Safe and Sustainable Fleet Management with Data Analytics and Reinforcement Training

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Abstract **- The University of Virginia's Facilities Management (FM) Fleet consists of around 260 total vehicles and is committed to safe and sustainable driving. The fleet vehicles contain telematic tracking systems which provide feedback on a multitude of driving behavioral measures, including speeding, harsh braking, hard acceleration, seat belt usage, harsh cornering, and idling time. In a previous study, data collected on these measures was used to develop relevant educational materials on mindful driving. This paper aims to further improve safe and eco-friendly FM driving behaviors by analyzing if reinforcement training, additional scorecards and manager conversations, proved to be effective when given proactively or reactively to increased violations of driving behavioral measures. This paper outlines the process we used in determining when and how to administer the two different training programs and which vehicle shops to involve. One group of shops received in-depth training before any notable violations were detected, which was deemed proactive training. A separate shop received the reactive training after any significant increase in vehicle incidents was detected. These reinforcement training programs were largely based on the professional FM education modules and provided conversation templates for managers to use in order to re-educate their shop's respective drivers. The research showed that reactive reinforcement training was statistically significant for speeding while proactive reinforcement training was not statistically significant; however, further expansion upon both trainings may still be warranted.**

Keywords - Data Analytics, Eco-Driving, Safety, Telematics, Training Program

I. INTRODUCTION

Facilities Management (FM) fleet managers are responsible for establishing proper driving protocols for their vehicles and optimizing organization operations with a focus on reducing costs and risk of accidents. These responsibilities include adherence to rules and regulations, monitoring infractions, and providing training modules to employees to improve or maintain proper safety protocols. Recently, eco-driving has been included to this list of responsibilities to improve sustainability in fleets, which also furthers safety as appropriate behaviors to achieve the two often overlap. Eco-driving is defined as "the behaviours that characterise fuel-efficient driving in any private road vehicle" [1]. There are three main decisions within eco-driving: strategic, tactical, and operational decisions [2]. This type of training, focusing on analyzing operational decisions using in-vehicle telematics sensors, has proven to be effective in reducing fuel consumption by up to 20% while also decreasing crash risk [3]. Last year, a team of researchers developed a new training program for University of Virginia's FM Fleet centered around eco-driving. Their training, FM training as it will be known in this paper, is "an interactive data-driven training program which provides basic information about safe and sustainable driving coupled with data regarding the fleet's holistic driver performance historically" [4]. FM training focused on six driving factors: hard acceleration, harsh braking, harsh cornering, seat belt usage, speeding, and idling. The goal of FM training was to reduce the carbon footprint, strengthen compliance-related behaviors, and improve the safety and sustainability of the fleet. The team of researchers found that FM training displayed a significant reduction in hard acceleration, harsh braking, speeding, seat belt usage, and idling. The training group "experienced a 45.9% decrease in idling time per mile driven when compared to the control group" [4], and "a 73.7% decrease in seat belt violations" [4]. Based on these results from last year's research, the FM training proved effective at addressing driver behavior and accomplishing the three established goals [4].

To further improve the safety and sustainability of the fleet, we propose two reinforcement trainings, reactive and proactive, designed to use the in-vehicle sensor data and reinform drivers of the lessons on safe and sustainable driving learned in FM training. Both reinforcement trainings are distributed on a shop level basis, focus on the same six factors as the FM training, and consist of scorecards and manager conversations. The reactive reinforcement training is distributed when needed on a weekly basis while proactive reinforcement training is distributed on a twelve week schedule. The goal of both reinforcement trainings is to improve or maintain the eco-driving habits of the fleet. The study of these reinforcement trainings was conducted on multiple different shops within the University of Virginia's fleet and consisted of creating the reinforcement training materials, developing the two types of reinforcement trainings, implementing both reinforcement trainings, and collecting and analyzing the post-reinforcement training results.

