Deterioration Digital Twins of Commercial Trucks and Trailers for Targeted Inspection and Maintenance

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Chapter 1 Overview of the Completed Research Studies

Inspection and maintenance play a vital role in ensuring the safety of commercial trucks and trailers within a fleet, effectively reducing accidents and mitigating financial losses. Trucks and trailers are subject to a patchwork of state and federal safety inspections that manually and periodically check safety components like tires, brakes, and lights through planned or unannounced roadside inspections. It's possible that a vehicle drives on the road until the next inspection resulting in a lack of immediate inspection and maintenance. Moreover, inspections delay deliveries and increase costs regarding commercial fleets. Current inspection programs still need improvement in reducing unnecessary inspections, such as vehicle inspections in safe conditions.

Aiming to improve the safety of trucks and trailers and reduce costs due to inspections, the researchers proposed a predictive inspection planning program to predict the risky vehicles and components and only target them for inspection (Figure 1). In this way, the risky components can obtain immediate inspection and maintenance while the fleet can save unnecessary inspections on safe vehicles.

The project aims to enable targeted inspection and maintenance of commercial tractors and trailer fleets by a vehicle deterioration digital twin that integrates historical inspection records and real-time sensor data for predicting high-risk vehicles and components. Such a vehicle deterioration digital twin should support prioritizing vehicles and vehicle components for inspection and maintenance to balance fleet safety, mobility, and maintenance costs. Specific objectives of this study include: 1) generate process digital twins from inspection data and sensor logs of telematics system; 2) generate inspection plans for truck and trailer fleets; 3) prioritize potential component violations mostly involved in the crashes and approach safety agencies and fleet managers for identifying the potential of telematics. The research questions are: 1) what data analytics architecture can effectively organize and visualize vehicle information for better fleet management? 2) what inspection planning method can provide reliable inspection plans that improve safety while minimizing inspection costs? 3) what types of component violations are more likely to cause crashes, and what are the potentials of applying telematics?

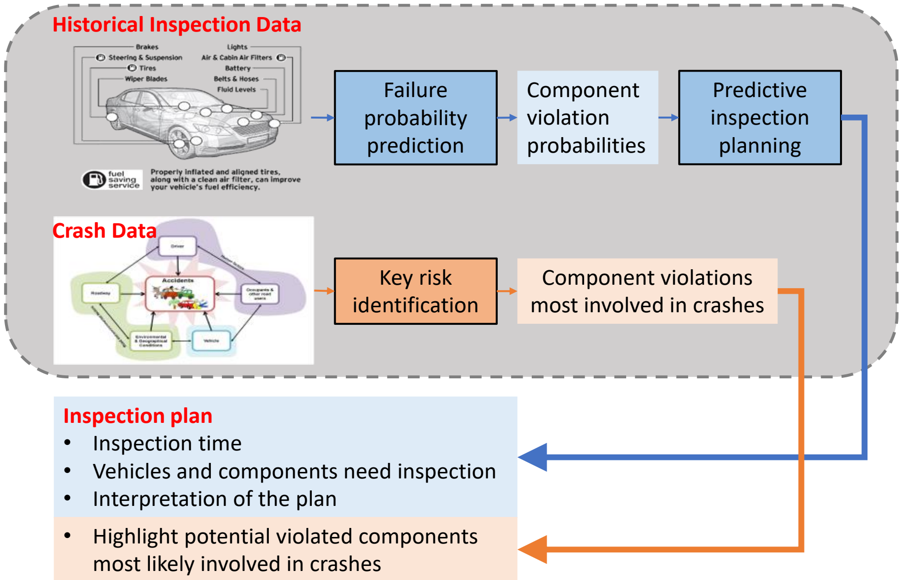

Figure 1. Framework for the predictive inspection planning

Chapter 2 Generating Process Digital Twins from Vehicle Inspection Data

2.1 Introduction

The project aims to develop a predictive inspection planning model to generate reliable inspection planning that ensures vehicle safety with a few costs. The inputs of the predictive inspection planning model include the trucks and trailers' properties (e.g., vehicle make, age) and inspection data (e.g., brake pad thickness, tire tread depth), which are collected from the physical fleet. The predictive inspection planning model is in digital space, while the fleet is in the physical world. Therefore, a platform that can interact between the physical and virtual spaces is essential. The platform must take in data from the physical fleet and store and process the information to generate the optimal inspection plan and guide fleer management. Digital twins could be a solution, which is defined as "a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems [1]." The digital twin can take in the fleet information from the physical fleet, build a virtual one on the computer, and conduct analysis to calculate the optimal inspection plan. The virtual trucks can also be updated along with the changes in the real world. Therefore, the project aims to propose a framework for building digital twins of the truck fleet to build a virtual space for calculating the optimal inspection planning.

Besides the inspection data collected from the fleet under management, data from other sources can also provide valuable information for fleet management. The project obtained heavy-duty trucks and trailers' inspection data from CompuSpections (renames in 2022 as "Safety Emissions Solutions") and Motor Carrier Management Information System (MCMIS) and create dashboard-like summaries of them in order to provide stakeholders with fast access to better information. For example, the dashboard will show managers the most failure-prone components of heavy-duty vehicles. In support of this effort, we will develop data analytic methods to operate on the large historical data archive to identify features such as trends associated with safety component failures (e.g., brakes, tires, or lights). However, the failure-prone components are different for vehicles with different properties, operation environments, and driving behaviors. Suppose we have a list of failure modes that point to component defects or operation problems in vehicles and carriers with certain background features and driving behaviors. In that case, inspectors can inspect vehicles customized and strategically with a more efficient pipeline. Meanwhile, drivers and fleet managers from carriers can also benefit from this failure mode identification because they can pay more attention to sensitive and fragile components. Another challenge comes from limited data sources information. For example, MCMIS Catalog contains detailed descriptions of the violations found during vehicle inspections while having no detailed mileages of vehicles [2]. On the other hand, some commercial vehicle inspection companies maintain databases that capture detailed mileage while only mentioning the problematic vehicle components without detailed descriptions of the violations [3]. So cross-database analysis can overcome information absence problems and embodies failure mode analysis in a more complementary and comprehensive way. The researchers aim at a more comprehensive failure mode identification from two databases that contain complementary inspection records for capturing different information related to the deterioration trends of various commercial vehicles. The research team used two historical inspection datasets to summarize violation patterns among various vehicle features or components. We introduce K-means clustering and Latent Dirichlet Allocation models to identify failure modes based on information integration cross-database. Finally, we used violation counts or probability as performance metrics to evaluate failure modes' effectiveness in identifying groups of vehicles of high risk. (KMeans and LDA advantages)

In this chapter, the researchers aim at developing a platform for building digital twins of fleet, which can store and visualize the information of the fleet under management, the historical dataset from other sources, and integrate the predictive inspection planning.

2.2 Related work

While legislators are trying to simplify and humanize the inspection process of inspections, motor carriers should also focus on self-inspection and real-time monitoring to avoid being cited or given a score below average on FMCSA Safety Measurement System. Besides the argument of the effectiveness of inspection programs, identifying each component's violation probability and crash risk probability can improve carriers' safety and efficiency performance. Randhawa et al. [4] found the most often cited component in incidence reports. They reviewed 3,600 selected police reports from six states, and brakes are reported as a major cited mechanical factor with 1.7% of involvements. Then comes components such as tires, wheels, coupling, and load securement, all at about 0.4%. Daniel Blower et al. also examined the relationship between the mechanical condition of heavy trucks and crash involvement [5]. They used the Large Truck Crash Causation Study (LTCCS) to test if trucks with defects and out-of-service (OOS) conditions were statistically more likely to be involved than trucks without these conditions. They also found that violations in the brake system (36% of all) and the lighting system (19%) were the most frequent, and violations related to brake adjustment increased the odds of the truck's being the striking vehicle by 1.8 times. Above all the discussion focusing on mechanical factors, researchers emphasize the importance of component healthy conditions with brakes, lights, and tires. But how valuable it is for different makes of vehicles and carriers with different operation patterns to schedule self-pre-trip inspections or install real-time monitoring devices like telematics remains unknown.

Failure mode identification can provide a tool for drivers and fleet managers to navigate through different combinations of critical vehicle components in various vehicles to avoid high-risk vehicle operation scenarios. Researchers used statistical approaches to identify individual high-risk vehicles from annual safety inspection records. Zheng et al. [6] tried a gradient boosting data mining model to evaluate several factors' relationship with crash injury severity. They classified the crash severity into four different categories. They concluded that wet road surfaces, bad visualization (dark or low light conditions, or fog/poor weather conditions), a strong crosswind, heavy gross vehicle weight, and collisions with opposite traffic would increase the likelihood of more severe outcomes. Liang et al. [7] tested the effectiveness of safety roadside inspections by exploring accidents caused by reduced caution in driving and lack of vehicle maintenance. They also applied a classical case in economics by Becker's research [8] to point out that if motor carriers or fleet managers are aware of this regulation, such practices will undermine the effectiveness of the regulation by reducing their compliance. Unfortunately, these studies have not yet traced how vehicle component defects interact with other features such as age, mileage, and vehicle properties, leading to high-risk operation scenarios and crashes.

The contributions of the paper include: 1) generalizing failure modes from millions of vehicle inspection records; 2) revealing distributions of different background features (such as age, mileage, and urbanity) in each mode; 3) synthesizing text recording into failure topics that represent a specific failure mode found during random roadside inspections.

2.3 Methodology of Generating Digital Twins of Vehicle Deterioration Processes

The project proposed a framework of the fleet digital twins as shown in Figure 2. The fleet digital twins include three major functions: 1) the visualization and lesson learning of historical dataset, 2) the training process of the predictive inspection planning model, and 3) the visualization of the fleet information and the generation of the inspection plan. The digital twin will store the historical dataset from DOT, inspection stations, and other stakeholders and visualize and analyze them to summarize lessons for fleet managers to have a better understanding of how to manage and maintain the vehicles. The historical database can also be utilized in training the inspection planning model, in which the lessons are feed in the model. Then the model can obtain the fleet information from the physical space to diagnose and prognose the vehicles' condition and finally generate inspection plans. The works can operate inspection and maintenance actions in the physical world according to the inspection plan generated from the digital space.

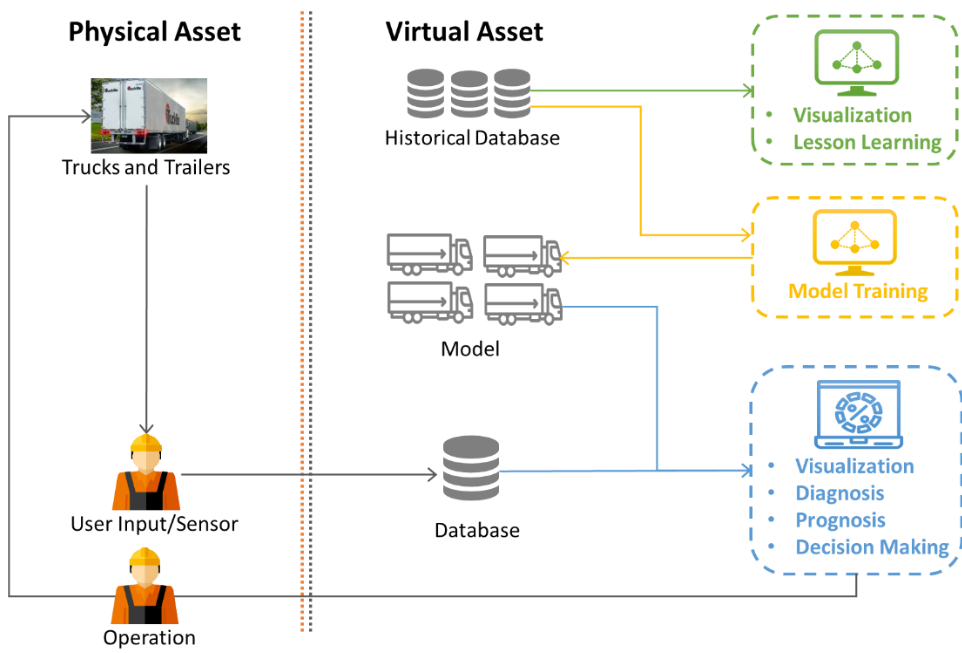

Figure 2. Framework of the fleet digital twins

In this chapter, the researchers focus on interpreting the visualization and lesson learning of historical dataset and the visualization of the fleet information and the inspection plan. The models under for generating inspection plans will be explained in the following chapters.

2.3.1 Inspection data from the fleet under management

The project delivers an interface for uploading fleet information and generating inspection plan, as shown in Figure 3. The fleet manager can type in the trucks and trailers' information one by one or upload a formatted CSV file with information of all vehicles in the fleet. Then by clicking on the "Save", "Process", and "Result" buttons in a row, the manager can save the fleet information, make the model start processing the data, and obtain the inspection plan.

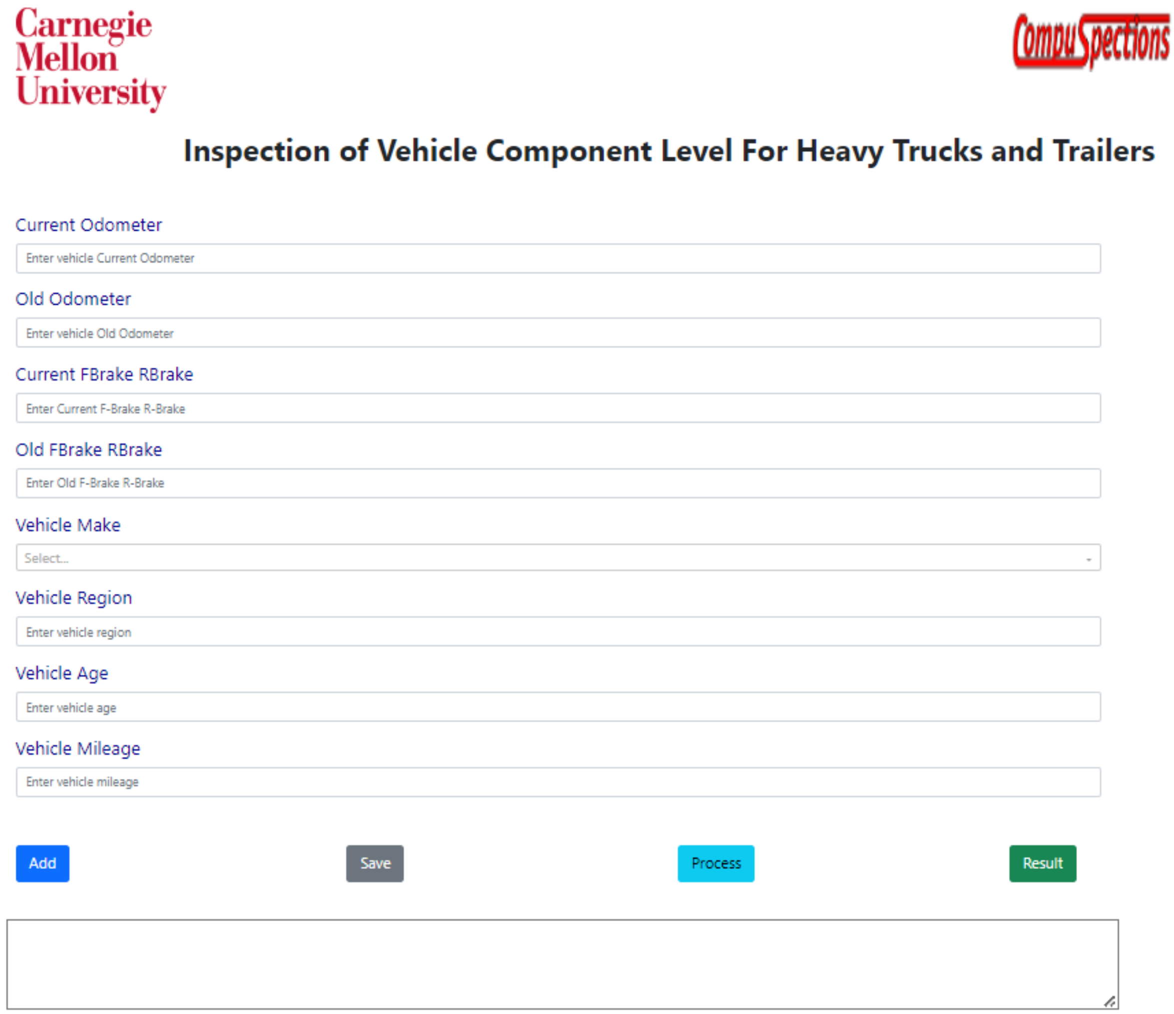

Figure 3. Interface for uploading fleet information and generating inspection plan

The project also developed a dashboard for presenting the inspection plan, as shown in Figure 4. The dashboard presents the rank of vehicle components by inspection priority and marks the components need inspection with red flags. By clicking on a specific component, the vehicle information like vehicle make, age, current condition, etc. will be presented. After presenting the vehicle information, the dashboard also presents the reasoning process of how the computer decides whether the component need inspection according to the vehicle information. Since vehicles with different properties, driving environments and driving behaviors have different deterioration patterns, the dashboard shows the component's deterioration pattern. In addition, the dashboard derives similar vehicles from the historical data of the fleet under management and the historical data from other sources to see whether such vehicle needs inspection according to the experience in the historical data. If the inspection plan suggests a specific component need inspection and most of the similar cases in history need inspection, then the inspection plan is highly validated.

