital comes with its challenges. Many fleets face significant upfront costs, both in terms of software development and the required hardware installations, such as tire sensors and vehicle telematics. In addition, training staff to use new systems and integrating these technologies with existing fleet management operations takes time and resources.

Benefits of digital systems—such as enhanced safety, reduced fuel consumption, longer tire life, and lower maintenance costs—are becoming increasingly evident over time amid these challenges. Fleets that have already made the transition to more advanced technologies are seeing measurable improvements in their operations. However, the broader industry is still in the early stages of this transformation, with mid and smaller size fleets gradually adopting these systems as they become more affordable and accessible. Given the initial investment and learning curve, the slow pace of change is understandable, but as technology evolves and the benefits become more apparent, it's clear that the future of tire management lies in digital solutions.

Several tire manufacturers, in collaboration with fleet management partners, have developed innovative solutions to enhance the monitoring and management of tire conditions. For example, Michelin offers Michelin Connected Fleet (MCF), a comprehensive fleet management system built on the expertise of acquisitions such as NexTraq, Masternaut, and SasCar, providing a wide range of services and solutions to address the diverse needs of fleet operations worldwide, with a particular focus on predictive tire maintenance. Predictive tire maintenance within MCF integrates a Tire Pressure Monitoring System (TPMS), advanced vehicle connectivity, and telematics to continuously analyze tire performance and proactively alert fleet managers about tire performance and potential maintenance issues, such as under-inflation or wear [6]. Similarly, Goodyear has developed tire inspection and monitoring technologies such as Tire Optix and TPMS Plus to complement its Goodyear SightLine platform for more holistic fleet management [7]. Bridgestone offers a Yard-Based tire monitoring system and utilizes real-time tire data through its subsidiary Webfleet and partnership with GeoTab, enabling fleets to effectively access and act on tire health information [8]. Continental's ContiConnect™ tire monitoring system provides real-time tire data along with other digital solutions designed to support fleet operators [9].

In the realm of fleet management, several technology companies are pioneering software platforms to support the broader logistics and operational needs of fleets. Notable companies include Maven Machines, which offers an integrated fleet management platform with telematics, Wabco (now part of ZF), and Fleet Complete, which provides end-to-end fleet tracking and management systems.

Despite these advancements, no commercial system currently exists that fully optimizes tire usage at the fleet level to maximize their lifespan. While the existing systems assist fleet managers by providing decision support, the decision-making process remains manual, and the automation needed for tire optimization is still in the initial stages. This paper aims to address this gap by introducing a fully automated fleet management system, leveraging artificial intelligence (AI) and machine learning (ML) algorithms. This approach will optimize tire usage, reduce waste at the fleet level, and contribute to sustainability at a larger scale in line with circular economy principles.

Technology Approach

Overview

Digital Twin (DT) technology has become a transformative tool for predictive maintenance in industries like automotive and manufacturing. By creating virtual replicas of physical assets, DT enables real-time monitoring and optimization of systems, including tire lifecycles. It predicts wear patterns, estimates remaining useful life, and supports proactive maintenance. Machine learning algorithms enhance DT's predictive capability by adapting to sensor data and changes in tire conditions. Advanced models like neural networks and Gaussian processes, combined with physics-based simulations, improve prediction accuracy and enable dynamic resource allocation, such as tire rotations and replacements, to maximize performance, reduce costs, and advance sustainability.