II. BACKGROUND

The transportation sector is the largest contributor to greenhouse gas emissions in the U.S [5]. As climate change intensifies and the number of vehicles on the road only increases, improving transportation sustainability is becoming more urgent [5]. Eco-driving is a proven short-term solution that is relatively easy to implement as it is cost-effective and requires acquiring less resources than other alternative technologies, such as switching to electric-powered vehicles. In addition, eco-driving not only reduces emissions but also improves driver safety [3]. Given the positive results from last year's eco-driving training, the training was expanded in order to reinforce previous learning and prolong its effectiveness. Reinforcement training was proposed as the method to continuing FM training because post-license driver retraining programs have been found in other research to significantly reduce accidents and traffic violations [6]. Unlike last year, the new reinforcement training provides feedback on vehicle performance as other vehicle improvement studies showed that doing so is significantly more effective than not receiving feedback at all [7]. The reinforcement training is also conversation-based as two-way communication enables collaboration between the instructor and learner for effective driving instruction [8]. Driving task reflection and communicating specific feedback also support the learner's perceived competence [8].

Proactive and reactive reinforcement trainings were conducted using information based on last year's training module. Proactive training aims to prevent negative occurrences before they happen, so it requires shops to review the original training material during a shop conversation regardless of their shop performance. Reactive training focuses on correcting negative issues after they've occurred, so it involves reviewing specific metrics that the shop performed insufficiently on during the previous week. Though reactive training is more targeted and could provide more immediate improvements, proactive training could be more realistic and logistically easier to implement for FM. Proactive corporate environmental practices have also been found in research to improve their environmental performance more than reactive practices, as proactive practices required a more thorough integration into existing processes and organizational priorities [9].

III. METHODOLOGY

Our goal was to design an additional reinforcement training to continue and supplement the training program instituted by the previous group of researchers working with FM [4]. Similar to their research, our team relied on GeoTab provided scorecards and the included data as a way to monitor and keep track of vehicle performance. GeoTab is a third party data monitoring platform that FM uses for their fleet to obtain vehicle driving data using small tracking devices installed in each vehicle. We used Geotab to obtain infraction counts of the five of the six metrics chosen to evaluate vehicle driving performance: harsh acceleration, harsh braking, harsh cornering, speeding, and seat belt usage and the time of infraction for the last metric: idling. In addition, the tracked vehicle mileage data was used to normalize the incident rates of all the vehicles the group inspected. For each of the six metrics, the group was able to calculate incident rates for every metric by dividing the number of infractions by miles driven, as outlined in (1).

$$Vehicle\ Incident\ Rate = \frac{Incident\ Count}{Miles\ Driven} \quad (1)$$

The team relied on the above incident rate calculation, which was applied at the vehicular level, as one of two techniques to monitor vehicle performance. The second was an incident rate calculated at the shop level. The team used (2), shown below, in order to calculate these shop-level incident rates.

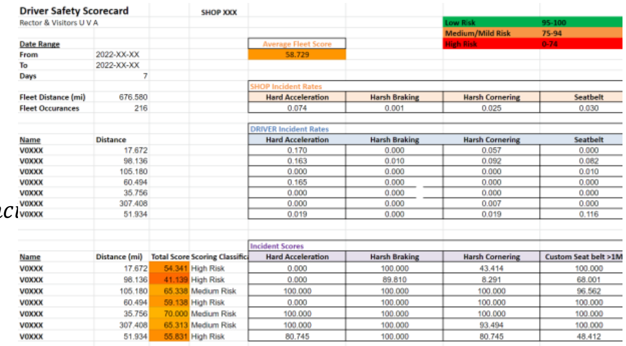
$$Shop\ Incident\ Rate = \sum_{i=1}^{\#Vehicles\ in\ Shop} \left(\left(\frac{Miles\ Driven_i}{\sum_{i=1}^{\#Vehicles\ in\ Shop} Miles\ Driven_i}\right)(Inci \right. \quad (2)$$