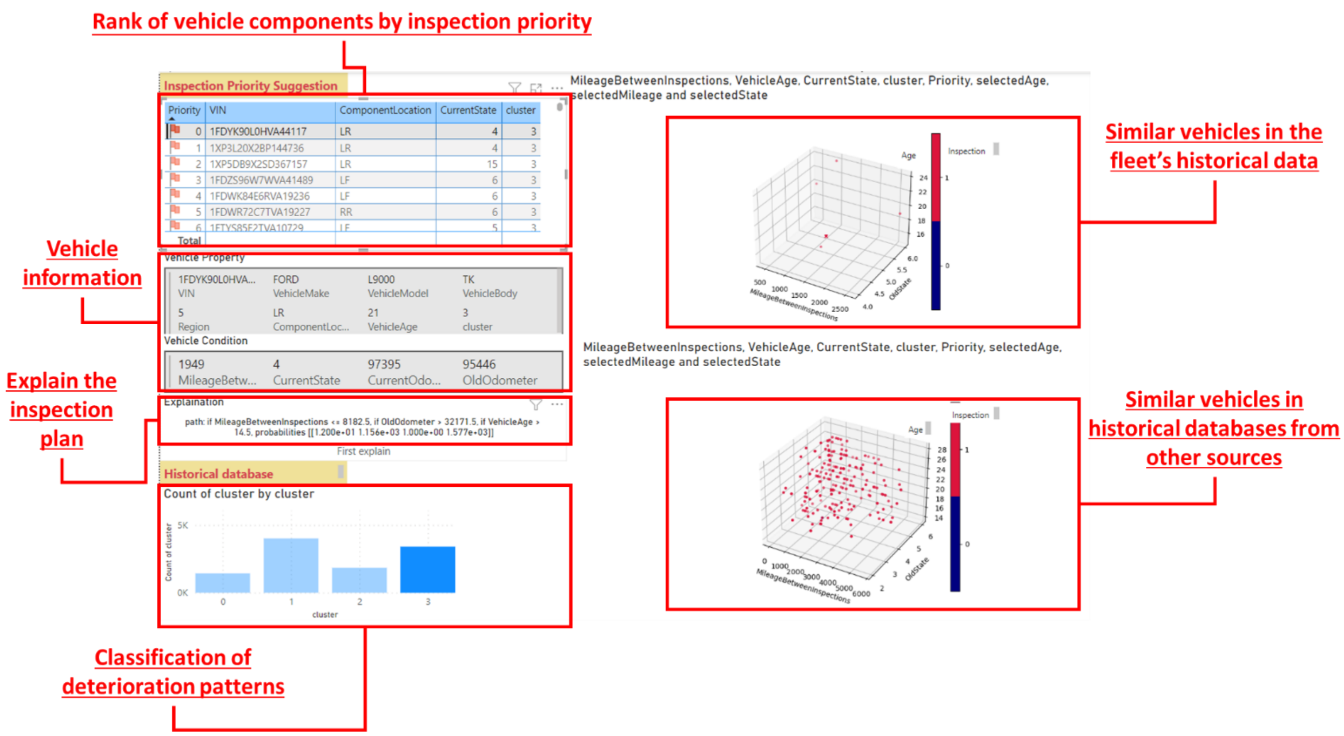

Figure 4. Dashboard for presenting the inspection plan

2.3.2 Historical dataset from other sources

In this paper, we utilized historical truck inspection data from different sources to explore potential failure modes behind historical inspection records. The first sub-section below describes data preprocessing pipelines defining reasonable time ranges and validating correct inspection records. The second sub-section introduces clustering methods, such as K-means clustering, and latent Dirichlet allocation methods applied to different datasets to cluster multiple failure modes based on descriptions and topics extracted from inspection records. Figure 5 shows the overall framework of the proposed method.

Data Sources and Preparation

This research uses two vehicle inspection databases. The first is a database maintained by a privately owned IT contractor in Pennsylvania. In many states, such as Pennsylvania, inspection data are collected by the state government and privately owned IT contractors and inspection companies. CompuSpections, LLC (renamed into "Safety Emissions Solutions" in 2022, to keep consistency, still call the dataset "*CompuSpections dataset*" hereafter) is a privately owned IT service company incorporated in 2003. Their work includes over 30 years of performing State Inspections and creating record management software services for inspection stations. Their software service, SIRPAWeb, is designed for Pennsylvania vehicle safety inspection stations for recording and printing accurate and uniform MV-431/480 safety inspection forms.

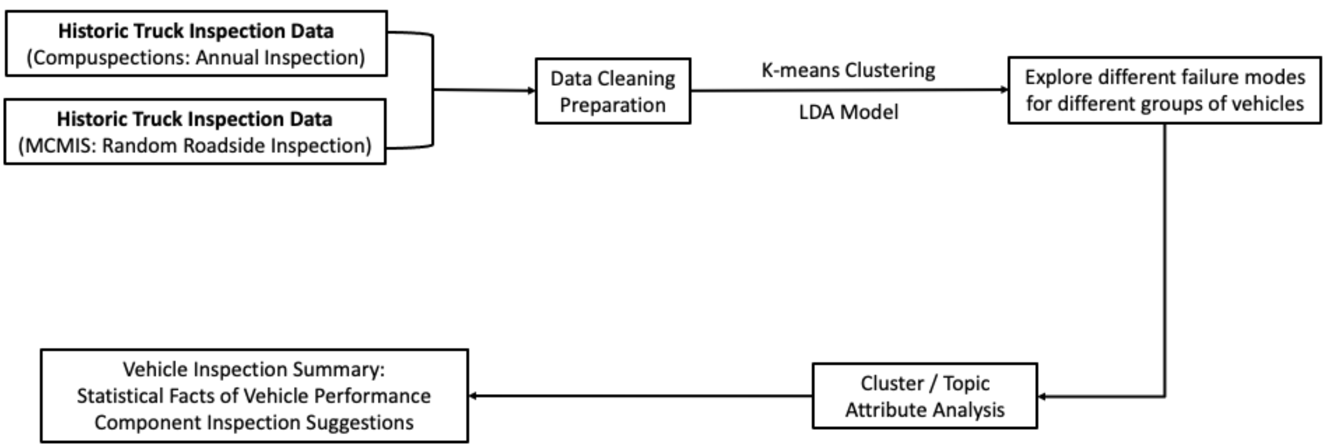

Figure 5. Research Process Designation.

MCMIS (Motor Carrier Management Information System), maintained by FMCSA. MCMIS is a source for FMCSA inspection, crash, compliance review, safety audit, and registration data [9]. From that database, multiple tables are used to extract useful information for each inspection with violations. These tables include the INSPECTION table, UNIT table, VIOLATION table, and INSP SUPP VIOLATION table.

Because different inspection stations and inspection agencies have their naming and recording regulations, dataset checks, transformation, and loading processes are essential for further analysis. Checking regulations will be introduced in the validation experiment design section to clean all invalid inspection records and filter commercial vehicles that are heavy-duty tractors or trailers. A dataset attribute summary is provided in Table 1.

Table 1. Data Summary for Two Different Sources

	Compuspections	MCMIS
Dataset Description	Inspection records that use Compuspections software service in Pennsylvania	Inspection records conducted by state personnel under the Motor Carrier Safety Assistance Program (MCSAP)
Data Source	Collected by Compuspections software service, SIRPA Web	Captured by FMCSA through SAFETYNET
Inspection Type	Annual Periodic Inspection	Random Roadside Inspection
Date Range	2007 - 2021	2021
Data Type	Vehicle identification number (VIN), make, model, model year, binary inspection geographic information, inspection overall result and component results, vehicle odometer reading	Vehicle identification number (VIN), make, model, model year, non-binary inspection geographic information, inspection overall result and component results, inspection defect descriptions

As for urbanity classification for registered vehicles in the Compuspections dataset, this research used the Urban-Rural classification scheme provided by The Center for Disease Control's National Center for Health Statistics (NCHS) [10]. This scheme distinguishes urban and rural areas into six categories, from Type 1 as most urban to Type 6 as most rural. After that, we used the 2010 Census data to assign the NCHS classification to all the counties shown in the dataset [11].

Inspected Vehicles Failure Mode Identification

Given that historical inspection records are high-dimensional and have unstructured values for some attributes (e.g., text descriptions of violations), generalizing thousands of inspection records into failure mode clusters is necessary but challenging. According to research by D. Peck et al. [12], the inspection failure rate is related to three parameters such as urban/rural county classification, age, and odometer reading. M. Beydoun also suggested that mileage, age, weight, and vehicle make such as Chrysler, Ford, GM, Hyundai, and Mazda have significantly impacted estimations for testing emission failure on passenger vehicles. Based on all the recent research, this research decided to organize different clusters based on vehicle information (e.g., mileage, age) and usage contexts (urban/rural county).

This research considered all component inspection results in the CompuSpections dataset to divide datasets into different clusters and considered violation descriptions in the MCMIS database to divide datasets into various topics. Perr-Sauer et al.'s research [14] about commercial vehicle time-series data analysis with K-means clustering shows three steps of K-means clustering. These steps include 1) extracting the overall and each historical component inspection results in the Compuspections dataset; 2) applying the elbow method to find the best performance k values for the components inspection dataset. The Silhouette coefficient assisted in evaluating the performance of the clustering method; and 3) calculating the difference between each cluster's average violation counts and the whole dataset's violation count, summarizing the failure modes behind them.

Regarding the fact that the MCMIS database has an individual file that records violation descriptions on the roadside, topic modeling is another technique that can help cluster inspection records specifically. This research adopted topic modeling techniques demonstrated in Subasish Das et al. [15]for processing the FARS database and NHTSA vehicle complaint database to test the effectiveness of state vehicle inspection. In the MCMIS database, the steps of establishing topic modeling in this research include 1) data prepossessing to clean violations unrelated to vehicle maintenance information. 2) tokenizing each paragraph, cleaning stop words, stemming, and lemmatizing words to get a final analyzable dataset about violation descriptions; 3) calculating the TF-IDF value to evaluate each word's frequency and importance; 4) distinguishing each vehicle's failure mode by the recorded descriptions and LDA topic modeling. Figure 6 shows the proposed method combining the K-means clustering method and the LDA model for identifying each vehicle's specific failure clusters/topics.

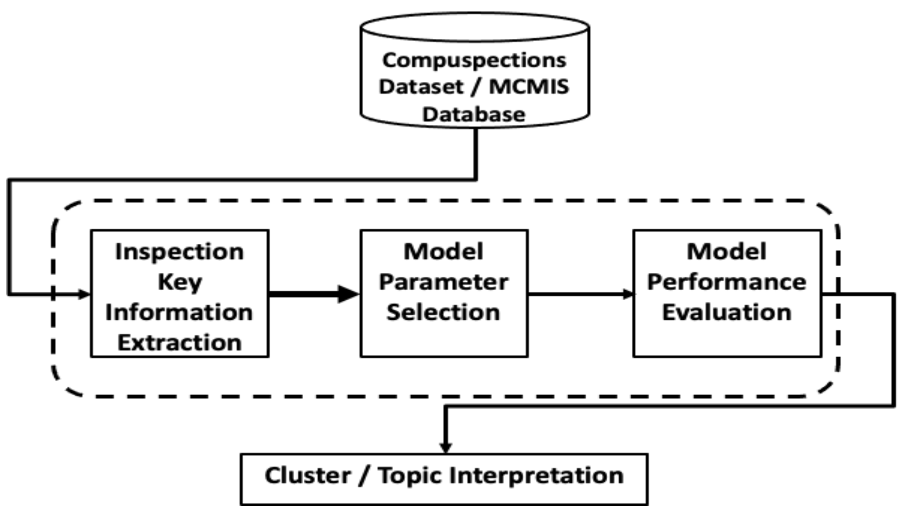

Figure 6. K-Means Clustering Method and LDA Model Design for Compuspections Annual Inspection Dataset and MCMIS Random Roadside Inspection Database

Since there exist fundamental differences between the recording formats of two data sources, the authors developed adaptive methods to identify failure modes. Compuspections count the number of defects from vehicles throughout the years, while MCMIS database uses text recording to describe what the defects are. Regarding this specialty, K-means clustering is more suitable for Compuspections dataset because all results are recorded in a number format. However, the LDA model can not only assigns the most probable topic to each vehicle, but also reflect which words are important in each topic. From there, inspectors and motor carriers can conclude the characteristics of vehicles once they have the historical random roadside inspection reports.

2.4 Experiment Design

2.4.1 Data Cleaning and Preprocessing

Cross-analysis of historical inspection data from different inspection types is essential to estimate the optimal inspection timing interval for drivers and fleet managers. According to FMCSA (Federal Motor Carrier Safety Administration), four types of inspection are daily driver inspections, periodic/annual inspections, roadside inspections, and onsite compliance reviews. From all the inspection types above, periodic/annual inspections and roadside inspections are required by the federal or state departments of transportation and have relatively uniform inspection standards.

Because different inspection stations and agencies have their naming and recording regulations, various checks, transformation, and loading processes are essential for further analysis. For cleaning all invalid inspection records and filtering commercial vehicles, heavy-duty tractors, and trailers, a checking regulation pipeline is designed, as shown below in Figure 7:

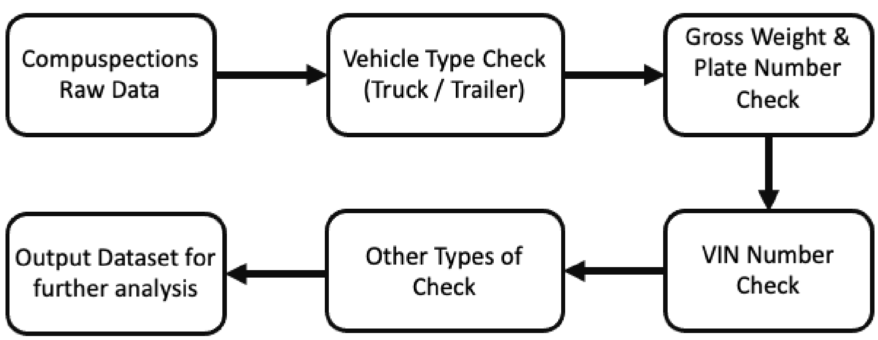

Figure 7. Compuspections Dataset Data Preprocessing Flow Chart

As for vehicle checks, this research first filtered commercial trucks and trailers and then used gross vehicle weight and plate number to exclude vehicles that were not heavy-duty tractors and trailers. There are also naming regulations for VIN numbers to check, such as total length, security check digit, and model year digit. All these naming regulations exclude invalid VIN numbers and corresponding illegal inspection records from further analysis. The last step is to exclude inspection records that are not correct.

The algorithm excludes outliers from further analysis depending on the “passorfailedinspection” column, component test columns, odometer reading columns, brake thickness, and tire tread columns.

The authors also performed a similar data preprocessing flow for the MCMIS database compared to CompuSpections data. We use “INSPECTION_ID” as a key to join the inspection table, unit table, and violation table, and “INSP_VIOLATION_ID” as a key to join the violation table with the violation supplement table so that we can combine each violation record with text descriptions. In addition, a similar VIN naming regulation check was manipulated as CompuSpections data to exclude incorrect VIN numbers from further analysis. For vehicle types and gross weight, the further investigation also only kept heavy-duty trucks and trailers. Only vehicle types related to trucks and trailers are kept according to “INSP_UNIT_VEHICLE_ID_NUMBER” column. What differs from the CompuSpections dataset is that the MCMIS database also recorded vehicle violations unrelated to component defects. So only maintenance violation codes related to components are chosen here.

2.4.2 K-Means Clustering Algorithm

Clustering algorithms can use various vehicle attributes or vehicles’ background features (e.g., mileage, age, and urbanity) to identify similar vehicles in multiple aspects. A good set of vehicle attributes or background features can lead to clustering results with clear boundaries and fewer overlaps between clusters, where some vehicles fall into both categories and hard to tell the differences between two clusters. In this research, the authors established five feature sets based on the annual inspection dataset (CompuSpections dataset) that captures vehicle attributes and background information to test the clustering algorithms and identify relative feature importance levels. Feature Set 1 includes an “overall inspection result” that indicates the final evaluation of the vehicle condition and each component’s inspection result, which checks registration documentation, doors, lighting, steering, exhaust, fuel, glazing, brakes, road test, tires, and other components. Besides the “basic inspection result” feature set, feature sets 2 – 5 include other background features combinations. Based on the inspection records of CompuSpections, they also examine the registration zipcode, mileage driven, and model year of inspection objects. All this information can be interpreted into mileage, age, and urbanity. Using different feature sets in clustering, the authors can infer which features are more critical in helping identify vehicles with specific failure modes. Table 2 elaborates on the details of each feature set and their clusterability with different metrics.