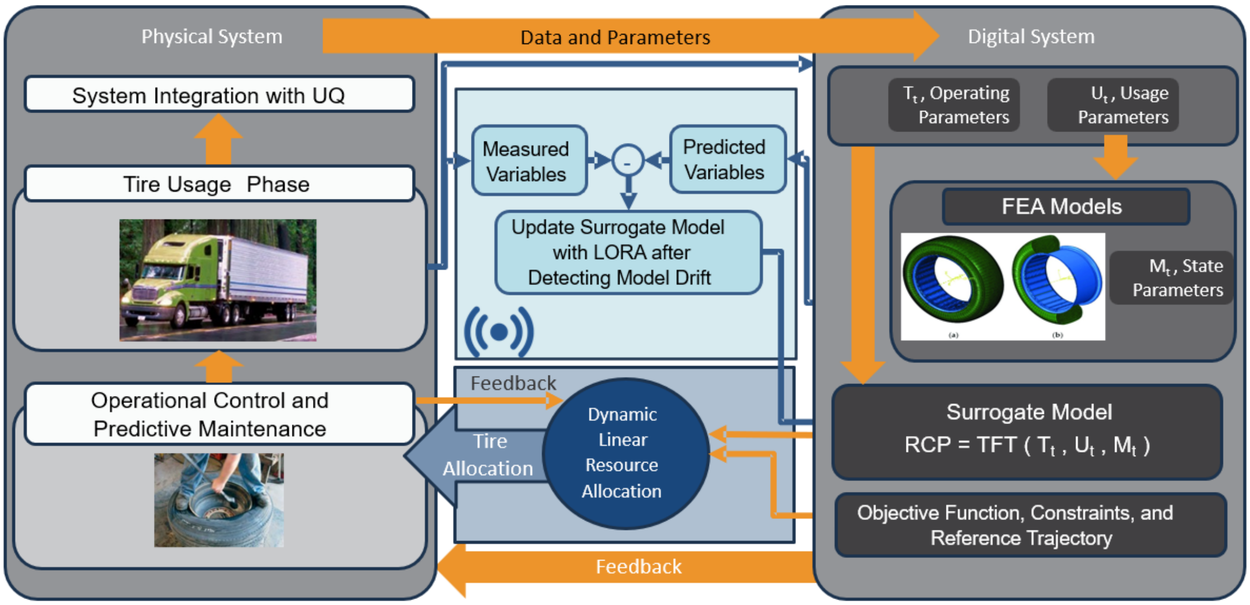

Figure 1: Digital Twin Framework for Tire Management

The schematic in Figure 1 represents a Digital Twin framework for predictive maintenance and operational control of tires, integrating physical and digital systems through a continuous feedback loop. The physical system includes real-world tire usage, where data on variables like ***pressure***, ***temperature***, and ***wear*** is collected during operation. This data feeds into the digital system, which houses physics-based and surrogate models that simulate tire behavior under various conditions, predicting critical parameters such as ***carcass wear*** and ***stress***. A dynamic linear resource allocation module optimizes tire usage by allocating resources based on these predictions, while the surrogate models are continuously updated using techniques like LoRA (Low-Rank Adaptation) to ensure accuracy and adapt to model drift. The bidirectional flow of data enables ***uncertainty quantification (UQ)*** and supports real-time decision-making, enhancing tire reliability, extending their lifecycle, and improving overall maintenance strategies.

Model Validation and Update

The prediction performance of model is evaluated by comparing predicted RCP values to empirical measurements, ensuring the model accurately captures the underlying physics and tire degradation processes. The two metrics utilized to evaluate the model's performance are defined in equations 1 and 2. Let y_i^{actual} represent the actual RCP values obtained from tire inspections and $y_i^{predicted}$ the corresponding predicted values from the model. The mean absolute error (MAE) is calculated as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i^{actual} - y_i^{predicted}| \qquad (1)$$

where n is the number of observations. Additionally, the Mean Absolute Percentage Error (MAPE) metric assesses the goodness of fit:

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n} \left|\frac{y_i^{actual} - y_i^{predicted}}{y_i^{actual}}\right| \qquad (2)$$

These metrics allow us to evaluate the model's performance under different operational and environmental conditions. Moreover, discrepancies between predictions and inspections highlight areas where the model might require adaptation. The evaluation results reveal that the tire health TFT model achieves a MAE of 0.39 and a Mean Absolute Percentage Error (MAPE) of 34.8% on average when its prediction performance is tested with tires that it was not trained on. These findings suggest that the model performs reasonably well across diverse conditions, which shows its potential for generalization. However, it also implies that there's room for improvement, especially if we can identify tires with significant drift and address them to enhance overall performance.

Drift detection is a critical component in ensuring the model remains robust over time. Drift occurs when the distribution of new data deviates significantly from the training data, leading to performance degradation. The adaptation process begins with identifying drift through statistical and ranking-based methods. Drift detection uses Maximum Concept Discrepancy (MCD) to quantify differences between the training and incoming data. Let X_{train} and X_{new} represent the training and new datasets, respectively. The MCD metric is defined as:

$$\mathrm{MCD}(X_{train}, X_{new}) = E[\kappa(X_{train}, X_{train})] + E[\kappa(X_{new}, X_{new})] - 2E[\kappa(X_{train}, X_{new})], \qquad (3)$$

where $\kappa(\cdot,\cdot)$ is a kernel function (e.g., Radial Basis Function (RBF) kernel). A threshold for significant drift is set dynamically using the training distribution.