A. Vehicle Selection

Our research focuses on the implementation of reinforcement training in vehicle fleet management to supplement an existing training program. As a result, the reinforcement training was only given to shops that had already been given the FM training program developed last year. Initially, this limited our control over shop selection for treatment, but as the year progressed more shops were trained. The control vehicles selected were pulled from shops that had received no training at all. Our team worked to find similar vehicle types and behavior for each control-experimental pair in order to have more conclusive and translatable results by attempting to reduce variability between the shops. The factors we considered for comparing vehicle type were model, vehicle type, class, and gross vehicle weight rating (GVWR). For vehicle behavior we considered patterns such as the type of trip typically made or job the vehicle would be used for. In order to get this information we relied on input from FM representatives. While no individual vehicles or drivers were singled out in this experimental design, we emphasized monitoring vehicle performance on top of how an entire shop might perform.

B. Training Materials

Both reactive and proactive training programs used the same materials as the content covered is not different, only when they are given. The training materials included a scorecard, based on the ones available from GeoTab, that was sent out to shop managers along with a conversation template with key speaking points on how to improve driving performance. The scorecards included weekly data on average shop score, shop incident rates per metric, vehicle incident rates per metric, vehicle incident scores overall and by metric, and miles driven by the shop and vehicles. The scores are GeoTab generated values similar to academic grades. A portion of a sample scorecard is shown in Figure 1 and depicts how they were designed to be streamlined ways of directly getting performance data into the hands of those in charge of good shop performance.



Driver Safety Scorecard — SHOP XXX

Rector & Visitors U V A

Low Risk	95-100
Medium/Mild Risk	75-94
High Risk	0-74

Date Range	
From	2022-XX-XX
To	2022-XX-XX
Days	7
Fleet Distance (mi)	676.580
Fleet Occurances	216

Average Fleet Score: 58.729

SHOP Incident Rates

Hard Acceleration	Harsh Braking	Harsh Cornering	Seatbelt
0.074	0.001	0.025	0.030

DRIVER Incident Rates

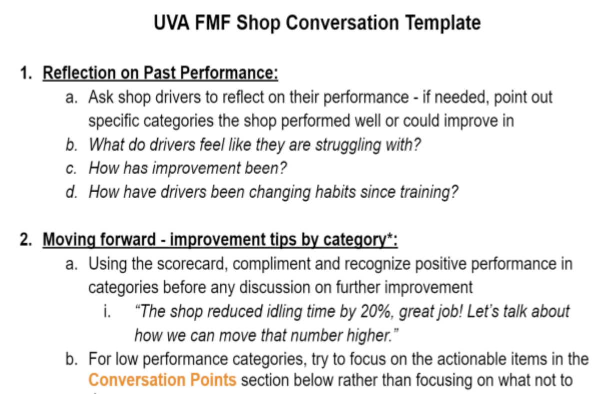
Name	Distance	Hard Acceleration	Harsh Braking	Harsh Cornering	Seatbelt
V0XXX	17.672	0.170	0.000	0.057	0.000
V0XXX	98.136	0.163	0.010	0.092	0.082
V0XXX	105.180	0.000	0.000	0.000	0.010
V0XXX	60.494	0.165	0.000	0.000	0.000
V0XXX	35.756	0.000	0.000	0.000	0.000
V0XXX	307.408	0.000	0.000	0.007	0.000
V0XXX	51.934	0.019	0.000	0.019	0.116

Incident Scores

Name	Distance (mi)	Total Score	Scoring Classific	Hard Acceleration	Harsh Braking	Harsh Cornering	Custom Seat belt >1M
V0XXX	17.672	54.341	High Risk	0.000	100.000	43.414	100.000
V0XXX	98.136	41.139	High Risk	0.000	89.810	8.291	68.001
V0XXX	105.180	65.338	Medium Risk	100.000	100.000	100.000	96.562
V0XXX	60.494	59.138	High Risk	0.000	100.000	100.000	100.000
V0XXX	35.756	70.000	Medium Risk	100.000	100.000	100.000	100.000
V0XXX	307.408	65.313	Medium Risk	100.000	100.000	93.494	100.000
V0XXX	51.934	55.831	High Risk	80.745	100.000	80.745	48.412