Hopkins statistics measure the clustering tendency of a feature set [16]. This metric aims at measuring how different the distances are between the data points in a real dataset from their neighbors, comparing the distances of a uniformly distributed dataset. A Hopkins Statistic greater than 0.9 indicates a dataset far different from the random uniformly distributed dataset, with highly clusterable performance. From the results in Table 2, every feature sets are highly clusterable (Hopkins Statistic > 0.9). Another value used for measuring the quality of clustering and selecting proper features/attributes is the "Silhouette Coefficient" [17]. The Silhouette Coefficient value closer to 1 means that clusters have clear boundaries and not too much-overlapped area among them.

Table 2. Summary of the Clusterability Analysis for each Feature Set

Feature Set	Information Included	Hopkins Statistic	Silhouette Coefficient
Feature Set 1	O(1) + EC(2) inspection results	0.9907	k = 4, SC(3) = 0.8765; k = 7, SC(3) = 0.8860;
Feature Set 2	Mileage + O(1) + EC(2) inspection results	0.9269	0.6305
Feature Set 3	Age + O(1) + EC(2) inspection results	0.9863	0.5652
Feature Set 4	Urbanity + O(1) + EC(2) inspection results	0.9902	0.6279
Feature Set 5	All Feature Included	0.9219	0.4027

(1) O = Overall (final inspection results of vehicle condition)
(2) EC = Each Component (Including items such as checks registration documentation, doors, lighting, steering, exhaust, fuel, glazing, brakes, road test, tires and other components)
(3) SC = Silhouette Coefficient

After checking that each feature set is suitable to proceed with the K-Means clustering method, determining K, the number of clusters, is vital to find failure modes. The elbow method [18] is the first criterion to identify K and Silhouette coefficient assisted in evaluating if clusters have a clear boundary with fewer overlaps. Based on the performance and evaluation by both the elbow method and Silhouette coefficient, only feature set 1, with overall inspection result and each component inspection result has two selections for K value. Clustering feature set 1 with K equaling 7 has a better Silhouette coefficient performance than K equaling 4. However, Data Version 5 has a Silhouette coefficient that is below 0.5, which shows uncertain boundaries with clusters and overlapped areas. So, in this case, feature set 5 is not considered further for clustering and failure mode analysis.

2.4.3 Topics Modeling for Failure Modes Identification

MCMIS, a roadside inspection database established by FMCSA, has a different pattern of inspection recording compared to Compuspections annual inspection dataset. It has a detailed description of each violation on commercial trucks and trailers to illustrate the current conditions of component defects. Based on the information provided, the authors used topic modeling, such as latent Dirichlet allocation modeling, to explore topics rather than clusters.

Before measuring word importance by TF-IDF for each document, text cleaning is performed before measurement. A full text cleaning step includes:

Message Clearance: remove numbers and punctuations and transform all letters to lower cases.

Message tokenized: splitting a text object into words from whitespaces.

Stopword removals: remove all words that have no semantic relevance to the document. For example, words such as articles, pronouns, and prepositions are stopwords that need to be removed.

Stemming and Lemmatization: stemming refers to the process of reducing each word to its root or base. For example, words such as “warning,” “warned,” and “warner” are all reduced to the stem “warn.” However, there are still words such as “good,” “better,” and “best” that cannot be solved by stemming. Lemmatization is introduced to operate on a single word with knowledge of the context. Lemmatization can discriminate between words with different meanings depending on the part of speech.

Based on all the text cleaning processes above, a “word list” was generated for each vehicle’s inspection documents, and their word importance (TF-IDF) is measured from there on to implement the LDA model. LDA model is a popular way to convert an unstructured and complex textual dataset into topics [19]. In this method, LDA model assigns each document with different probabilities of topics, and also assigns each topic with different probabilities of words. When topics with sets of words are listed, LDA model gives a parameter (per-topic-per-word probability) to each word in a certain topic. This parameter shows how likely this word can be generated in this topic. All these processes can be done by many open-source tools such as NLTK [20].

After text cleaning and TF-IDF calculation, we should define the exact number of topics for the LDA model. In general, the number of topics, K, can adjust the granularity of the topic model. The more topics accepted, the narrower results it will get, or vice versa. According to the nature of the LDA model and previous studies, we used a grid search method to assign the best performance value for each parameter [21]. Finally, the best number of topics is eight.

2.5 Results

2.5.1 K-Means Clustering Results

This research interprets clusters into different failure modes by failure rate analysis. The authors set up a baseline model that calculates the average violation counts of the overall inspection result and each component's inspection result for the whole dataset. Then for each feature set, the authors calculated the average violation counts for each cluster. If some indicators or components' average number of violation counts is significantly different from baseline average violation counts, then we can identify this cluster with a specific failure mode.

Based on this logic, Figure 8 - Figure 12 show how significantly different each cluster's average violation counts are from baseline (the whole dataset average) average violation counts by intensity on the heatmap. For example, in Figure 8, failure mode 1 (cluster 1) has lighting, brakes, and other problems defects, so the intensities of lighting, brakes, and others are darker than other cells in this figure. Their colors also represent how different they are from the baseline average, indicating high average violations among the vehicles in this mode. Figure 8 - Figure 12 also show the interpretations of failure modes conclusions on the right vertical axis.

After cluster interpretation analysis, k-means clustering can divide the whole vehicle fleet into four or seven clusters based on Figure 8 and Figure 9. From there, it shows that groups of vehicles with lighting, brake, and tire problems are significantly above average. This conclusion suggests that lighting, brakes, and tires can be key inspection components during annual inspection processes.

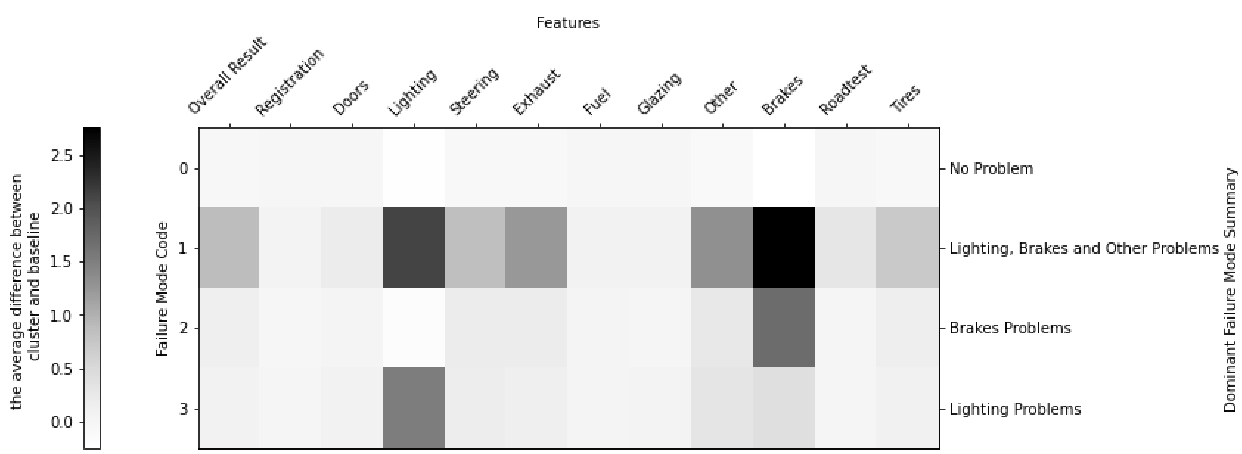

Figure 8. Failure Mode Heatmap Summary of Feature Set 1 (k = 4)

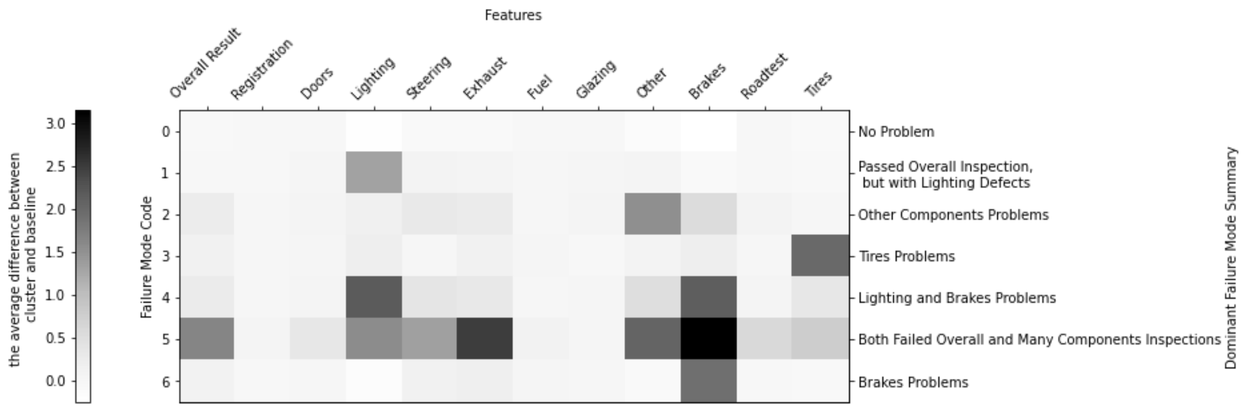

Figure 9. Failure Mode Heatmap Summary of Feature Set 1 (k = 7)

The K-means clustering that uses feature set 2 (overall plus milage) divides all vehicles into four groups depending on mileage driven per year. Figure 10 shows the clustering results using feature set 2. The clustering result shows that the vehicle group with slightly above average mileage (2988.23 miles) has the most significant lighting and brakes problems. It indicates that vehicles with average mileage driven per year are the most noticeable cluster if inspected, especially with lighting and brake components. Identical results are found by adding age and urbanity features (Figure 11 and Figure 12). Medium age generation and vehicles registered at the large fringe and medium metro area also have significant problems with lighting and brakes problem, compared to other age groups and urbanity areas. In conclusion, brakes, and tire problems are the most common failure mode when annual inspections are performed based on different vehicle properties. While talking about background information such as mileage, age, and urbanity, vehicles with certain features can be key important features to give extra attention to when doing annual inspections, such as vehicles with average mileage driven, medium vehicle age and vehicles from large fringe and medium metro area.

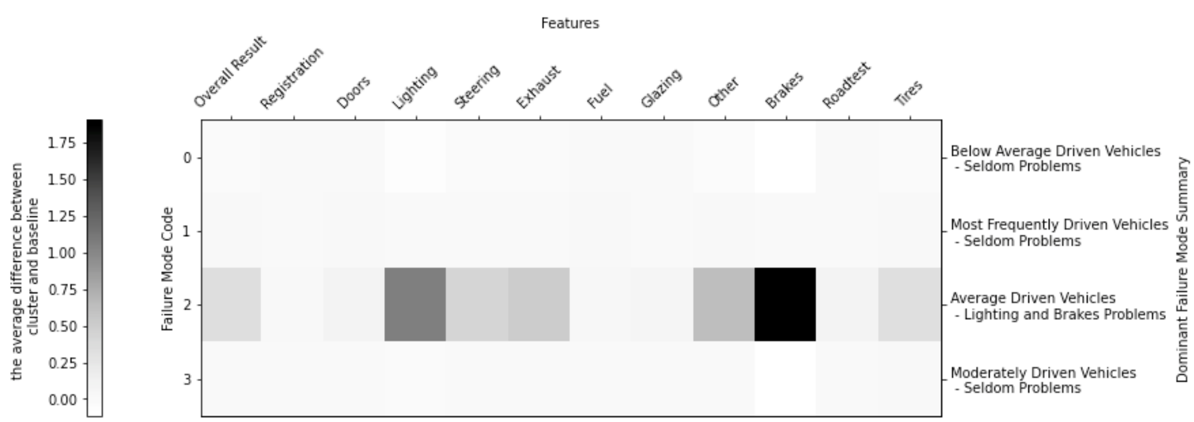

Figure 10. Failure Mode Heatmap Summary of Feature Set 2 (with mileage, k = 4)

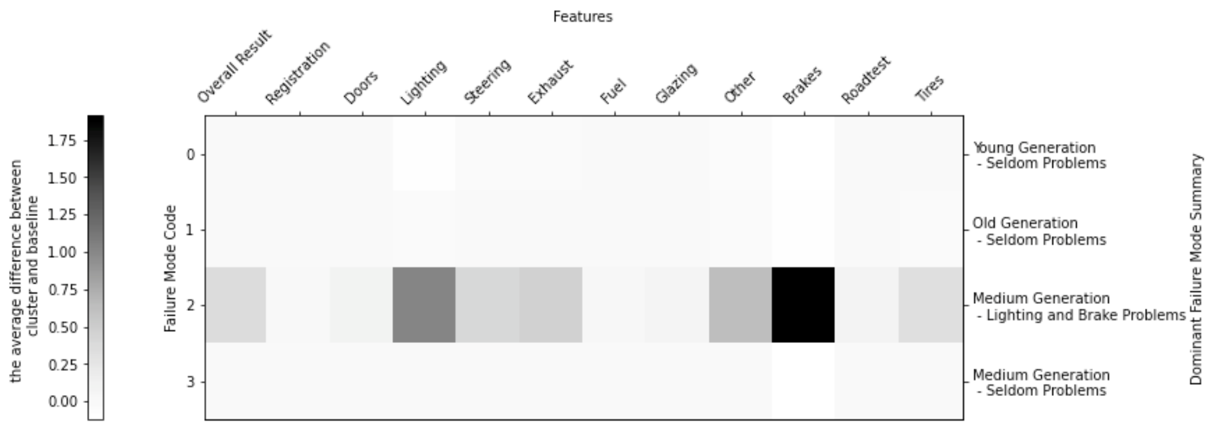

Figure 11. Failure Mode Heatmap Summary of Feature Set 3 (with age, k = 4)

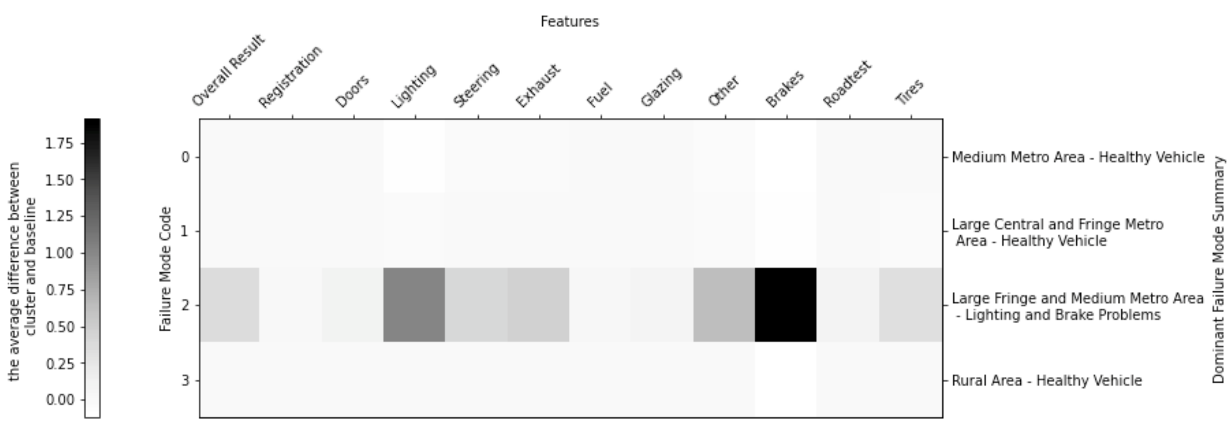

Figure 12. Failure Mode Heatmap Summary of Feature Set 4 (with urbanity, k = 4)

2.5.2 LDA Topic Modeling Results

By training the LDA model and selecting the best parameters, we can obtain the list of topics and analyze the meaning of each failure mode. Table 3 shows the list of topics and the top 10 words of each topic, ranking words by per-topic-per-word probability. For example, the probability of term “lamp” is generated in topic 1 is 0.045.