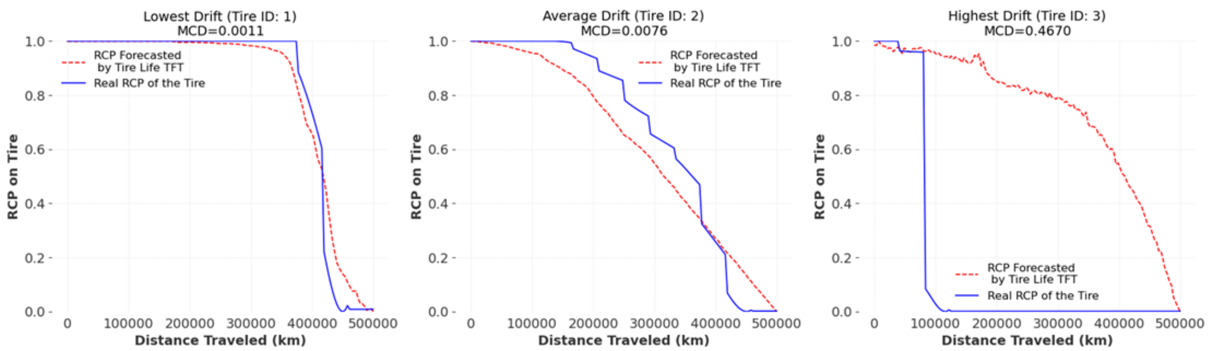

Figure 2: Concept Drift Plots for Tires with the Lowest, Average and Highest Drift left to right

Figure 2 illustrates the concept drift across three tires with the lowest, average, and highest drift levels, as quantified by the Maximum Concept Discrepancy (MCD) metric. For the lowest drift tire (MCD=0.0011), the predicted RCP closely aligns with the real RCP, indicating minimal deviation between the training and new data distributions. For the average drift tire (MCD=0.0076), moderate discrepancies emerge, reflecting slight deviations that highlight the model's capacity to handle typical operational changes. In contrast, the highest drift tire (MCD=0.4670) exhibits significant mismatches between the forecasted and actual RCP, demonstrating the impact of substantial data distribution shifts. These results underscore the importance of drift detection and adaptation mechanisms to maintain the model's predictive reliability and ensure robust performance across varying conditions.

Next, a lightweight update mechanism is introduced to remove drift and incorporate new data. This process leverages Low-Rank Adaptation (LoRA) to efficiently fine-tune the model without retraining it entirely. LoRA introduces a low-rank perturbation to the model's weights, defined as:

$$\Delta W = A \cdot B^{\top}, \qquad (4)$$

where $A \in R^{d \times r}$ are low-rank matrices, and $r \ll d$. The updated weights become:

$$W_{new} = W_{base} + \Delta W \qquad (5)$$

The updated model is fine-tuned on the drifted data to adapt to new distributions. To ensure smooth transitions, only tires identified with significant drift ($\mathrm{MCD} > \mathrm{threshold}$) are included in the update. The effectiveness of the update is validated by re-evaluating the MAE and MAPE metrics post-update. Furthermore, drift compensation is verified by recalculating τ for tire rankings and confirming consistency.

$$\mathrm{Threshold} = \mu + \sigma \qquad (6)$$

where μ is the mean and σ is the standard deviation of drift scores. Additionally, a percentile-based threshold (85th percentile) is used as a fallback, ensuring a robust criterion. The final threshold is set as the maximum of these two values, and tires with drift scores exceeding this threshold are flagged for adaptation. The final threshold is set as:

$$\mathrm{Final\ Threshold} = \max(\mathrm{Threshold}, 85\mathrm{th\ Percentile}) \qquad (7)$$

For this analysis, the final threshold was calculated to be 0.312. Tires with MCD scores exceeding this value were flagged as exhibiting significant drift and included in the adaptation process. The model's performance was evaluated both before and after applying LoRA. Before applying LoRA, the Mean Absolute Percentage Error (MAPE) was exceedingly high at 264.7%, indicating significant inaccuracies in the model's predictions due to drift. After applying LoRA, ***the average MAPE was reduced to 32.2%***, showcasing a substantial improvement in predictive accuracy. The rule of thumb is that a MAPE between 30-40% is still considered acceptable for decision-making in fleet optimization. With this level of accuracy, the model can effectively support operational decisions despite the inherent variability in real-world data. This reduction highlights LoRA's effectiveness in adapting the model to handle drifted data while preserving computational efficiency.