Figure 1: Partial Sample Scorecard

The conversation template, the beginning of which is shown in Figure 2 below, was made in order to better equip shop managers with pedagogical techniques for reinforcement training. The template includes the sections Reflection on Past Performance, Moving Forward - Improvement Tips by Category, and Questions and Feedback for general tips on holding an effective conversation and also sections for each of the six driving metrics with specific ways of driving for better performance in that metric. While the scorecards show performance data, the main reasoning behind the scorecard was to help managers how to get that information across.



UVA FMF Shop Conversation Template

1. **Reflection on Past Performance:**
   a. Ask shop drivers to reflect on their performance - if needed, point out specific categories the shop performed well or could improve in
   b. *What do drivers feel like they are struggling with?*
   c. *How has improvement been?*
   d. *How have drivers been changing habits since training?*
2. **Moving forward - improvement tips by category*:**
   a. Using the scorecard, compliment and recognize positive performance in categories before any discussion on further improvement
      i. *"The shop reduced idling time by 20%, great job! Let's talk about how we can move that number higher."*
   b. For low performance categories, try to focus on the actionable items in the Conversation Points section below rather than focusing on what not to

Figure 2: Beginning of Shop Manager Conversation Template

The distinctions between the two training programs are outlined in the sub-sections that follow.

C. Reactive and Proactive Trainings

We first administered reactive training on February 16th, 2022 to one selected shop roughly three months after they received their first FM training. Reactive training was characterized by being less intensive and more variable from week to week. Our team calculated standard deviation values every week for the duration of reactive training testing in order to determine if vehicle shops needed training or not. The standard deviation values were based on vehicle performance variability from the initial training to the week in question. If a shop's performance were to drop below one standard deviation, then it would trigger a necessary ‘reactive’ training. Reactive training consisted of informal, shorter conversations between managers and the drivers within their shop. The manager was given a scorecard to better understand where the specific problem was occurring and a conversation template for how to address it. Reactive training also only had the manager address the underperforming metrics that triggered the training.

Proactive training was given to a different set of two previously trained shops twelve weeks after their initial training. Twelve weeks was chosen as the timeline in order to model a quarterly reinforcement training program for FM as it may be more logistically feasible for management than the constant monitoring required for reactive training. Proactive training was longer and more thorough than reactive training and was meant to be a less frequent but more consistent form of instruction. The same scorecards and template were used in this training; however, now managers would be expected to spend more time with their shops going over all the points laid out in the template covering every metric. Consequently, proactive training requires considerably more time and is presented in a more formal manner. Proactive training would not be based on past week performance and would instead be given on a quarterly basis to shops as a way to maintain their awareness and understanding of proper driving technique.

D. Measuring Effectiveness

Both the reactive and proactive trainings were evaluated at a metric specific level using statistical tests on vehicle performance before and after the respective training was given. A paired Wilcoxon test was used where a p-value less than 0.05 deemed a training significant. Wilcoxon was preferred over other tests, such as a simple t-test, because the data analyzed was all from the same single population before and after an administered treatment. Other tests cannot compare the same population before and after it received a treatment in the way that Wilcoxon is designed. Our group looked at vehicle driving data before training was given and compared it to the same set of vehicles after training was given. Initially, our team looked at weekly comparisons, using one week before and one after; however, due to the lack of data points, we also looked at day to day statistical comparisons for the same weeks. This would mean that the Monday in the week leading up to training would be compared to the Monday in the week following training. This gave us more data points than the initial two, three, and seven points available for three shops given reactive training. The results from these tests are used to evaluate the effectiveness of each training strategy.