Table 3. Top 8 topics with ten keywords by LDA model from the MCMIS Database

Topic 1 Word: 0.051*"inop" + **0.045*"lamp"** + 0.034*"inoper" + 0.031*"rear" + 0.030*"turn" + **0.029*"signal"** + 0.026*"front" + 0.026*"right" + 0.026*"left" + **0.025*"light"**
Topic 2 Word: **0.034*"air"** + **0.024*"leak"** + 0.024*"axl" + **0.021*"brake"** + 0.019*"hose" + 0.016*"x" + 0.015*"l" + 0.014*"chamber" + 0.014*"r" + 0.013*"v"
Topic 3 Word: **0.051*"tire"** + 0.050*"axl" + 0.036*"psi" + 0.035*"right" + 0.031*"left" + 0.027*"side" + 0.026*"insid" + 0.021*"outsid" + 0.021*"inop" + 0.021*"flat"
Topic 4 Word: **0.027*"display"** + **0.026*"number"** + 0.025*"name" + 0.024*"usdot" + 0.023*"dot" + 0.022*"carrier" + 0.022*"lb" + 0.017*"vehicl" + 0.016*"compani" + 0.015*"truck"
Topic 5 Word: 0.021*"none" + **0.020*"trailer"** + 0.019*"secur" + **0.019*"chain"** + 0.018*"breakaway" + 0.016*"cabl" + 0.015*"unit" + 0.015*"attach" + 0.013*"strap" + **0.012*"connect"**

Topic 6 Word: **0.016*"oil"** + 0.015*"miss" + **0.014*"leak"** + 0.014*"rear" + **0.014*"engin"** + 0.012*"right" + 0.012*"side" + 0.011*"left" + 0.010*"inop" + 0.009*"cover"
Topic 7 Word: **0.049*"expir"** + 0.035*"" + 0.034*"registr" + 0.019*"current" + 0.016*"plate" + 0.016*"inspect" + **0.014*"proof"** + **0.014*"insur"** + 0.013*"card" + 0.013*"display"
Topic 8 Word: **0.027*"window"** + **0.024*"windshield"** + 0.023*"tint" + 0.021*"fluid" + 0.018*"washer" + 0.017*"measur" + 0.016*"crack" + 0.016*"driver" + 0.014*"side" + 0.013*"adjust"

In Table 3, each topic represents a specific failure mode based on the words selected. For example, Topic 1 is related to lighting violation because it includes words such as "lamp," "rear," "turn," "signal," and so on, which represents problems such as signal light problems and inoperable lights detected during the roadside inspection. Topic 2 refers to another major violation category, brake problems, because "air," "leak," and "hose" are all components related to the brake system. Topic 3 can also be interpreted as "tire problems" since tire violation terminology such as "tire," "psi," and "flat" is included. Topic 4 and Topic 7 are related topics that both refer to registration and equipment problems. Topic 4, with words such as "display" and "usdot," shows that vague display numbers on vehicle bodies can be a major cause of registration violations. Topic 7, with the words "expir" and "insur," discloses another important insurance proof issue for the registration violation. Other topics, such as topics 5, 6, and 8, also have specific keywords in their content. Topic 5 implies tractor-trailer connection issue, topic 6 implies engine oil leak issue, and topic 8 implies windshield problem.

Any vehicles from our database can be assigned to the most probable topic based on the LDA model. Generally, the LDA model assigns a probability vector to each vehicle. We select the most probable topic for each vehicle and categorize it to that failure mode. Figure 13 shows how popular each topic is, and how many vehicles are in there.

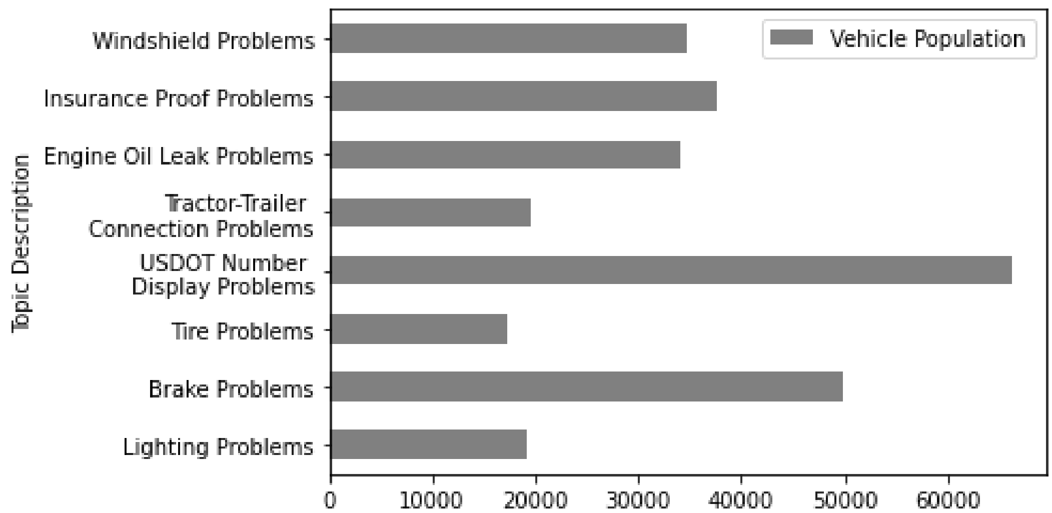

Figure 13. Vehicle Population Counts for Each Topic

Figure 13 reveals that USDOT Number Display Problems are the most popular. The vague and incomplete USDOT numbers on the body of vehicles could be a common question for motor carriers. The following comes to brake, insurance proof, and windshield problems. That indicates brake and windshield problems lead to failure-prone components during roadside inspections.

2.5.3 Combination Comparison Between Two Failure Modes Identifications

From clustering analysis and topic model analysis based on previous studies, there are some possible failure modes that historical inspection data can define. But how much two analysis methods conclude in common and make–failure modes relationships remained unknown. This part of the analysis aims to compare and correlate the failure modes found from different databases' records for a potential cross-database analysis that reveals more comprehensive failure mode information of various vehicles. Though annual and random inspection discrepancy exists theoretically, understanding their mutual and different inspection focus can help motor carriers with more intelligent maintenance strategies. This analysis can also disclose vehicle makes' failure mode tendency in different inspection occasions. That will help inspectors to focus on certain makes of vehicles with critical components and save time on irrelevant components to improve inspection efficiency. Here the authors select the most popular vehicle makes that exist in both vehicle datasets and analyze their information as a combination comparison. This research adopted feature set 1 with k equaling 7 (since its accuracy among other feature sets) compared with MCMIS topic modeling results to see if the results are similar.

Table 4. Population Percentage(%) for Each Make and Each Failure Mode from Compuspections

Dataset

Make / Failure Modes	P_{pass}	P_{light}	P_{other}	P_{tires}	$P_{light\&brake}$	P_{fail}	P_{brakes}
Make 1	51.2	13.0	1.3	0.6	32.9	0.0	0.9
Make 2	74.1	4.8	6.7	1.1	6.0	4.9	2.3
Make 3	69.9	10.6	6.1	0.8	6.0	1.5	5.1
Make 4	84.0	6.0	2.1	0.1	2.3	1.6	3.8
Make 5	90.4	2.1	2.1	0.2	2.2	1.8	1.2
Make 6	74.2	4.3	5.4	5.5	5.2	1.7	3.5

P_{pass} – Pass overall and each component inspections

P_{light} – Passed Overall Inspection, but with Lighting Problems

P_{other} – Other Components Problems

P_{tires} – Tires Problems

$P_{light\&brake}$ – Lighting and Brakes Problems

P_{fail} – Both Failed Overall and Many Components Inspections

P_{brakes} – Brakes Problems

From comparison of Table 4 - Table 5, it shows mutual failure modes with light, brake, and tire. Though inspectors can easily find light and tire defects by visual observation during random roadside inspections, those three failure modes still take a considerable percentage in each makes. This finding recommends inspectors and motor carriers check these components more frequently and thoroughly to avoid potential risks. The brake component is most noticeable among all three components, because it takes a large percentage of vehicles in this failure mode compared with others in both scenarios. Among the six makes, make 1 has the significant percentage in brake failure mode, with 33.8% of the vehicles in Compusections failure modes and 35.4% of the vehicles in MCMIS database failure modes. The MCMIS Database also shows some special failure modes trends that don't exist in the failure modes identified from Compuspections' dataset. For example, Make 4 has the lowest percentage of brake and tire failure modes, but it has the highest engine oil leak problems. MCMIS database failure modes also point out that there are more than 10% of vehicles in each make exist windshield failures. Of all six makes, make 6 is the highest in windshield failures. To sum up, makes – failure modes analysis discloses some potential relevance, providing essential information when inspectors and motor carriers want to perform targeted inspections.

Table 5. Population Percentage (%) for Each Make and Each Failure Mode from MCMIS Database

Make / Failure Modes[**]	P_{light}	P_{brake}	P_{tires}	P_{number}	$P_{connection}$	P_{oil}	$P_{insurance}$	$P_{windshield}$
Make 1	6.9	35.4	6.1	13.1	5.7	5.7	13.7	13.4
Make 2	6.0	35.1	5.2	16.6	5.2	6.7	14.0	11.2
Make 3	6.5	34.3	5.7	10.8	6.3	7.8	16.5	12.2
Make 4	6.9	5.4	4.8	35.1	7.2	18.7	11.3	10.6
Make 5	7.1	29.4	7.5	11.9	7.6	9.1	14.0	13.5
Make 6	6.5	38.4	6.9	10.6	4.9	5.0	12.1	15.6

P_{light} – Light Problems
P_{brake} – Brake Problems
P_{tires} – Tires Problems
P_{number} – US DOT Number Display Problems
$P_{connection}$ – Tractor-trailer Connection Problems
P_{oil} – Engine Oil Leak Problems
$P_{insurance}$ – Insurance Proof Expire Problems
$P_{windshield}$ – Windshield Problems

2.6 Discussion

Previous research only discussed possible optimization strategies based on individual vehicles on a statistical level. This paper proposes a new way to generalize different vehicles operated by carriers into groups, showing that potential groups of vehicles need extra attention when inspected. By exploring potential failure modes with different formats of inspection recording datasets, the inspection process can be optimized by targeting and strategic plans.

This study considered how to categorize inspection records into groups of failure modes, and if carriers own similar conditions vehicles, how to make preventive maintenance ahead to avoid unnecessary risks. For annual inspection, we derive failure-prone components from Compuspections Dataset, which indicates failure-prone components are brakes, lighting, and tires. When features such as age, mileage, and urbanity are involved, groups like middle-age generation, average mileage driven groups, and large fringe and medium metro areas are highly attention groups to check if there are any unsafe components. These results are consistent with previous research about brake pad and tire tread deterioration because all these components are perishable if age and mileage get older and longer.

When it comes to roadside inspection with the MCMIS database, a topic model indicates that mechanical component problems are not only popular topics, but some registration problems such as USDOT number display and insurance proof can also be trivial but critical violations that influence carriers' performance in the FMCSA rating system. If motor carriers concentrate on improving their rating scores on the FMCSA website, these mistakes should be prevented. Besides that, high probability also makes brake, windshield, and engine violations very popular. That result suggests that motor carrier workers such as drivers and fleet managers include more precise and detailed pre-trip inspections or install real-time monitoring devices such as telematics.

2.7 Conclusion

From Compuspections Dataset (annual periodical inspection), this research concludes that there are approximately four different failure modes, most of which point to brake and light failures. When background information is included, these feature sets also correlate with component inspection results. For example, from Figure 10 - Figure 12, vehicle groups with medium mileage driven, middle age, and from the large fringe metro and medium metro areas have significant differences compared to the baseline overall average model (more than 1.9 violation cases). When inspectors inspect vehicles with these features, they should pay extra concern with key components. From MCMIS Database, eight topics are not only related to component failures but also to registration and insurance proof problems. That means a basic pre-trip check is essential for basic display and paperwork materials to prevent the negative influence of tiny mistakes and ignorance, such as a reduction in CSA safety score and ranking. Both results indicate that brakes, lights, and tires are failure-prone components that form obvious failure modes.

Chapter 3 Inspection and Maintenance Planning for Truck and Trailer Fleets

3.1 Introduction

An appropriate inspection plan is essential for improving vehicle safety by identifying component failures. Vehicle-related problems caused by malfunctions in components such as tires, brakes, steering, suspension, transmission, and engine are a critical cause of accidents [22] [23]. To prevent such malfunctions, an inspection plan is necessary to provide information on when and what vehicle and component to inspect.

Currently, some states in the U.S. have vehicle inspection procedures that make regulations to enforce periodic inspections to check the risky component with a violation that fails to reach the state's allowable condition. The routine inspections might ignore the vehicle component violations between successive inspections [24], which might cause an accident due to vehicle malfunction. A vehicle subject to annual inspections can drive on the road with component violations for months until the next inspection, with a high potential for accidents. Shortening the inspection interval reduces the driving time exposed to the component violation. However, shortening the inspection interval induces higher safety assurance of vehicles' operation safety while increasing inspection costs [25], including financial costs for inspection and uptime losses due to vehicle outages. Therefore, optimal timing for inspection is vital to achieving a safety-cost balance.

Roadside inspection is another practice, selecting and inspecting vehicles with apparent violations visualized roadside to identify violations ignored in routine inspections. Identifying vehicles with high risks and focusing on inspecting anomalous vehicles could have high accuracy in finding problematic vehicles. However, the roadside inspection can pull over only a small number of vehicles compared to the total number of vehicles on the road. Moreover, the roadside inspection can only inspect the vehicles with evident violations while ignoring those with unobtrusive violations. Integrating roadside inspection with periodic inspections can potentially miss risky vehicles, as shown in Figure 14. Therefore, identifying vehicle-related violations with a higher detection rate is essential for ensuring driving safety, improving inspection efficiency, and saving fleet operating costs. In addition, selecting risky vehicles relies on the inspectors' experience and subjectivity. Therefore, automatic inspection planning that uses historical and real-time vehicle data for instantly selecting high-risk vehicles for targeted inspection is necessary.

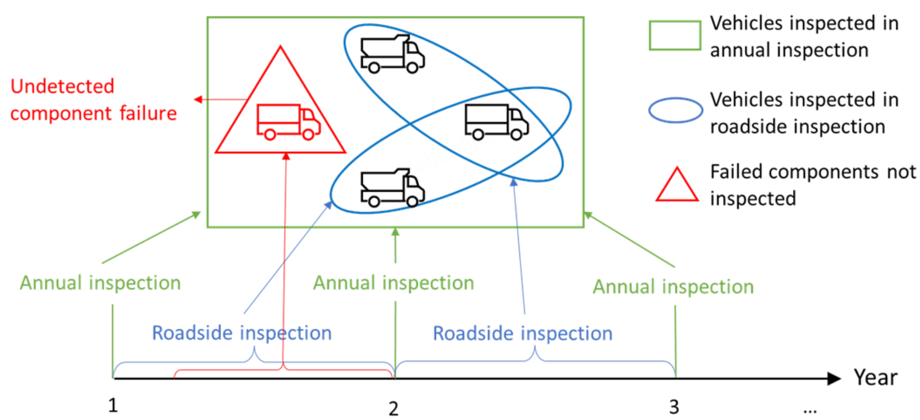

Figure 14. The potential of failing to achieve instant inspection in current inspection practice

In order to achieve optimal vehicle safety at the lowest inspection cost, an effective inspection plan must accurately identify risky vehicles and components for inspection while saving inspections on those that are safe. To accomplish this, the inspection plan typically relies on knowledge of the vehicle component deterioration process, which is hidden within historical data on vehicle component condition degradation. However, access to such historical data is limited due to its private nature within commercial companies. Furthermore, since heavy-duty vehicles only constitute approximately 5% of registered vehicles in the United States [41], the availability of historical data for heavy-duty vehicles is further restricted. Therefore, the development of an effective inspection plan that balances safety and cost requires the development of data augmentation techniques.

Many inspection planning difficulties arise as data is limited. Inspection planning algorithms cannot extract adequate information from the limited historical data, so algorithms would generate inappropriate inspection plans that fail to keep safety and save costs. Therefore, the development of an effective inspection plan that balances safety and cost requires the development of data augmentation techniques that can artificially extend the dataset. Additionally, current inspection planning algorithms select risky vehicles according to their degradation in the time dimension. However, the mileage driven is more related to the vehicle component degrading at that time [26]. A deterioration model for predicting component failure risk after driving a specific mileage can indicate worn-out degradation. Therefore, an inspection plan with a mileage-based deterioration model is necessary. However, the inspection practice is to generate an inspection plan that specifies the time intervals. So the component failure risk transition from mileage-based to time-based is needed.

This paper aims to explore the safety-cost-aware inspection planning for commercial fleets that optimizes vehicle and component selection to ensure vehicle fleet safety with fewer inspections with limited and noisy inspection records. However, several challenges form barriers to establishing a safety-cost-aware inspection plan. Specifically, it is *hard to achieve reliable inspection planning that identifies correct risky vehicles 1) based on limited historical inspection records;2) using a time-based model since driving mileage is more related to vehicle component degradation*. Therefore, the following research questions are essential for tackling these challenges: *1) What data augmentation method can improve the reliability of deterioration prediction; 2) What inspection planning algorithm can consider the deterioration in the mileage dimension while specifying the inspection plans in the time dimension*?