Fleet-Level Optimization

Effective decision-making for fleet-level tire management requires a comprehensive framework that optimizes tire usage while balancing operational efficiency, cost reduction, and sustainability. The decision-making process involves three critical aspects: tire allocation and rotation, retreading timing, and tire removal from service. These decisions are informed by the RCP value, a key metric for assessing the structural integrity and retread potential of a tire over its lifecycle.

Tire allocation involves strategically placing tires in specific positions across the fleet to balance tire degradation and maximize tire lifespan. Optimal tire positioning is critical, as steer tires (e.g., 1L – first axle left position) often experience higher stress and require tires with maximum reliability, while drive and trailer tires can tolerate higher wear levels. To ensure this balance, the dynamic programming algorithm systematically determines the optimal tire placement by solving a linear programming problem where the objective is to maximize the total RCP across the fleet. RCP values are used to guide the decision-making process, with higher-RCP tires prioritized for critical positions, while lower-RCP tires are rotated to less demanding locations. Rotation helps distribute tire workload more evenly, extending overall tire life while minimizing operational risks.

Retreading is a sustainable practice where a tire's worn tread is replaced while preserving the casing for continued use [10]. In the proposed model, tires with an RCP value above a specified threshold (e.g., 9.2%) are retreaded, provided the casing's structural health is sound. The dynamic programming approach identifies these tires and strategically reintroduces them into critical positions within the fleet (e.g., 1L). This process not only extends tire life and reduces waste but also minimizes procurement costs.

Tires are removed from service when their RCP value falls below a critical threshold, indicating insufficient casing potential for another retread. In the proposed framework, tires with an RCP below ~9.2% are automatically flagged for removal and replaced with new tires. New tires are introduced into the fleet with zero mileage with an RCP of 100%. This systematic removal ensures fleet safety while preventing unplanned downtime and costly failures.

The decision-making process uses a constrained dynamic linear programming (DLP) framework aimed at maximizing cumulative RCP across the fleet. In addition to basic operational requirements, such as ensuring all vehicles are equipped with the required number of tires and each tire is assigned a unique position, constraints may also include rules and best practices outlined in tire management policies. The model tracks tire states, including RCP values, mileage, and previous locations, enabling data-driven optimization. The tire state prediction framework, validated in prior research with machine learning models like the Temporal Fusion Transformer (TFT), supports real-time RCP forecasting to guide dynamic decision-making.

Objective Function (Maximize Total RCP):

$$\max \sum_{i=1}^{N} \sum_{j=1}^{L} \sum_{k=1}^{T} RCP_{i,j,k} . x_{i,j,k} \qquad (8)$$

where:

- N = Number of tires
- L = Number of locations
- T = Number of trucks
- $RCP_{i,j,k}$ = Remaining Casing Potential of tire i at location j on truck k
- $x_{i,j,k}$ = Binary decision variable, 1 if tire i is placed at location j on truck k, otherwise 0

Constraints:

- Each tire must be assigned to a unique position:

$$\sum_{j=1}^{L}\sum_{k=1}^{T} x_{i,j,k} = 1 \qquad \forall i \qquad (9)$$

- Each location must have exactly one tire assigned:

$$\sum_{i=1}^{N} x_{i,j,k} = 1 \qquad \forall j, k \qquad (10)$$

- RCP update based on mileage and forecast:

$$RCP_{i,j,k}^{t+1} = f\left(RCP_{i,j,k}^{t}, \Delta M_i\right) \qquad (11)$$

where:

- ΔM_i = mileage increments for tire i during the current interval and
- f = forecast function using TFT for RCP prediction. Mileage update equation:

$$M_i^{t+1} = M_i^t + \Delta M_i \qquad (12)$$

The simulation scenario demonstrates a simple yet powerful example of optimizing tire management, designed to highlight the system's potential benefits while maintaining generality. The setup includes two trucks with differing loads: one carrying 16,000 kg and the other 36,000 kg. Each truck has 10 tire positions—two steer, four drive, and four trailer positions—ensuring the allocation reflects real-world operational diversity. For a truck used up to 1 million miles, four maintenance cycles at 200,000, 400,000, 600,000, and 800,000 miles ensure consistent monitoring and replacement. The simulation scenario compares a fleet management system using the DLP approach with a random tire allocation method. The random allocation approach operates under the same constraints; however, RCP prediction is only used for tire removal, with no automatic decision-making based on RCP.

The DLP approach demonstrates significant improvements in tire lifespan and resource utilization across the fleet. The difference between DLP-managed and random allocation methods shows nearly a ***50% improvement in tire lifespan***, highlighting the efficiency of the optimized tire placement strategy. The decision-making in each service cycle further underscores the advantages of the DLP framework. In the selected cases, tires under the DLP approach were retained for up to three service cycles, while the random allocation strategy resulted in most tires being removed after only two service cycles. This reduction in tire replacement frequency not only minimizes downtime but also directly contributes to operational cost savings.

Moreover, when measuring overall tire utilization efficiency, the DLP framework demonstrated a significant reduction in the number of tires required for fleet operation over a fixed distance. To cover 1 million miles, the dynamic linear programming approach utilized ***only 28 tires***, whereas the random tire allocation approach required ***34* tires** to cover the same mileage. This reduction in tire usage highlights the optimization benefits of the DLP strategy, directly contributing to sustainability goals by minimizing waste generation and the need for frequent tire replacements. A normalized comparison of tire mileage across both strategies reveals a higher degree of uniform performance and extended operational life across the fleet. On average, the normalized end mileage for DLP exceeded ***90% of the maximum achievable tire life***, while the random allocation strategy ***remained closer to 60%***.

The results summarized above validate the effectiveness of the decision-making framework in optimizing tire resource allocation while maintaining safety and reliability. By leveraging historical tire data, RCP predictions, and service cycle optimization, the proposed method ensures both cost-effective and sustainable fleet management.

Discussion

Results of this study demonstrate the potential of the Digital Twin framework in advancing predictive tire maintenance and fleet-level optimization. The study primarily focuses on model validation, model updates, and tire usage optimization at the fleet level.

Regarding model validation, the prediction results obtained for a new dataset are reasonably accurate on average, considering the variety of driving conditions. However, the overall results include some tires with significant deviations from real measurements. These tires are identified by drift detection algorithms and corrected for drift, improving the overall performance of the system. The algorithms have been shown to adapt effectively to significantly different datasets, correcting themselves without the need for full retraining. This capability ensures that the system remains reliable in dynamic and unpredictable operational environments.

The system shows promise for optimizing tire usage at the fleet level by leveraging automatic decision-making algorithms. In a straightforward but realistic proof-of-concept scenario involving two vehicles, the system successfully extended tire lifespan and reduced the number of tires needed for a given total distance traveled. These outcomes were achieved by using predictive models for tire tread and carcass life, which informed decisions on retreading and tire removal. Validated under basic operational constraints that somewhat reflect real-life tire management policies, the approach shows promising results. Although these constraints are simplified, the outcomes underscore the framework's capacity to deliver meaningful results even at this early stage of development.

The fleet-level optimization of tire usage through dynamic linear programming relies on the system's ability to continuously monitor tire usage, predict carcass and tread states in real-time, and incorporate these insights into decision-making. This enables uniform workload distribution across the fleet's tires over their lifetimes. The steer, drive, and trailer axles each impose distinct demands, with the steer axle requiring greater carcass endurance and the drive axle emphasizing wear resistance. While tire rotations can follow tire management policies, determining the optimal timing for these rotations has long been a challenge. The developed system, utilizing vast datasets, predictive capabilities, and sophisticated algorithms, addresses this complexity, ensuring far more efficient tire usage than a fleet manager could manually achieve.