IV. DATA ANALYSIS AND RESULTS

A. Reactive Training Analysis

In the study of reactive training, the performance of two shops were analyzed for the need for training for four weeks. As one of the shops had vehicles that did not drive every week and therefore did not have sufficient data, it was removed from the analysis and only the other shop was used. To determine whether reactive training was needed each week, we found the average incident rate for each metric for all of the weeks starting at the first FM training until the current week. Then we also calculated the standard deviation for those weeks and added it to the average. If the current week’s incident rate was higher than the sum of the average and standard deviation of previous weeks, the shop would receive reactive training for that metric. Based on these value determinations, the only reactive training administered was for the first week analyzed, and it was triggered by speeding. The significant results of the weekly and daily paired Wilcoxon test are below for the trained shop as well as the controls.

Daily Data	Trained Shop p-values	Control Shop 1 p-values	Control Shop 2 p-values
Speeding	0.013	0.977	0.572

Using a significance level of 0.05, daily performance improved for speeding in the week after the training. This is further supported by none of the controls showing significant improvement in speeding, so it does not appear there was an external factor affecting the fleet that was the cause.

B. Proactive Training Analysis

Proactive training was given to its chosen two shops once, twelve weeks after they received FM training. None of the metrics proved to significantly improve in performance the week following the training when analyzed on a weekly level or on a daily level. The control shops also not having significant results confirms that there were again no external factors affecting the fleet that may have influenced the analysis.

C. Graphical analysis

We decided to analyze reactive training graphically after finding the statistically significant result for speeding to determine if the improvement can be seen visually. The graph in Figure 3 supports the result that reactive reinforcement training is effective at decreasing the incident count rates. The week of February 9th to February 15th, or the fifth point from the right, was analyzed to determine if reactive reinforcement training should occur. As shown in Figure 3, the blue line, representing speeding, had a large spike, an increase of approximately 20 times the normal incident rate, which triggered a training. There was not an increase in the other five factors that warranted reactive reinforcement training which can also be seen in Figure 3. The week after the shop received reactive reinforcement training for speeding there was a large decrease in incident rates that visually displays the improvement in speeding due to the reinforcement training. This visual analysis confirms the result that reactive reinforcement training is effective for speeding.

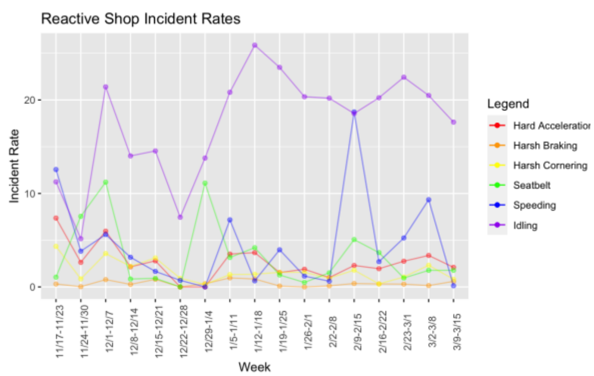


Figure 3: Reactive Training Incident Rates for All Metrics in the Shop

Proactive training shops were also analyzed graphically since using measures of statistical significance alone for data analysis may fail to acknowledge trends seen over longer time periods or trends that are visually noticeable though not necessarily significant. For example, in Figure 4(a), the graph shows incident rates per metric for a shop starting on the date of their FM training and ending two weeks after their proactive training. For several metrics, the incident rates drop after the proactive training was given on the week of March 4th. There is a clear drop in seat belt usage, idling, and speeding. This pattern is present, despite not proving statistically significant.