3.2 Related work

3.2.1 Vehicle Inspection Planning Methods and Their Limitations

Current inspection practice of annual inspection and roadside inspection has the potential to ignore risky vehicles, as illustrated in the introduction section. To improve vehicle safety researchers improved vehicle safety by improving inspection frequency and validated that increasing inspection frequency can improve vehicle safety [27]. For example, [27] found that biannual inspection can achieve a significant 8% reduction in injury crash involvement rate compared to the annual inspection. However, researchers found that the cost-benefit ratio of strategies to prevent road crashes based on increasing the frequency of inspections may be low [28],[29]. Therefore, a more cost-efficient method for achieving an acceptable vehicle safety level with minimal inspection costs is essential.

Predictive inspection that estimates when the vehicle is likely to fail and determines what vehicles need inspections at which time can be a safety-cost-aware inspection planning. The main idea of predictive inspection for ensuring safety while minimizing inspection costs is to reduce the excessive inspections where it is in good condition that inspection is inessential while never ignoring risky vehicles [30],[31]. Automobile sector researchers proposed multiple predictive inspection methods and validated their performance in safety improvement and cost reduction. Researchers conclude the general process of predictive inspection planning as data collection, data pre-processing, faults diagnosis and prognosis, and decision-making on the maintenance strategy [32],[33]. Data collection is to collect condition data of equipment in the system. Data pre-processing can involve steps such as data cleaning, missing values treatment, outlier detection, feature selection, or imbalance compensation [34]. Fault diagnosis and prognosis are to diagnose the equipment's current condition and predict failure in the future. Such information related to future failure risks can support the inspection decision-making, which is to generate inspection plans for selecting risky equipment at an appropriate time for inspection.

There are mainly three types of predictive inspection methods: physics-based [35] [36], knowledge-based [37], and data-driven [38]. The physics-based model is sensitive to the physical parameters, so accurate physical parameters are essential for a high-accuracy model. However, such a high-accuracy model is complex and computing expensive. The knowledge-based models are typically rule-based systems imitating human decision-making processes. However, such knowledge-based models can only implement manually defined rules, which cannot process scenarios that need unknown human rules. The data-driven method develops a deterioration model using statistical and machine learning methods based on historical data to predict the failure probability in the future. A reliable and accurate data-driven model needs sufficient data. However, the available inspection data is limited [32] since the vehicle condition data are private to commercial fleets. Moreover, the research is for heavy-duty vehicles which belong to a specific vehicle group in a small size, which further limits the available historical inspection data. Researchers used simulated methods to generate data for the data-driven model, which caused a limitation because it is difficult to develop deterioration models and evaluate the validity of developed methods using real data. Since the real data is so important, there is a research gap lacking data augmentation methods to handling with limited real data to extend the real dataset. Therefore, developing a method to extend the current historical dataset is necessary for a reliable and accurate deterioration model.

Additionally, most of the current deterioration models are in the time dimension due to the intuition that equipment deteriorates as time goes on. However, worn out is one of the main factors of vehicle component failure, such as brake and tire failure, which indicates that deterioration is more related to usage than time. Therefore, a deterioration model over usage, which also can be mileage, needs exploration. Researchers utilized deterioration rates, which is the component condition difference over mileage driven during the condition change, to predict the vehicle component's future condition after driving a certain mileage given an original state [26]. However, the inspection planning requires an estimate of the future condition and risk in the next scheduled inspection, which is in the time dimension. Limited research transfers the future risk estimation from the mileage domain to the time domain. Therefore, this research aims to develop a deterioration model over mileage and transfer the risk estimation from the mileage dimension to the time dimension.

3.2.2 Data Augmentation Methods for Vehicle Inspection Planning with Limited Data

The data-driven model cannot extract adequate information when historical data is limited. Data augmentation artificially generates data while still being realistic for extending the training dataset and improving data-driven model performance. Researchers have proposed multiple data augmentation methods for image [39], textual [40],[41], audio, time series [42], and tabular data. Normally, researchers apply a heuristic transformation to the existing training dataset to generate additional training data [43]. For example, to augment image datasets, researchers transform existing images by flipping [44], cropping [45],[46], rotating, scaling up [47], color space transformations [48],[49], etc. The transformation functions of heuristic data augmentation are rules defined by domain experts, which are interpretable but need manual design. Researchers also utilized machine-learning-based data augmentation methods, such as Generative Adversarial Networks (GAN) [50].

The vehicle component deterioration data in this research is in tabular format. A major data augmentation method for tabular data is synthetic sampling, which generates new data points by interpolating between existing points in the feature space. In this method, the interpolation is linear. However, the vehicle component deterioration is not in a linear way. Therefore, data augmentation method that can extend the limited vehicle inspection dataset in a non-linear manner is essential.

Though multiple data augmentation methods have been proposed in other domains, these methods have limitations for handling sparse vehicle inspection recordings. The current major method for augmenting tabular data is not suitable to the data with non-linear relationship among features. Researchers also found that redundant or overly aggressive augmentation can hurt performance and introduce biases into the dataset [36, 37, 40]. Thus, the data augmentation method should extend the dataset without bringing in biases. Exploring applicable data augmentation methods for vehicle inspection datasets and validating the augmentation performance is essential.

This paper proposed an inspection planning method to balance safety and costs using components' deterioration patterns learned from limited historical inspection records. The objectives are to 1) identify the deterioration modes and establish the deterioration model of heavy-duty trucks and trailers, 2) predict the probability of vehicle defects in the future using the deterioration model and select the risky vehicles for inspection; 3) validate the feasibility of the proposed inspection planning that can detect vehicle defects with little violation time while using relatively low costs and losses of uptime, and 4) augment the dataset using the limited historic inspection records to pursue better performance.

3.3 Method

This research proposed a risk-based inspection (RBI) planning ensuring vehicle safety with minimal inspection costs. The proposed method considers vehicle safety using exposure time with risks, which is the time a vehicle is in a condition violating regulations. For example, the exposure time of a vehicle's brake pad would be counted as the thickness is smaller than 2/32 inches until such a violation is discovered in the next inspection. The inspection costs include the number of labor costs and losses of uptime occurring during the inspection process, which are directly related to the number of inspections. In this case, the research utilizes the number of inspections to evaluate the inspection costs. Therefore, the research's objective would be to search for the optimal inspection plan to keep the fleet vehicles' total exposure time at an acceptable level with fewer inspections. The main idea for reducing the number of inspections with an acceptable vehicle safety level is to merely focus on vehicles and components with high failure risks in periodic inspections. The idea can help save the inspections for vehicles and components in safe conditions. The RBI planning can determine what vehicles and components have high failure risks in the next periodic inspection and mark them as needing inspection.

The framework of the inspection method consists of four major parts (Figure 15): data augmentation, the Markov deterioration model, the conditional probability formula, and risky vehicle and component selection. The data augmentation is to extend the limited historical inspection data to provide sufficient historical data for generating a reliable inspection plan. The deterioration model summarizes the vehicle components' deterioration pattern along the mileage dimension based on the augmented historical dataset and predicts a certain component's failure risk after a certain mileage. For example, the deterioration pattern along the mileage dimension could be the rules that a component transitions from one state to another after operating a certain mileage. And then, the deterioration model can predict a component's future condition and the failure probability after operating a certain mileage based on the summarized deterioration pattern. The conditional probability formula is to transfer the component failure probability on the mileage dimension to that on the time dimension and achieve the component's failure probability at the time of the next periodic inspection. Finally, the risky vehicle and component selection section select risky vehicles and components with failure probabilities larger than a pre-defined threshold at the time of the next periodic inspection and marks them for inspection. The subsections below interpret the four major parts in detail.

Data obtained from accident response units indicates that tires and brakes were the main contributors to mechanical failures resulting in crashes [51]. Therefore, this research takes the brake as a case to examine the proposed inspection planning method at the component level.

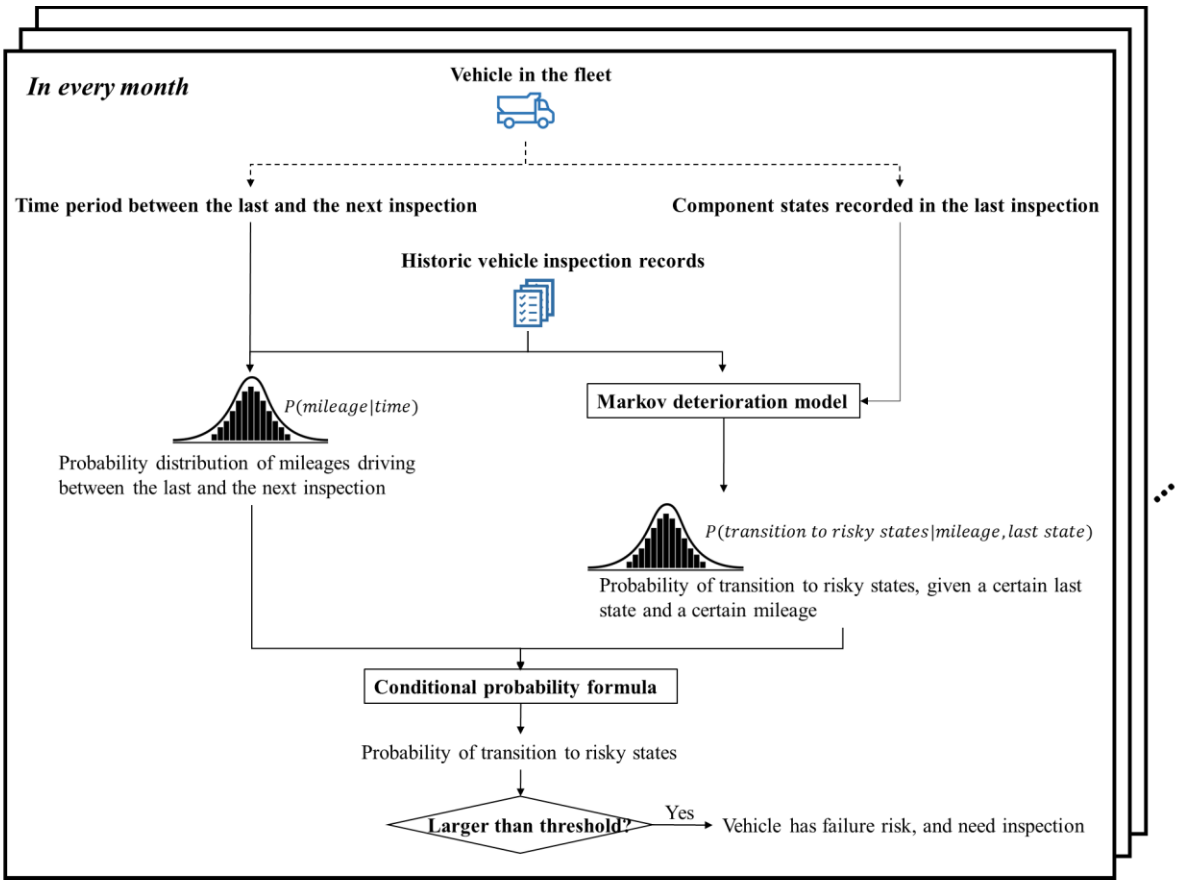

Figure 15. The framework of the RBI planning

3.3.1 Data Augmentation

As shown in Figure 16, when developing a deterioration model for a vehicle, the historical cases with similar characteristics, such as the original state and the mileage driven, are acquired to support the deterioration modeling. However, current historical vehicle inspection datasets have limited inspection recordings and provide limited information for summarizing the vehicle components' deterioration patterns. The deterioration modeling would be unavailable or unreliable when similar cases are unavailable or limited in the historical dataset. Such an unreliable deterioration model could potentially lead to incorrect prediction of the vehicle's future state. Therefore, a data augmentation method is necessary to extend the historical data when historical cases are limited.

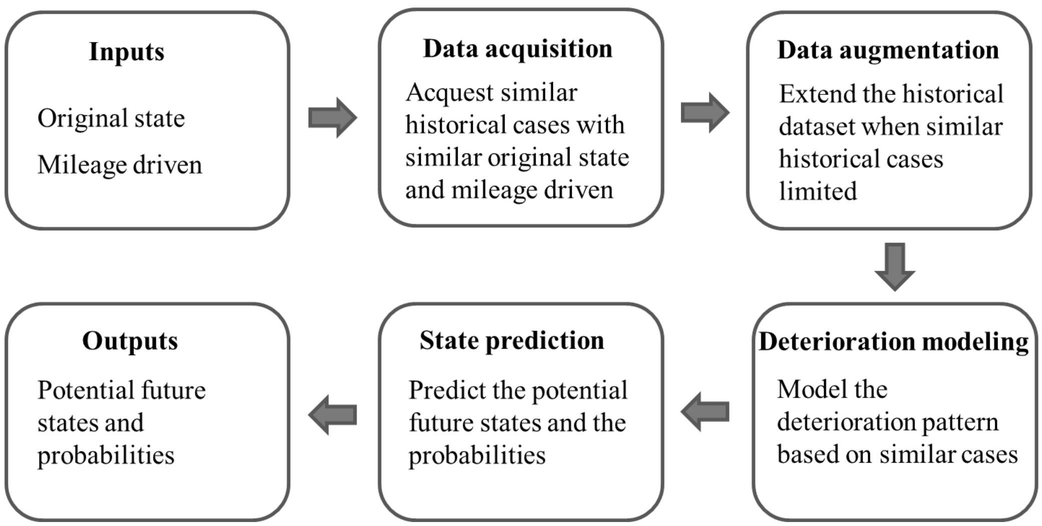

Figure 16. The process of reliable deterioration modeling and future state prediction with data augmentation

The main idea of the data augmentation method is to generate synthetic data based on the cases with similar deterioration rates given a certain combination of original state and mileage driven. The deterioration rate is defined as the difference between a component's state over the mileage driven
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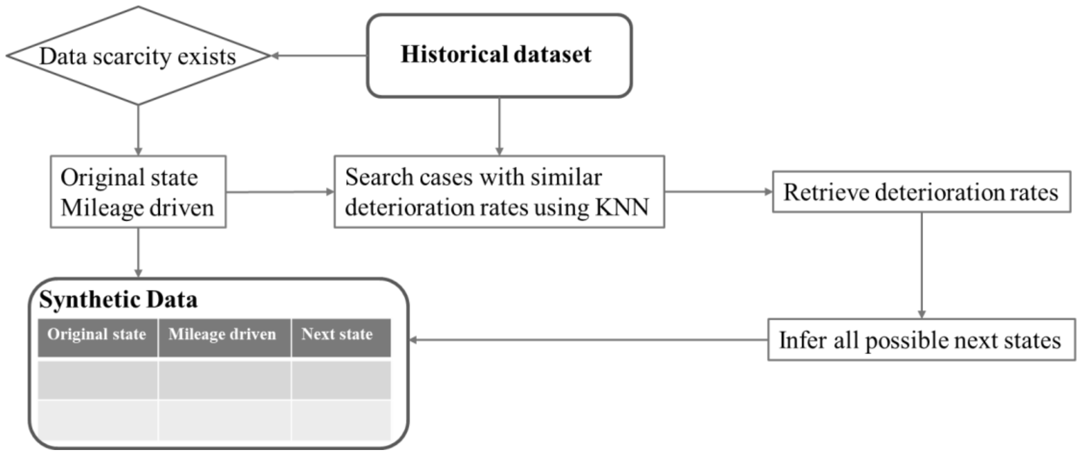

Figure 17. Proposed data augmentation method

$$dr = -\frac{X_{M+m} - X_M}{m} \quad (1)$$

$$next\ state = original\ state - mileage\ driven\ \times deterioration\ rate \quad (2)$$

One challenge of the method is to search for cases with similar deterioration rates given the original state and mileage driven. This research utilizes the historical inspection data of brake pad thickness to explore what type of cases have similar deterioration rates to those given certain original states and mileage driven. The historical inspection records reveal that the original state and the vehicle miles of travel after the original state have intense relationships to the deterioration rates of brake pad thickness. As shown in Figure 18, the deterioration rates decrease monotonically with the vehicle miles of travel increase. Meanwhile, the deterioration rates tend to decrease with relatively good or poor original states, as shown in Figure 19. It is because the brake deteriorates slowly when in good condition and starts to deteriorate faster as worn out. When the brake is in poor condition, the driver tends to drive more carefully, leading to a low deterioration rate. The data augmentation method assumes that cases with the same original state and vehicle travel miles would have similar deterioration rates. Thus, the augmentation method utilizes the vehicle miles of travel and the original state as two features to calculate the distance from each available inspection record to the lacking data.

