Machine Learning for Predictive Analytics in Autonomous Vehicle Fleet Management

By Dr. Carlos Hernández

Associate Professor of Information Technology, National Autonomous University of Mexico (UNAM)

1. Introduction to Autonomous Vehicle Fleet Management

1. Introduction The increased interest and pilot deployment of autonomous vehicle technologies, in addition to the industrial and research investments, show the importance and impact of employing asset sharing and high automation technologies in logistics and last-mile operations. The breakthrough in machine learning and power-efficient computation techniques enables the use of sensors and systems that allow the deployment of self-driving cars. These vehicles can leverage multiple sensors to build digital maps, localize themselves, and estimate the traffic elements in their surroundings without missing or falling into autonomous position mismatching problems. Additionally, localization is complemented by sensors with wireless communication capabilities for stationary DGPS or RTK stations, in addition to CAN bus relative positioning techniques. Lastly, terrain and environmental adaptive security access measures can be instantiated through cooperative spectral algorithms. Although the exact mix of technologies is evolving, the use of predictive analytics and machine learning techniques in logistics and transport is presented in this paper.

The main operational advantages linked with the above technologies include, although not limited to, personal mobility as a service, increased traffic safety, reductions in labor costs, fuel costs, and emissions. Specifically, impacts on cost savings, efficiency, individual convenience, and human workload reductions in last-mile operations are also linked to the deployment of smart buses and driverless cars, reducing related costs by over three times. The main challenges include route and schedule planning, and the dispatching and recharging operations, due to vehicle variation and demand. Data play a central role in the systems' operation and support. It enables data-driven real-time adaptive planning, dispatching, and recharging operations that support centralized services and demand-driven last-mile and long-range automated planning, which can continuously evolve over time. The arrival of data-driven operations is promoted through two main approaches: predictive analytics and machine learning. The integration of these two technologies and data sources aims to operationally update the inherent vehicle routing, scheduling, and pricing in real time. This paper presents a predictive analytics and machine learning-based modeling framework for automated last-mile autonomous vehicle fleet management and the extended planning framework. The detailed models and solution methods are presented in the next sections.

1.1. Overview of Autonomous Vehicles in Fleet Operations

1.1.1. Autonomous Vehicles Automated or self-driving vehicle development is currently carried out by a plethora of companies. Agencies categorize automated or self-driving vehicles as those that can take full or partial control of their vehicle. The automation level is grouped in five different modes from level 0 (standard vehicle without automation features) to level 5 (driverless automation, no driver required). At the lowest level of automation, basic driver-assist technologies have been developed and are widely used. These extensions of a human driver are focused mainly on safety-critical functions, e.g., to avoid accidents, and may influence the acceleration and deceleration of a vehicle. The most advanced stages are capable of providing the user with control-free functionalities for the entire journey, though the release is still limited by geographical, technical, and environmental boundaries. As of October 2021, there are presently no commercialized level 5 fully driverless vehicles, and very few level 4 vehicles that are capable of automated driving over large geographic areas. These technologies have largely been implemented, experimentally or otherwise, in level 3, the middle ground between passive systems and fully automated vehicles.

Currently, vehicle producers, tech companies, and startups are less interested in autonomously driving passenger cars and more focused on utilizing highly automated vehicles for goods transport in the contexts of urban last-mile delivery as well as regional and multimodal distribution of goods. With the technological focus turning toward the last stage of Level 4 automation, so too the size of vehicles is increasing. Studies in on-road platoon testing are now common and target the goods transport industry, where a company typically has a single vehicle operator that leads a small column of unmanned vehicles. In land transport, vehicles of all sizes are of interest to this research, including both last-mile delivery vehicles such as vans and heavy goods vehicles. All AVs are propelled and steered for horizontal plane motion with sensor perception systems, containing an array of object detection methods and algorithms. At the most complex, these are typically using artificial neural networks and other artificial intelligence schemes to extract features from the data collected by the vehicle and inform trajectory planning. Perception sensors used by the robotic system to gather information on the surrounding environment include LIDAR technology that utilizes laser beams to produce a 3D landscape map, RADAR, SONAR, ultrasonic, and conventional RGB cameras. Sensors are installed at intersections and overhead gantries to provide information to the cooperative perception and traffic management data processor so that delays in platoons can be anticipated accordingly. For example, sensors are used to construct a 3D road surface map that is annotated with the status of the road.

2. Fundamentals of Predictive Analytics

Predictive analytics uses historical data and statistical algorithms to forecast future outcomes. It has applications in a variety of domains such as finance, e-commerce, and healthcare. Businesses use predictive analytics to forecast sales and incidents like fraud and product defects. In the case of autonomous vehicle fleet management, it can be used by the vehicle operator to predict user ride requests, trip durations, and fuel consumption costs. Managers can make more informed decisions about empty vehicle movements as well as operations and maintenance staffing levels. As with any model-based approach, the more accurate and up-to-date the input data, the more accurate the model predictions will be. Incorrect results can be generated if historical data is incorrect.

Predictive analytics is the practice of extracting information from existing data sets, using it to predict trends and behavior patterns, or lack thereof. Predictive models use regression analysis, decision trees, and other methods to predict outcomes in statistical analysis. Predictive modeling is a procedure used in predictive analytics to build a predictive model. Time series forecasting is a major model built for predicting future values depending upon the gliding data. Data collected from autonomous vehicles for use in predictive analytics must adhere to ethics and respect end-user privacy. Machine learning is essential in this context. Predictive analytics can be used by the fleet manager to predict likely upcoming user ride booking requests, connection requests, and trip durations. As with predictive analytics for predicting ride booking requests and trip durations, the data must be ethical. Researching and discussing these issues plays a major role in a multidisciplinary setting. It is recommended to take a broad perspective on data analytics in terms of autonomous vehicle fleet operations. With technological advancements, analytics tools and data sources are constantly improving. Modern data analytics tools can handle larger datasets and a greater number of attributes.