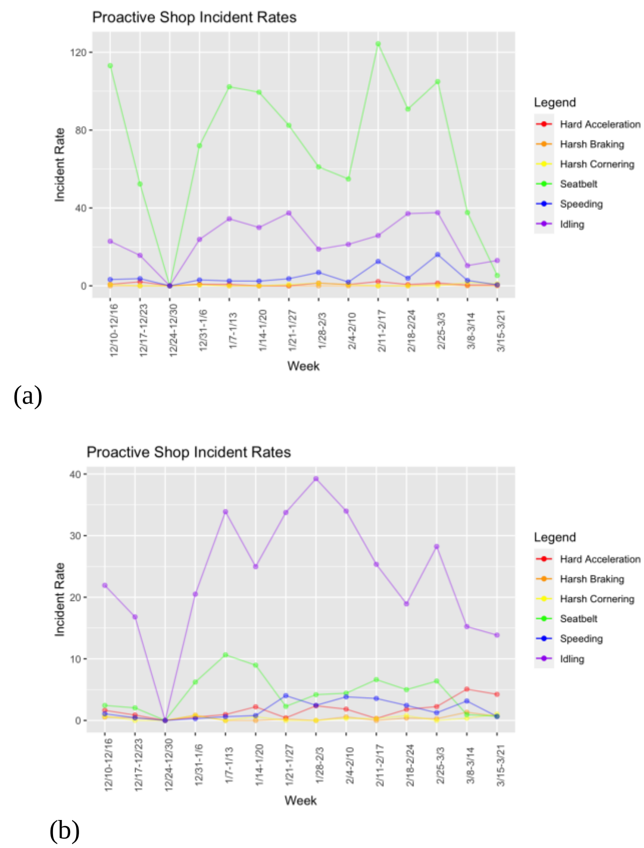


Figure 4: Proactive Training Incident Rates for All Metrics in Two Shops

In figure 4(b) above, showing the incident rates for each metric for another proactively trained shop, there is less of a definitive trend to be seen in the two weeks following the training, though some metrics do appear to drop slightly. Nevertheless, further research could draw information from the trends in metric behavior seen visually over various timeframes.

V. CONCLUSIONS

Our research indicates that the reactive training method showed statistically significant improvement in the speeding metric. This was the only metric that required reactive training, so it is yet to be determined if the same results would occur from the other five metrics. The proactive training was not significant for any metric. These results were obtained over a short time period and thus are more susceptible to outliers and biases, but we believe they represent a foundation on which future results can build upon. UVA FM will be able to reproduce this method across all its divisions and determine the long-term effectiveness of the program on a larger sample size. We believe any noticeable increase in infractions in any of the six metrics should be addressed as soon as possible to have the most effect on performance. However, our literature review also agrees that maintaining a consistent training schedule can have positive effects on performance over time, and proactive training can offer that consistency to FM.

One major limitation we faced was the secondary nature of our training. In order to receive our reinforcement training, the subject shops needed to have already received the previous year's training. As such, we did not have a large data set to choose from and did not have much say in which shops could be studied. This flaw in the experimental design will not hinder future iterations of this project as most if not all FM shops and drivers will receive the initial FM training in the near future.

Another limitation we faced is that our research project was a continuation of a previous project that we wished to further. Due to the limited number of shops and vehicles involved in the study, we had to be cognizant of potential outliers and biases in the data, as they would significantly affect the overall results.

We believe this project can continue to provide value to UVA FM and can be improved upon by adjusting aspects of the current system. One major aspect is to focus the study on individual driver data, as opposed to shop level data. Instances where a vehicle must idle to perform a necessary function or when a vehicle is loaned outside of the FM network can report infractions that are not indicative of the UVA fleet's performance. A more structured and consistent monitoring of vehicles and their behavior along with their performance data would allow for better understanding of the data, as well as control over outliers and a more focused training program. UVA FM initially had concerns regarding privacy when reviewing individual driver performances but appeared to become more open to more individualized study as this project and its results developed. Another goal of this capstone project was to create a scalable method to apply reinforcement training across all divisions of UVA FM as well as other university fleets. To broaden the scope of this study, we recommend researching different incentive methods with a large sample size in order to monitor different variable levels and determine if there is any benefit to supplementing the training programs with incentives.

VI. ACKNOWLEDGEMENTS

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