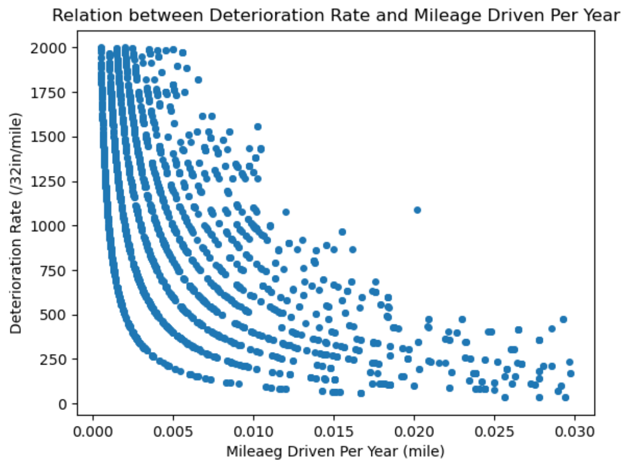

Figure 18. The relationship between the deterioration rate and the vehicle miles of travel

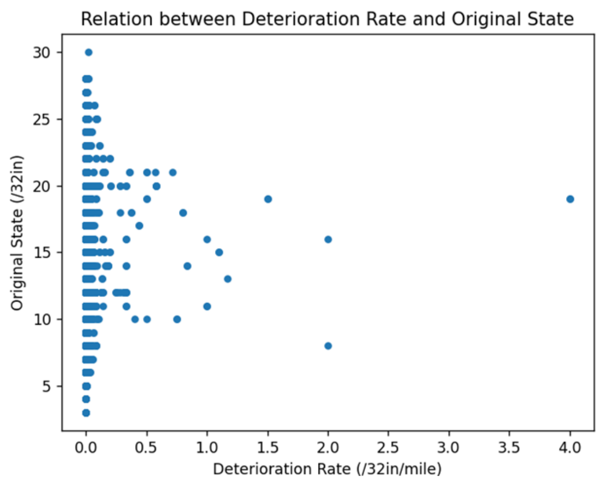

Figure 19. The relationship between the deterioration rate and the original state

To implement the KNN searching, the first step is to normalize the features using min-max scaling to scale down the data so that the normalized data falls between 0 and 1. Eq. (1) and Eq. (2) show the process of scaling the two features, respectively. Then the method calculates the distance between the two features of each available data l, represented as $\{\hat{X}_{Ml}, \hat{m}_l\}$, and those of the lacking data, represented as $\{\hat{X}_{M0}, \hat{m}_0\}$, and select top k nearest as the similar cases from the n available records. With the original state and miles driven of the lacking data and the deterioration rates of the top k similar cases, the state can be calculated after driving the given mileages. So that the virtual cases with information on the original state, miles driven, and the state after driving the given miles is available to fill in the lacking data.

$$\hat{X} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

$$\widehat{m} = \frac{m - m_{min}}{m_{max} - m_{min}} \qquad (2)$$

$$similarity(l) = \ (\hat{X}_{Ml} - \hat{X}_{M0})^2 + (\widehat{m}_l - \widehat{m}_0)^2, l = 1,2, \dots, n$$

(3)

Where $\hat{X}$ is the normalized state using the min-max scaling,

$\widehat{m}$ is the normalized vehicle miles of travel using the min-max scaling,

$\hat{X}_{Ml}$ is the normalized state of each available record,

$\hat{X}_{M0}$ is the normalized state of the lacking data,

$\widehat{m}_l$ is the normalized vehicle miles of travel of each available record,

$\widehat{m}_0$ is the normalized vehicle miles of travel of each lacking data.

3.3.2 Inspection Plan Generation

Markov Deterioration Model

This research develops the Markov deterioration model, which derives the deterioration patterns of heavy-duty vehicle components from historical inspection data. Given the original state of the vehicle (or vehicle components) and the mileage driven, a mapping function can predict the next state and the corresponding probability of the vehicle or vehicle components. Previous research developed deterioration models along the time dimension, which explored the deterioration process along driving time. But for the components like brakes and tires, the future state has a stronger relationship with the mileage driven than the time driven because such components deteriorate as usage, not the time. So this research explores the deterioration process along the mileage driven.

The vehicle deterioration follows the assumption of Markov chain theory [52] that the probability of transition from the last state to the next depends only on the last state and has no dependence on the states before the last. Therefore, the Markov deterioration process only involves states $X_{.M.}$ and X_{M+m}, the component state when driving M mileage, and the predicted future state after m mileage. As a result, the Markov model can extract transition probabilities from one state to another, given a certain mileage. The statistical statement of the conditional probability of transition from state i to state j is shown in Eq. (4).

$$\mathrm{Pr}(\mathrm{X}_{\mathrm{M+m}} = \mathrm{j} | \mathrm{X}_{\mathrm{M}} = \mathrm{i}) \ = \ \mathrm{Pr}(\mathrm{X}_{\mathrm{M+m}} = \mathrm{j} | \mathrm{X}_{\mathrm{M}} = \mathrm{i}, \mathrm{m})$$

(4)

These transition probabilities satisfy two conditions: 1) all probabilities are not smaller than 0, which is $\Pr(X_{M+m}=j|X_M=i) >=0$; and 2) the sum of all transition probabilities transition from the same state should be 1, which is $\sum_j \Pr(\mathrm{X_{M+m}} = \mathrm{j}|\mathrm{X_M} = \mathrm{i}) = 1$.

The proposed method counts the number and the proportion of cases in the component transition from state i to j, given the mileage driven, and uses the proportion as the transition probability in the Markov model, as stated in Eq. (5).

$$\Pr(\mathrm{X_{M+m}} = \mathrm{j}|\mathrm{X_M} = \mathrm{i}) = \frac{number\ of\ cases\ transition\ from\ i\ to\ j\ after\ driving\ m\ mileages}{number\ of\ cases\ transition\ from\ i\ with\ driving\ m\ mileages} \quad (5)$$

Conditional Probability Formula

The Markov model can predict the probability of transition to risky states given a certain mileage. However, the inspection schedules are based on time. So it is necessary to predict the probability of transition to risky states given a certain time interval. This research used conditional probability formula to convert the probability of transition to risky states on the mileage dimension to the time dimension, as stated in Eq. (6). $\Pr(m|t)$ is the probability that the vehicle drives m miles in time interval t, which can be derived from historical inspection data with information on miles m' and time t' between two inspections using Eq. (7).

$$\Pr(\mathrm{X_{T+t}} = \mathrm{j}|\mathrm{X_T} = \mathrm{i}) = \sum_{All\ possible\ mileages:\ m} Pr\,(\mathrm{X_{M+m}} = \mathrm{j}|\mathrm{X_M} = \mathrm{i}) * \Pr(m|t) \quad (6)$$

$$\Pr(m|t) = \frac{\#\ cases\ driving\ m\ miles\ in\ t}{\#\ all\ historical\ cases} = \frac{\#\ cases\ that\ (m'/t' * t == m)}{\#\ all\ historical\ cases} \quad (7)$$

Risky Component Selection

With the probability of transition to any certain state, the failure probability can be calculated by summing up the probabilities of transition to each risky state. For example, defining the risky states as the group of $\{j_1, j_2, \dots, j_n\}$, the transition probability from state i to risky states could be the sum of the transition probabilities from state i to each risky state j, as stated in Eq. (8).

$$\Pr(\mathrm{X_{T+t}} = \text{risky states}|\mathrm{X_T} = \mathrm{i}) = \sum_{risky\ states:\{j_1, j_2, \dots, j_n\}} \Pr(\mathrm{X_{T+t}} = \mathrm{j}|\mathrm{X_T} = \mathrm{i}) \quad (8)$$

In vehicle inspections, the vehicle inspection regulation defines the violation states of vehicle components, which is less than or equal to 2/32 inch for brake pad thickness. The regulated violation states could be risky for vehicles with higher accident risks. So using the violation state threshold (2/32 inch) as a risky state threshold is one reasonable option. However, the inspection results vary around the ground truth due to measuring variations in manual inspections. For example, when a brake pad's actual thickness is 4/32 inch, it might be inspected and recorded as 5/32in, which is an acceptable measuring variation; however, when calculating the next state, the results of using 4/32 or 5/32 inch as the original state would be different and might affect the inspection plan. It is possible that brakes with a 5/32-inch original state do not need inspection, while that with 4/32-inch original state need an inspection. So a more flexible risky threshold might ensure all risky components are included in the inspection plan. The proposed method considers the inspection measuring variations by examining different settings of risky state threshold (such as 2/32inch, 3/32inch, and 4/32inch) and exploring the optimal setting.

With the future failure probability at the time of the next periodic inspection, the proposed method selects the risky components for the next inspection. The method defines a probability threshold as a line for risky component selection. If a component's future failure probability is over the threshold, the component will need attention in the next inspection. Otherwise, if a component's future failure probability is under the threshold, the component will not need attention in the next inspection. Therefore, the inspection plan for the next inspection practice would mark the components with future failure probability higher than the threshold as needing inspection.

Defining the risky state threshold and the probability threshold is one major issue. The main idea is to find the optimal probability threshold that maximize the inspection planning's performance. This research utilized the true positive rate (TPR) and false positive rate (FPR) to evaluate the performance of the inspection planning. TPR is a synonym for recall (Eq. (9)), which reveals the percent of cases inspected in the group of violation cases. The inspection method would detect more violation cases as the TPR is higher. FPR reveals the percent of cases inspected in the group of cases without violations (Eq. (10)). More resource wastes like inspection costs and losses of uptime while FPR is high. So the optimal probability threshold leads to a high TPR and a low FPR, in which case the safety-cost balance is achievable. The objective function could be minimizing FPR with an acceptable TPR, as shown in Eq. (11).

$$TPR = \frac{TP}{TP+FN} \tag{9}$$

$$FPR = \frac{FP}{FP+TN} \tag{10}$$

Where T.P. is true positive, which is the number of violation cases correctly inspected;

F.N. is false negative, which is the number of violation cases incorrectly not inspected;

F.P. is false positive, which is the number of safe cases incorrectly inspected;

T.N. is true genitive, which is the number of safe cases correctly not inspected.

$$objective\ function: minimize(FPR), subject\ to\ TPR \geq TPR_{acceptable} \quad (11)$$

3.4 Experiment Design

This section introduces experiment design, including data pre-processing, the performance metrics for evaluating the deterioration model, the performance metrics for the inspection planning, and hyperparameter tuning.

3.4.1 Data Pre-processing

This research used the CompuSpections dataset to build, tune and test the RBI model. CompuSpections is a private company that sells record management software services to inspection stations. The dataset contains annual inspection recordings using Compuspections software service in Pennsylvania, with vehicle property information (such as vehicle make and model) and component conditions required for inspection in regulations (such as brake pad thickness and tire tread depth). This research uses the brake pad thickness to examine the proposed method. The CompuSpections dataset would provide essential inspection recordings for the RBI model development, including the heavy-duty vehicle's successive inspection dates, odometers in two successive inspections, and the brake pad thickness in two successive inspections. As shown in Figure 20, each row indicates a brake's deterioration process of transition from a last state to another state after a certain time and mileage driven. Sufficient deterioration process recordings can support the development of the RBI model.

Last Inspection Date	Inspection Date	Last Odometer (mile)	Current Odometer (mile)	Last State (/32in)	Current State (/32in)
11/9/2020	11/11/2021	22642	11033	13	15
1/18/2013	9/20/2013	21829	11097	8	13
9/20/2013	2/25/2014	30209	21562	7	8
9/16/2014	2/27/2015	46593	38017	10	14
2/27/2015	10/2/2015	55958	46593	10	10

Figure 20. Screenshot of essential attributes from the Compuspections dataset

The data pre-processing has two major tasks: filtering the heavy-duty vehicles and cleaning the essential data. When filtering the heavy-duty vehicles, only the inspection recordings of vehicles with Gross vehicle weight rating (GVWR) over 26,000 lbs remained. In data cleaning, the data pre-processing cleaned cases with invalid values shown below:

Inspection dates, miles driven between inspections, or brake pad thicknesses with empty values

Inspection date not in a time format

Odometer readings with non-numeric characters

Brake pad thickness is either below 2/32 inch or above 18/32 inch (which is infrequent in real operations)

Duplicate records

3.4.2 Cross-validation of the Deterioration Model

After data pre-processing, the dataset contains 10,700 historical inspection recordings. To evaluate the performance of the deterioration model, this research implemented 5-fold cross-validation where 80% of the recordings are retained for training, and the remaining 20% are for testing. The cross-validation was repeated five times by selecting the different groups of testing data.

The Markov model validated the predicted states after a certain mileage. The inputs of the deterioration model are the original state and mileage driven from the inspection to the next inspection. The outputs are the probability of transition to any state at the time of the next inspection and the state prediction based on the transition probabilities. This research utilized mean squared error (MSE) to quantify the accuracy of the predicted transition probabilities, as shown in Eq.(12). The predicted transition probabilities are calculated based on the training dataset. The true transition probabilities are calculated based on the testing dataset, where underlying the assumption that the transition probabilities derived from the testing dataset are the ground truth.

$$Mean\ squared\ error = \frac{\sum_{N\ test\ samples} \sum_{j=2}^{j=17} (Prob_{pred} - Prob_{true})^2}{16 * N} \tag{12}$$

The MSE can evaluate the deterioration model directly by comparing the predicted transition probabilities with the ground truth. In addition, this research utilizes the future state prediction accuracy to evaluate the deterioration model indirectly. The inputs of the deterioration model are still the original state and mileage driven from the inspection to the next inspection. The outputs are the state prediction based on the transition probabilities from the deterioration model. The state prediction is to select a deterministic state according to the transition probabilities. The predicted states after a certain mileage are proportionally sampled according to the probabilities of transition from a given last state to all possible states after a given driven mileage, which is calculated using Eq.(5).

This research used the exact accuracy and soft accuracy to evaluate the performance of the deterioration model on the brake pad thickness prediction, as stated in Eq. (13) and Eq. (14). The soft accuracy allows the fuzzy prediction caused by the measure variation of the original state.

$$accuarcy = \frac{\#\,(y_{pred} == y_{true})}{\#\,y_{pred}}$$

(13)

$$soft\ accuracy = \frac{\#\,(y_{pred} == (y_{true} \pm 1))}{\#\,y_{pred}}$$

(14)

Where y_{pred} is the predicted next brake pad thickness (/32in) using the deterioration model, and y_{true} is the ground truth of the next brake pad thickness (/32in).

3.4.3 Cross-validation of the Inspection Plan

Validation on TPR and FPR

This research evaluated the inspection planning using 5-fold cross-validation, which is the same as that in deterioration model evaluation. In the cross-validation, TPR and FPR are two metrics to evaluate the performance of the inspection planning. TPR is a synonym for recall (Eq. (9)), which reveals the percent of cases inspected in the group of violation cases. Therefore, the inspection method would detect more violation cases as the TRP is higher. FPR reveals the percent of cases inspected in cases without violations (Eq. (13)). High FPR indicates more inspections on safe vehicles, which leads to resource waste. Therefore, the inspection planning with a lower FPR and an acceptable TPR, which indicates using fewer inspections while achieving an acceptable safety level, performs best.

Validation on Quantitative Safety and Costs of a Simulated Fleet

In addition to the cross-validation, this research tested the inspection planning in a simulated fleet with 250 vehicles and quantified its safety and cost levels in practice. This research utilized the number of inspections and the exposure time with violations in one year period to quantify the cost and safety level, respectively. The number of inspections is to sum up the number of vehicles that need an inspection in each periodic inspection in one year. The exposure time with violations is to sum up the time exposed to violation once a violation occurs in one year.

3.4.4 Hyperparameter Tuning

There are two hyperparameter tunning tasks. One task is to tune the hyperparameters of the data augmentation to improve the deterioration model without inducing errors from the synthetic data. Another task is to tune the hyperparameters of the inspection planning model for optimal inspection decision makings.

In the first task of fine-tuning the data augmentation model, the hyperparameters are the threshold of determining whether to implement data augmentation and the number of synthetic samples to be generated. The optimal values minimize the MSE of transition probabilities, whose calculation function is stated in Eq.(12). This research utilizes the grid search to explore the optimal hyperparameter values.

In the second task for fine-tuning the inspection planning model, the risky state and probability threshold are two hyperparameters that need fine-tuning. The method tunes the two hyperparameters by searching the optimal values that optimize the objective function stated in Eq. (11). The potential risky state threshold of brake pad thickness could be 2/32, 3/32, or 4/32 inch, and the probability threshold could be in the range from 0 to 1. This research utilized the grid search to explore the optimal hyperparameter values in such ranges.

3.5 Results

3.5.1 Data Augmentation Process

The data augmentation method filled in the lacking data using the cases generated based on the deterioration rates of similar cases. Identifying similar cases used the original state and the mileage driven. Figure 21 shows that the data augmentation method can fill in the lacking data without mitigating information from the available data.