While the findings are promising, some barriers and limitations remain. Integrating an automated decision-making system may disrupt existing business processes, requiring significant changes to workflows, roles, and coordination with third-party vendors, which can be challenging for businesses. The RCP used in model validation represents a tire state that is difficult to observe directly, as empirical RCP values only approximate the true underlying phenomenon. Enhanced inspection systems could improve the accuracy of RCP representation and boost system performance. The current simulations compare the framework's performance against a simplified base case, which may not fully capture real-world conditions. Due to limited access to fleet data, the system's performance has yet to be assessed in actual fleet operations. Future work should incorporate more complex scenarios with additional vehicles and tires, using real-world fleet management data as it becomes available. Expanding the simulation constraints to align with a wider range of tire policies and best practices could better reflect the expertise of fleet managers. Additionally, studying the frequency of service cycles in more detail could reveal further impacts on system outcomes.

Looking ahead, future work should prioritize empirical validation using operational data from real fleets to assess the system's effectiveness across diverse conditions. Scaling up fleet sizes in simulations will require the development of faster and more efficient algorithms. Incorporating detailed and varied tire management policies will enable the model to tackle a broader range of operational challenges. These advancements will further establish the Digital Twin framework as a next-generation solution for fully automated fleet management, aligning with sustainability goals by minimizing tire waste and optimizing resource utilization.

Conclusions and Recommendations

In this paper, the Digital Twin framework previously developed for predictive tire maintenance operations has been validated and enhanced to include automated decision-making for optimal tire usage at the fleet level. An overview of the current state of tire management technology is provided, emphasizing the inevitable shift from manual operations to digital solutions over time, supported by examples.

The predictive capabilities and drift rejection mechanism of the developed model have been evaluated and validated using tire inspection results. On average, the model, trained with historical data, produced moderately accurate predictions for tires used under a wide range of driving conditions. The introduction of drift detection and removal algorithms, targeting tires with poor predictions, further improved prediction performance. The validated model continuously processes new data, effectively eliminates drift, and updates rapidly without requiring a full re-training. This ensures the system remains adaptive and responsive to changing conditions.

The developed prediction model has been expanded to optimize tire usage at the fleet level, incorporating automated decision-making capabilities. Constrained DLP is employed for robust decision-making in tire allocation, rotation, and retreading, with particular emphasis on optimal timing based on the tire's condition. Fleet managers often struggle with this aspect due to the vast amounts of data and the complexity of balancing multiple factors—such as tire condition, usage patterns, and environmental conditions—making it a challenging problem to solve manually. Carefully selected constraints, mirroring the tire management policies used by fleet managers, ensure the system aligns with real-world practices. The environmental impact of the developed system grows with fleet size and becomes more pronounced in larger fleets, thereby improving both operational efficiency and sustainability.

By integrating advanced data analytics, real-time operational feedback, and continuous model refinement, fleets can achieve a more proactive approach to tire management. This paper underscores the potential for technology to ***reduce waste***, ***improve fleet efficiency***, and ***extend tire lifespan***, ultimately contributing to ***sustainability*** and ***cost savings*** in fleet operations.

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References

1. Leslie, A. and Murray, D., An Analysis of the Operational Costs of Trucking: 2024 Update, American Transportation Research Institute, 2024.
2. C. Siuta, V. Karkaria, D. Lim, W. Chen, R. Radulescu, Optimizing Long-Haul Truck Tire Retread Practices Using On-Board Telematics, 2024 CETSC
3. Karkaria, V et. al., A Machine Learning Based Tire Life Prediction Framework for Increasing Life of Commercial Vehicle Tires, Journal of Mechanical Design, 23, 1435, 2023.
4. D. Lim, Method for Measuring Tire Wear Using Vehicle Speed, US Provisional Patent 2023PAT00064US, assigned to Michelin, 2023
5. Trends in State-of-the-Art Fleet Technology, https://www.automotive-fleet.com/349912/trends-in-state-of-the-art-fleet-technology, 2020.
6. Michelin Connected Fleet – Services and Solutions https://connectedfleet.michelin.com/en-us/, 2025
7. Goodyear Sightline – Fleets, https://www.goodyearsightline.com/fleets, 2025
8. Bridgestone Fleet Car, https://commercial.bridgestone.com/en-ca/fleet-care, 2025
9. Continental Fleet Solutions, https://www.continental-tires.com/about/technologies-and-innovations/fleet-solutions/, 2025
10. Michelin Retread Technologies, https://business.michelinman.com/michelin-retread-technologies, 2025

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