In addition, this research dug into a specific historical data lacking scenario to explain the data augmentation process. Considering the scenario where the original state is 4/32inch and the mileage is 398 miles, there is no samples in the historical dataset with the exact same original state and mileage. Hence, data augmentation is essential in this scenario. The data augmentation method can search similar cases with the similar original state and the similar mileage in the historical dataset. When relaxing exact constraint of the original state (4/32inch) to neighborhoods, there are 2 samples with the similar original state and the same mileage, whose deterioration rates guide the brakes stay in 4/32inch. When relaxing the exact constraint of mileage (398miles), there are 10 samples with the same original state and the same mileage, whose deterioration rates guide 30% brakes transitioning to 3/32inch from 4/32inch. When relaxing both the original state and the mileage, there are 8 samples guiding 25% brakes transitioning to 3/32inch from 4/32inch. Finally, the transition probability of transitioning from 4/32inch to 3/32inch after applying data augmentation considers the samples relaxing the original state and mileage, through transition distributions guided by their deterioration rates.

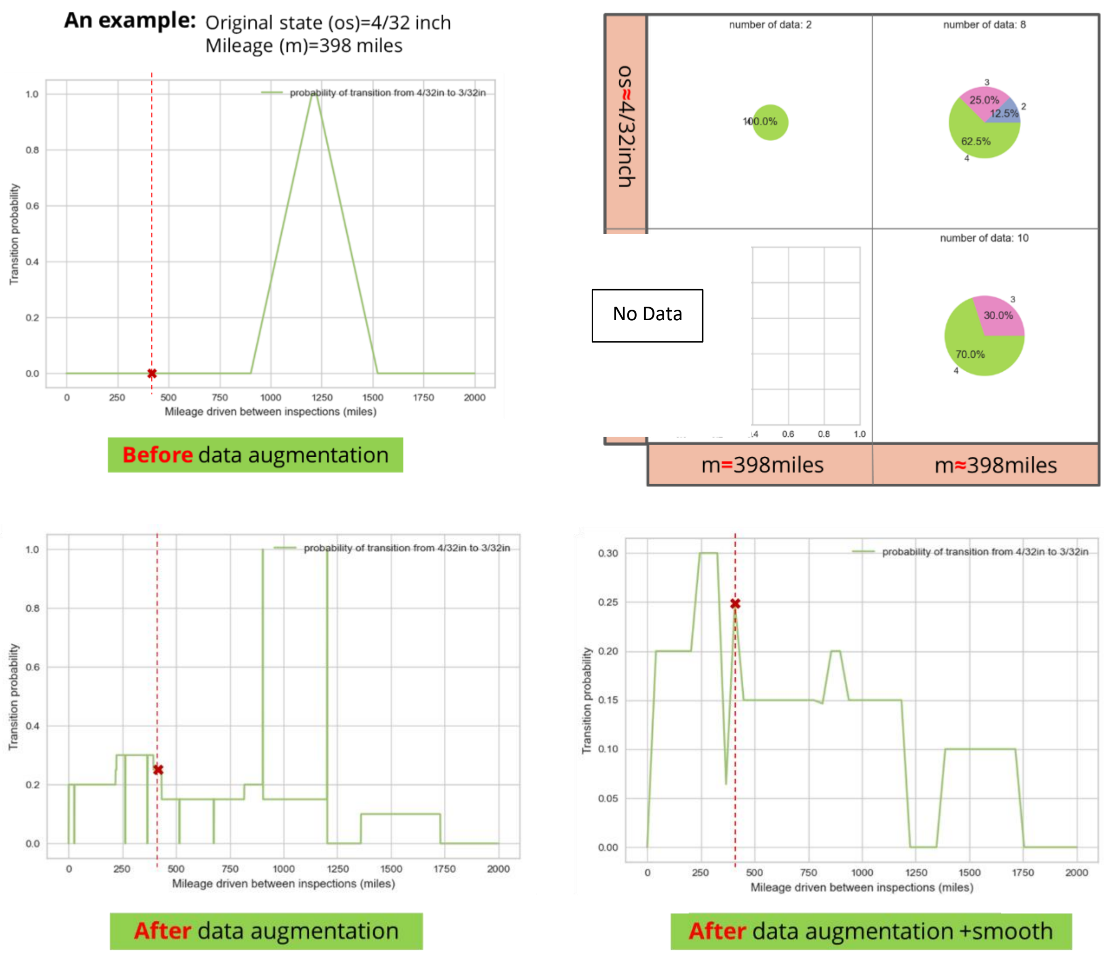

Figure 21. An example: data augmentation process

3.5.2 Cross-validation of the Deterioration Model

This research calibrated the deterioration model by searching for the optimal hyper-parameters of data augmentation. The optimal hyperparameters are: the threshold of determining whether to implement data augmentation is 1; the number of nearest samples for augmentation is 20. In addition, this research validated the deterioration model using the mean squared error of the transition probabilities. As shown in Table 6, the deterioration model with data augmentation obtained a reduced mean squared error, which means the predicted transition probabilities are closer to the ground truths than those without data augmentation.

Table 6. Evaluation of deterioration models with or without augmentation

	MSE-with augmentation	**MSE-without augmentation**
Transition probability	0.0188	0.0447

This research also validated the predicted states after a particular mileage of several deterioration models by comparing the developed deterioration model with or without data augmentation. Table 7 shows the comparison result. The Markov model without data augmentation has an accuracy of 44.5% and a soft accuracy of 62.9%. In comparison, the Markov model with data augmentation has a higher accuracy of 82.1% and a higher soft accuracy of 89.3%.

Table 7. Accuracy and soft accuracy of the deterioration model with or without data augmentation

Deterioration Model	**Prediction states after a certain mileage**	
	Accuracy	**Soft accuracy**
Deterioration model -with data augmentation	82.1%	89.3%
Deterioration model -without data augmentation	44.5%	62.9%

3.5.3 Cross-validation of the Inspection Plan

Validation based on TPR and FPR

Fine-tuning the hyperparameters of the risky state threshold and the probability threshold is to search for the optimal values with minimizing FPR and an acceptable TPR. For example, typically the commercial fleet has a strict restriction on vehicle safety that does not allow the vehicle to operate with any component failure, then the acceptable TPR should be 1. Meanwhile, the commercial fleet hopes to minimize the cost on inspections, then the FPR should be the minimum. Thus, for the inspection model with augmentation, the optimal risky state threshold is 3/32inch and the probability threshold is 0.003. And the corresponding TPR is 1 and the FPR is 0.37. Table 8 shows the TPRs and FPRs of inspection plans with and without using data augmentation under different thresholds.

Table 8. Hyperparameter tuning of the risky state and probability thresholds

Hyperparameters -thresholds		**With augmentation**		**Without augmentation**	
Risky state (/32in)	**Probability**	**TPR**	**FPR**	**TPR**	**FPR**
2	0	0.88	0.41	0.2857	0.2693
2	**0.005**	**0.88**	**0.12**	0.2857	0.0244
3	0.002	1.00	0.46	0.7500	0.3107
3	**0.003**	**1.00**	**0.37**	**0.813**	**0.2495**
3	0.004	0.88	0.31	0.7500	0.2231
3	0.005	0.88	0.28	0.6875	0.2151
4	0	1.00	0.68	**1**	**0.8986**

The inspection plan with data augmentation can obtain a higher TPR, which indicates higher vehicle safety. In addition, the FPR of inspection plan with data augmentation is only a little bit higher than that without data augmentation. The result indicates that the data augmentation can improve vehicle safety with spending a little bit more inspections.

Validation of Quantitative Safety and Costs of a Simulated Fleet

This research tested the method on a virtual fleet with 1,000 vehicles randomly sampled from the CompuSpections dataset. The validation used the annual inspection method and monthly inspection method as baselines. Three metrics include the number of inspections, the percentage of detected violations, and the time vehicles drive with accident risks. The number of inspections indicates the costs and losses of uptime caused by vehicle inspections. The percentage of detected violations and the time vehicles drive with accident risks reflect the vehicle's driving safety.

As shown in Table 9, the proposed method spent fewer inspection numbers than the monthly inspection while ensuring the minimum time exposed to violation risks. Meanwhile, the proposed method caused less time exposed to violation risks while only costing a few inspections. The results show that the proposed method can minimize the costs and losses of uptime while minimizing the safety risks and performs better than annual and monthly inspection strategies.

Table 9. Results of inspection method validation on a fleet with 1,000 vehicles (risky states: [2,3]/32in; probability threshold: 0.003)

Evaluation metrics	Baseline methods		Proposed method
	Annual inspection	Monthly inspection	Risk-based monthly inspection
Number of inspections	1,000	12,000	4,839
Time exposure to risks (month)	7.2	1.2	1.2

3.6 Discussion

The comparison between the inspection planning without data augmentation and that without data augmentation shows that the data augmentation could effectively extend the dataset and improve the inspection plan by improving the safety level with minimizing costs. The comparison between the deterioration models with and without data augmentation shows that the proposed data augmentation method significantly reduced MSE by 60% and improved the future state prediction accuracy by almost 40%. The proposed deterioration model with data augmentation has a better performance than the deterioration-rate-based model, which improves the future state prediction accuracy by over 60%.

The result also shows that data augmentation improves the deterioration model's performance. The future state prediction accuracy is improved by almost 40% after data augmentation. When evaluating the TPR and FPR of using different inspection strategies with or without data augmentation, the result shows that data augmentation can improve TPR while also improving FPR.

This research also evaluated the proposed inspection method in simulated fleets. The results show that the proposed method can improve operation safety with relatively fewer costs than traditional periodic inspections. The proposed method can constantly achieve the same accuracy of problematic vehicle detection with a 59.7% reduction in the number of inspections compared with the monthly inspection. In addition, the new method can achieve an 83.3% reduction in the time of having certain vehicles operate under brake violations compared with the annual inspection plan.

This research assumes that all heavy-duty vehicles deteriorate following the same deterioration pattern, which is different from vehicles in other weight levels. However, heavy-duty vehicles could have different deterioration patterns. For example, under the same original state (10/32 inch) and a similar mileage driven (2,000 miles), some vehicles deteriorate slowly and might remain in the original state, while some deteriorate fast and might reduce to 5/32 inch. Such variation in deterioration rates implies that heavy-duty vehicles have different deterioration patterns. In the future, revealing the deterioration patterns is important for designing a more customized deterioration model for each vehicle and achieving a more reliable inspection plan.

3.7 Conclusion

This paper proposed an inspection planning approach that inspects risky components periodically for safety-cost balance. The inspection planning includes four parts: (1) data augmentation for limited historical inspection records, (2) the Markov deterioration model for predicting the risk of component failure on the mileage dimension, (3) conditional probability formula for predicting the risk of component failure on the time dimension, and (4) vehicle and component selection for inspection. This paper compared the inspection planning with data augmentation to that without data augmentation. The results show that the data augmentation method improved the model performance by reducing the mean squared error of transition probabilities. This paper also tested the deterioration model's performance in predicting vehicles' future states. The proposed data augmentation method can improve the accuracy of state prediction by 37.6%.

This paper also evaluated the overall inspection planning approach using cross-validation and a simulated virtual fleet. In cross-validation, the inspection planning can achieve a one hundred percent detectable rate of vehicle violations with a relatively low false inspection rate. In the test on a simulated commercial fleet, the proposed inspection planning is validated to detect all vehicle violations with relatively few inspections. The method can achieve an optimal balance between vehicle safety, financial costs, and uptime losses compared with current practices of periodic inspections.

The predicted transition probabilities to potential states can indicate the importance of the components in inspections. Such characteristics could contribute to telematics, a future trend in vehicle condition monitoring. The transition probability can help answer the questions: which vehicle and component need continuous monitoring, and what is the optimal data collection frequency. In this way, it is applicable in enhancing periodic inspections to improve vehicle safety with fewer costs by only selecting the important components for inspection and the optimal inspection frequency. In addition, it is also applicable in saving the transfer bandwidth and storage space of data collected from telematics by only monitoring the important components at important timing. In the future, integrating the proposed method into vehicle monitoring could contribute to finding the optimal data collection strategy for telematics data.

Chapter 4 Investigation of Component Violations likely to Cause Crashes

4.1 Introduction

Commercial heavy-duty trucks and trailers play a crucial role in the efficient movement of goods and services across various industries. However, despite their importance, they are often susceptible to crashes and inspection violations, posing significant challenges to fleet management and operational efficiency. According to National Highway Traffic Safety Administration, in 2021, there were 5,788 people killed in traffic crashes involving large trucks, which was a 17-percent increase from 4,945 in 2020. Seventy-two percent of people killed in large-truck traffic crashes in 2021, were occupants of other vehicles. In addition, the percentage of large trucks involved in fatal traffic crashes was 10 percent or higher in 21 States.

As the demand for timely deliveries and reliable logistics continues to grow, fleet operators face increasing pressure to maintain high safety standards and comply with rigorous regulations. The occurrences of crashes and inspection violations not only result in substantial financial losses but also pose risks to road safety and public well-being.

By identifying patterns and common risky vehicle components in crashes, fleet managers can take proactive measures to prevent potential accidents and minimize downtime due to inspection failures. This, in turn, leads to significant cost savings and contributes to the overall efficiency of fleet operations. Understanding the factors contributing to crashes and inspection violations is vital for fleet operators and managers seeking to optimize their operational processes and achieve better safety records although it is very difficult to consider all of them. In this chapter, we have explored the relationship between crashes and inspection violations in the commercial heavy-duty truck and trailer industry.

4.2 Related work

Many researchers have studied crashes and the safety of heavy-duty vehicles from different aspects. [53] studied accident risk of road and weather conditions on different road types. [54] analyzed the time of day affecting injury severities in large truck crashes. In another study, [55] investigated the effects of vehicle types and driver behavior in crashes. However, there are limited studies focusing on the relationship between crashes and vehicle-related inspection violations of trucks to identify the risky components to get more attention while planning for inspection and maintenance.

4.3 Method

4.3.1 Data cleaning and merging the datasets

We conducted the investigation using the MCMIS (Motor Carriers Management Information System) crash and inspection violation datasets to identify the most frequent inspection violations associated with vehicles involved in crashes. Our primary focus was on heavy-duty vehicles, requiring the extraction of vehicles with gross weights above 26,000 lbs. from classes 7 and 8. To achieve this, we decoded the VINs (Vehicle Identification Numbers) from the crash dataset, which provided some information such as gross weight, make, model, model year, and body type of the vehicles contributing to crashes. Subsequently, we utilized Excel to filter the dataset, resulting in 62,000 remaining heavy-duty vehicles out of the initial 104,000 in the crash dataset. Also, we checked all VINs to exclude the incorrect ones from further analysis.

To further enhance our analysis, we merged the inspection report and inspection violation report using "INSPECTION ID" as a key, employing data frames in Python. Next, we merged this combined dataset with the previously filtered crash dataset based on "VINs" shared between both datasets. This step allowed us to connect the information from all three datasets effectively. Figure 22 demonstrates these connections.

Upon completing these data merges, our analysis revealed that only 8,194 vehicles remained in the dataset. This means that a total of 8,194 vehicles, which had inspection violations, also contributed to crashes in 2021.

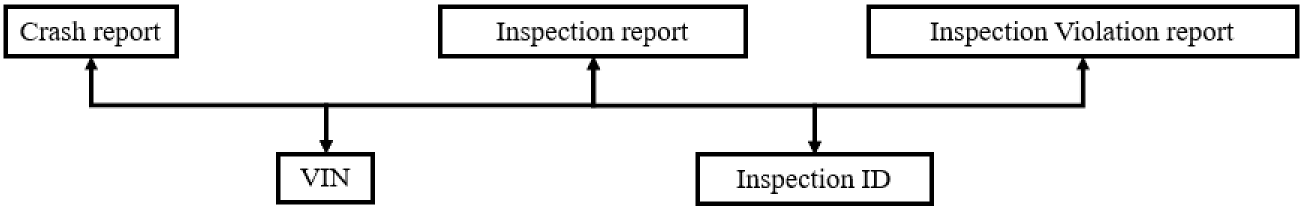

Figure 22. Merging the three datasets

4.3.2 Visualizing the results by Power BI

After preparing the final dataset, we imported it into Power BI to get the percentage of each inspection violation in crashes and to visualize it by a pie chart. Power BI is a user-friendly and powerful tool developed by Microsoft that helps us turn our data into interactive reports and dashboards. We will discuss the results in the following section.

4.4 Experiment

The results show that the most frequent inspection violations that showed up in crashes were “lighting” (15.11%) and “Brake all others than out of adjustment” (11.39%). The percentage of each inspection violation is indicated in Figure 23, and each inspection violation ID is reported in Appendix 1**:**.Based on these findings, the inspection plan prioritizes potential component violations frequently involved in inspections. This approach ensures that the inspection planning focuses on the critical component violations that have the highest impact on crash prevention and overall road safety.

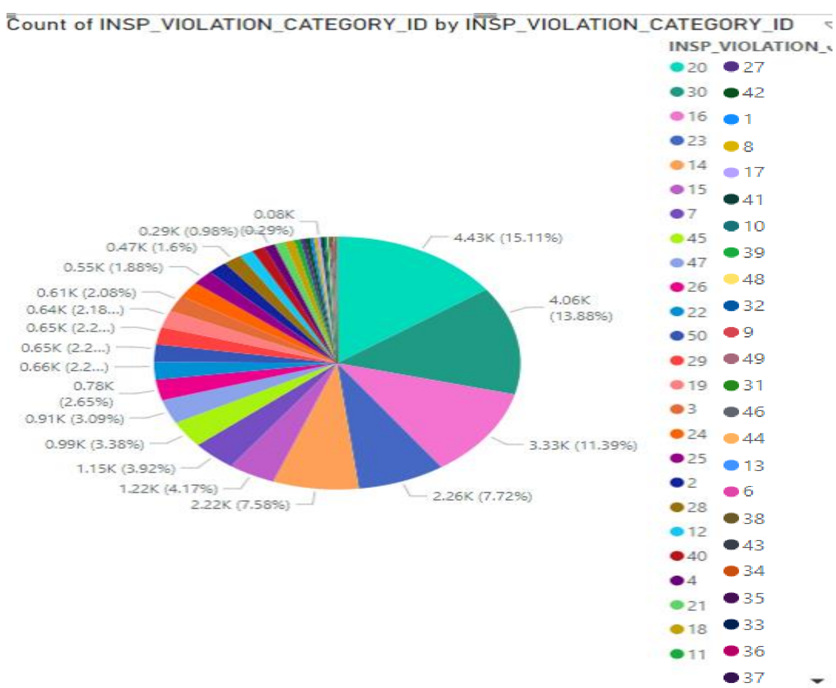

Figure 23. Percentage of each inspection violation in crashes (2021)

The dataset we used contained other attributes related to crashes, such as weather conditions, road surface conditions, and light conditions, which all are subsets of environmental conditions. The results show that 77% of accidents happened when there was no adverse condition, and 10.14% when it was rainy. In addition, in 75% of accidents, the road surface was dry and in 14.85%, it was wet. Also, 69.34% of accidents happened in daylight. However, from these percentages we cannot conclude that environmental conditions have negative correlations with the crash rates, because we do not have data about the vehicle's exposure to accidents in these environments, the total mileage driven in rainy weather for instance. The percentage of each weather, road surface, and light condition in crashes are illustrated in

Figure 24,

Figure 25, and

Figure 26, respectively, and their related ID descriptions are provided in Appendix 1**:**.

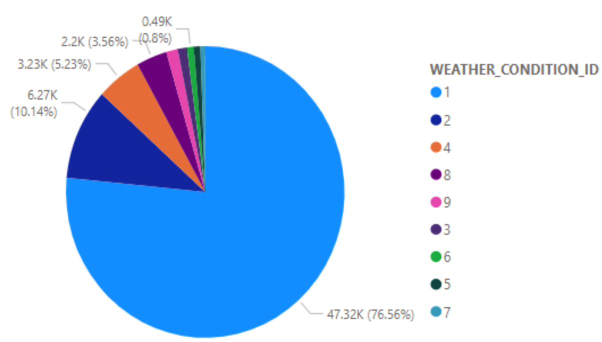

Figure 24. The percentage of different weather conditions in crashes (2021)

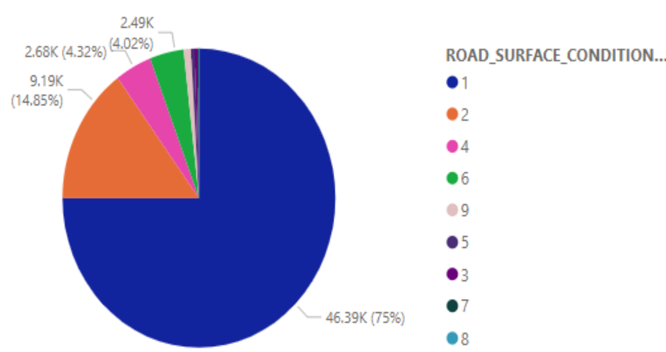

Figure 25. The percentage of different road surface conditions in crashes (2021)

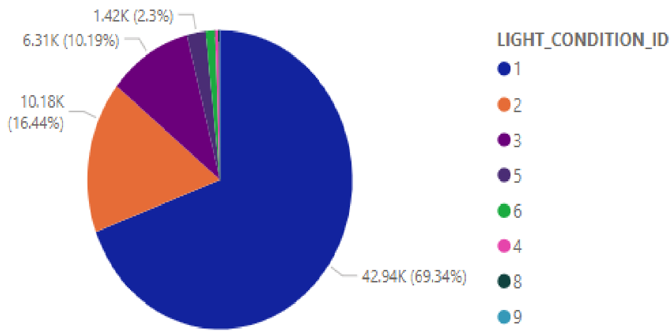

Figure 26. The percentage of different light conditions in crashes (2021)

We also did some critical analysis on motor carriers that contribute to crashes and inspection violations more frequently. First, we derived the total mileage of each motor carrier. Then divided the total number of crashes by the total mileage to obtain the crash rate for each motor carrier. We did the same to obtain the inspection violation rate as well. The results demonstrate that two of the motor carriers that had high crash rates are not authorized to operate anymore. However, there are still some limitations in this study; because some motor carriers have not updated their total mileage in the FMCSA (Federal Motor Carrier Safety Administration) database. In addition, we are suspicious about some of the total mileages reported as they do not correspond to the number of power units or the number of drivers.

Figure 27, and Figure 28 depict the motor carriers that have the highest crash rates and violation rates, respectively.

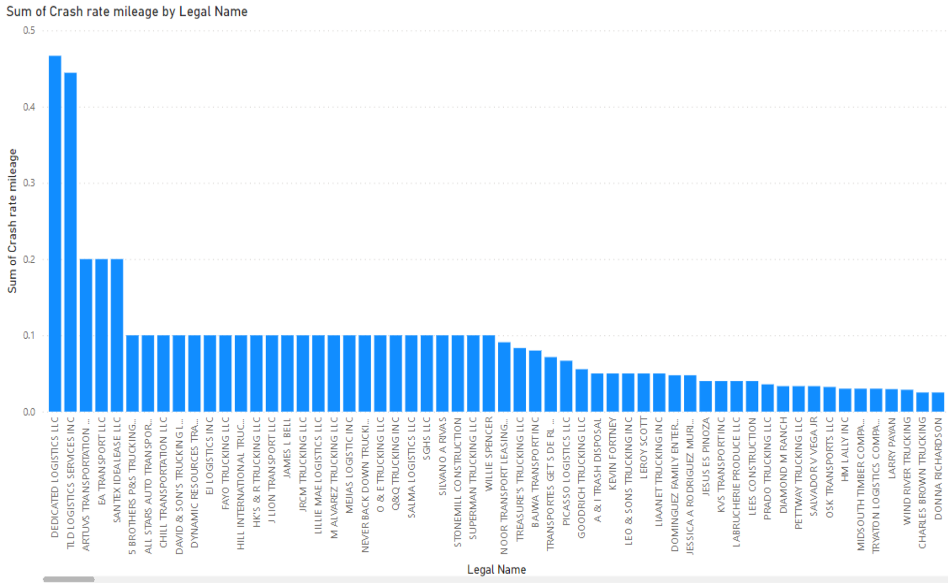

Figure 27. Motor carriers with high crash rates in 2021

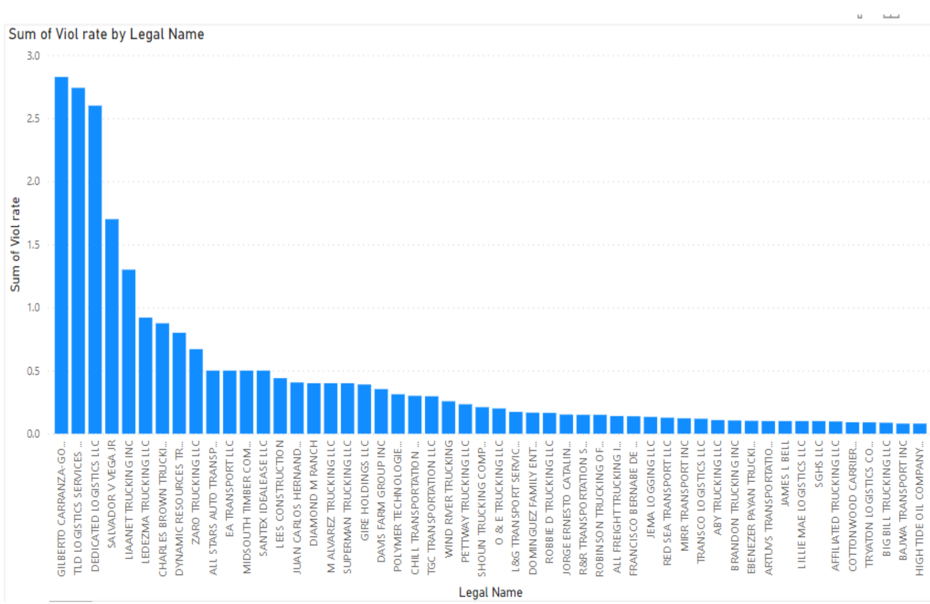

Figure 28. Motor carriers with high inspection violation rates in 2021

4.5 Conclusion and Future work

In this chapter, we examined what inspection violations are more frequent in crashes so that we can consider them with high priority in the inspection and maintenance plans. Lighting and brake inspection violations had the highest percentage among all components. In future, we will study what operation, inspection and maintenance strategies can proactively manage the fleets considering safety, efficiency, and cost-effectiveness.

Chapter 5 Discussion and Conclusion

5.1 Discussion

The project studies data of manual inspection, which is the most common way in fleets. As the development of telematics, more and more trucks and trailers start to install telematics, which can automatically gather real-time data from vehicles. This project discusses the benefits and limitations of telematics on trucks and trailers.

By leveraging advanced telecommunications and informatics, telematics enables fleet managers to gather real-time data from various sensors, monitoring vehicle conditions and driver behavior, ultimately leading to enhanced vehicle safety and a reduced likelihood of inspection violations. Additionally, telematics can provide predictive analytics to inform and guide decision-making processes. However, despite its numerous potentials, there are limitations to the implementation of telematics, such as cost considerations for mid-size and small-size fleets that need cost justification, concerns about privacy violation, especially when Dash Cam is also installed inside the truck and the challenge of managing data overload and effectively using raw telematics data. Overall, telematics represents a powerful tool for optimizing fleet management operations, by improving efficiency, safety, and cost-effectiveness. However, fleet managers must carefully consider the technology's limitations mentioned above.

5.2 Conclusion

This project delivered an effective solution of the fleet inspection planning, which ensures the vehicles in safe conditions with minimum costs. Key achievements of the project team include 1) the development of the dashboard for visualizing historical inspection data and exploring valuable experiences for fleet managers; 2) the development of an interface for fleet management, which can upload fleet information, visualize fleet information, and generate inspection plans; 3) the development and validation of a predictive inspection planning model; 4) the development and validation of a data augmentation method for generating synthetic data to provide sufficient information for a more reliable predictive inspection planning model; and 5) identification of component violations most related to crashes. These accomplishments form an inspection planning solution that improves vehicle safety while minimizing delivery delays and costs due to inspections.

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Appendix 1: Meta data of the coded vehicle attributes and inspection records

Table 10: Inspection Violation IDs Description

Inspection Violation ID	Description
1	Medical Certificate
2	False Log Book
3	No Log Book, Log Not Current, General Log Violations
4	10/15 Hours
5	15/20 Hours
6	60/70/80 Hours
7	All Other Hours-Of-Service
8	Disqualified Drivers
9	Drugs
10	Alcohol
11	Seat Belt
12	Traffic Enforcement
13	Radar Detectors
14	All Other Driver Violations
15	Brakes, Out of Adjustment
16	Brakes, All Other Violations
17	Coupling Devices
18	Fuel Systems
19	Frames
20	Lighting
21	Steering Mechanism
22	Suspension
23	Tires
24	Wheels, Studs, Clamps, Etc.
25	Load Securement
26	Windshield
27	Exhaust Discharge
28	Emergency Equipment
29	Periodic Inspection
30	All Other Vehicle Defects
31	Shipping Papers
32	Improper Placarding
33	Accepting Shipment Improperly Marked
34	Improper Blocking and Bracing
35	No Retest and Inspection (Cargo Tank)
36	No Remote Shutoff Control
37	Use of Non-specification Container
38	Emergency Response
39	All Other HM Violations

40	Failure to Obey Traffic Control Device
41	Following Too Close
42	Improper Lane Change
43	Improper Passing
44	Reckless Driving
45	Speeding
46	Improper Turns
47	Size and Weight
48	Failure to yield right of way
49	State/Local Hours of Service
99	Unknown

Table 11. Weather Condition ID Description

Weather Condition ID	Explanation
1	No Adverse Condition
2	Rain
3	Sleet, Hail
4	Snow
5	Fog
6	Blowing Sand, Soil, Dirt, or Snow
7	Severe Crosswinds
8	Other
9	Unknown

Table 12. Road Surface Condition ID Description

Road Surface Condition ID	Explanation
1	Dry
2	Wet
3	Water (standing, moving)
4	Snow
5	Slush
6	Ice
7	Sand, Mud, Dirt, Oil or Gravel
8	Other
9	Unknown

Table 13. Light Condition ID Description

Light Condition ID	Explanation
1	Daylight
2	Dark-Not Lighted
3	Dark-Lighted
4	Dark-Unknown Roadway Lighting
5	Dawn
6	Dusk
8	Other
9	Unknown

Appendix 2. Publications and Other Products

Chenyu Yuan, Ying Shi, Ruoxin Xiong, Pingbo Tang*. "Identifying Safety-Critical Heavy-duty Vehicles in Fleets with Complementary Vehicle Inspection Datasets through Cross-Database Clustering Analysis." The Transportation Record Board 2023. Microsoft Word - TRB Paper Final Version - Chenyu_ying_ruoxinx_ptang.docx (cmu.edu)

TrSafety - Towards Data-Driven and Continuous Safety Inspection of Commercial Trucks and Trailers: https://sites.google.com/andrew.cmu.edu/trsafety/home

Appendix 3. Final datasets from the research project

The two industry collaborators (Compuspections and Clarience Technologies) provided more truck/tractor inspection data and helped the project team clean and organize their data for supporting integrated analysis of historical inspection reports and real-time data. *https://github.com/yingshixzz/Commercial-Fleet-Management/blob/main/data/Heavy%20duty%20vehicle%20brake%20data_sample.xlsx*

The project utilized the MCMIS (Motor Carrier Management Information System) dataset from FMCSA (Federal Motor Carrier Safety Administration), which contains vehicle inspection recordings with the vehicle properties. The researchers extract text annotations in vehicle inspection recordings and cluster the vehicles based on vehicle failure modes. The final dataset contains the cleaned text annotations and clustering results. *https://github.com/yingshixzz/Commercial-Fleet-Management/blob/main/data/NLP%20with%20topic_sample.xlsx*

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Appendix 5. Other documented projects or outcomes resulting from the research project

Presentations

Ying Shi presented the research work on "Safety-Cost Aware Inspection Strategy for Commercial Vehicle Fleets" at Mobility21 Deployment Partner Consortium Symposium on October 31, 2022

Ying Shi presented the research work on "Identifying Safety-Critical Heavy-Duty Vehicles in Fleets with Complementary Vehicle Inspection Datasets Through Cross-Database Clustering Analysis" at TRB 102nd Annual Meeting in Washington, DC on January 10, 2023

Algorithms
Algorithms for 1) predicting vehicle conditions and identifying risky vehicles periodically to ensure the operation safety with the minimizing number of inspections; 2) clustering similar vehicles with similar brake deterioration patterns; 3) augmenting limited historical data for obtaining more reliable deterioration models; 4) explaining the clustering results by quantifying the influences of vehicle characteristics, driving behaviors, and driving environments on deterioration patterns given a certain component; 5) explaining the reasons for the variant deterioration rates of variant vehicles.

Models
(1) Deterioration models of commercial trucks and tractors for supporting the simulation of different inspection and maintenance policies for managing commercial vehicle fleets; (2) explainable models for interpreting the reasons for variant deterioration patterns for variant vehicles.

Educational aids or curricula
Education and outreach materials for training industrial professionals in the effective use of historical inspection records of commercial vehicles for preventive commercial vehicle fleet inspection and maintenance planning

Software or NetWare
Two interfaces for fleet management (one is for visualizing historical data and the other is for presenting inspection suggestions)