2.1. Definition and Importance in Fleet Management

What is predictive analytics? When data can provide an understanding of what has happened, and when there is reliable data extrapolation, there can be predictions of what is most likely to happen in the future. This is a form of predictive analytics. In fleet management, predictive analytics are used to provide important information; its application helps in decision-making from a strategic perspective to an operational perspective in order to enhance vehicle and driver performance. Examples of predictive analytics in a fleet optimization context are the prediction of when a vehicle or system is likely to fail, the preferred times of day for maintenance, repair, and refueling, and the amount to refuel with prime use.

In fleet management, performance indicators may include hard metrics such as downtime and fuel burn, as well as softer metrics such as customer service ratings. Dealing with maintenance repair can allow customers to take and fix their vehicles and decide when they want to perform maintenance at minimal cost. This involves routing, fleet optimization, traffic predictions, and fuel consumption in fleet fuel replenishment optimization. The metrics being measured are cost-benefit ratios; in a fleet case, fuel replenishment vehicles also become the goods to be relocated throughout the day. There are many exotic metrics and heuristics, but one of the most common is that fleet optimization revenue is equal to the cost of using vehicles and drivers at the time of delivery. Predictive text characterization based on a system understanding of the past and immediate context can allow effective decision-making in current resource allocation.

As the system adapts, predictive analytics must run continuously, retraining models and learning from new data. Among the earliest successful implementations of predictive modeling for industrial monitoring, gas turbine analytics have returned an increase in profits by saving approximately $1 at 1.5 billion in capital maintenance costs. Fleet management predictive analytics document similar total impacts that data analytics have on cost savings, increasing efficiency, and most importantly, identifying and detecting future trends. In general, the gains may differ, but in the best cases, significant value is clearly visible in the history of predictive analytics.

3. Machine Learning Techniques for Predictive Analytics

Predictive analytics is a branch of advanced analytics that applies various techniques and models of machine learning to datasets in order to predict future trends. Machine learning is a computational artificial intelligence-based system that has a history of learning and shaping patterns from large unknown datasets. These important predictions are useful for businesses, such as in obtaining higher profitability margins on fleets, the risks of accidents, and the analysis of the routes that would give drivers and companies the highest profitability. Machine learning follows two fundamental principles: (1) learning to adjust mobility predictive quantities according to specific travel requests; (2) the means by which the AI model uses these flow forecasts to perform optimization tasks in a way that can be quantified.

The learning processes can be classified into two paradigms: supervised learning, where patterns can be verified based on known findings, and unsupervised learning, where patterns are identified based on unknown findings. Both paradigms can be seen in terms of predictive analytics in data management because they provide models that consider every sample of the dataset to enhance predictive capabilities. Machine learning can examine large datasets to uncover hidden trends and intricate patterns. In this manner, the machine learning applications offer certain advantages to fleet management operators. For practical use, the most widely used models in predictive analytics include linear regression, decision trees, support vector machines, ensembles such as random forests and gradient boosting trees, neural networks, and genetic algorithms. Modeling the techniques that produce the most accurate predictions consistently is the primary goal. It is possible to use machine learning models to provide predictive capabilities in fleet management to make near-real-time decisions for intelligent solutions.

3.1. Supervised Learning Algorithms

Supervised learning algorithms are a class of machine learning techniques. Supervised learning refers to tasks with known outcomes and operational processes that involve training a model with labeled data to predict a given outcome for future data. Labeled data includes the outcome we are trying to predict, as expressed in feature labels or input variables, and feature values. The input is frequently referred to as the independent variable, and the output is frequently called the dependent variable, as it depends on the input. Afterward, we input additional data into the trained model to assess its accuracy and performance. These models can work towards both classification and regression predictive tasks. Classification predicts a discrete or categorical label or class, such as a 'yes' or 'no' outcome or the identification of spam emails. Common algorithms used for classifying problems include logistic regression and K-nearest neighbors. Regression outputs a numerical quantity or continuous numeric range. A common regression task in the shipping industry is demand forecasting, such as the number of orders or items fulfilled at a certain day and time. Linear regression is a popular example of a regression model. Examples of classification and regression problems encompass whether a vehicle needs to be inspected, whether a route is feasible, and how long delivering goods will take. These two learning styles find applicability to predictive analytics in fleet logistical challenges as our solution targets high-precision fleet management. Prior to predictive modeling, feature selection in the telematics data to be used is performed based on their impact using statistical tests. Furthermore, end models are evaluated using performance metrics including accuracy, precision, recall, F1-score, AUC, RMSE, R-squared, and so forth. One of the most well-known regression learning algorithms is linear regression. Linear regression models the relationship between dependent and independent input variables used for prediction tasks. Another regression strategy is support vector machines that use a process called the kernel trick to figure out the optimal hyperplane in higher-dimensional space. They employ a method of supervised learning classification algorithms for two-group classification problems. In terms of classification, the Random Forest learning system uses bagging algorithms, which build multiple models and merge the feature rankings. Weaknesses in the top-ranked features get optimized by the subsequent feature selection algorithm. Algorithms routinely used for classification in fleet management problems are decision trees and gradient boosting. The former have been used to assess the number of orders over time through the orientation of customer spending. In a study that used gradient boosting to assess the time of order occurrence, increases in achievable pick-ups were noted with the timely insertion of an additional vehicle. Furthermore, prediction models with gradient boosting algorithms predict customer behavior and identify the location of future demand surges for same-day shopping deliveries.

4. Applications of Predictive Analytics in Autonomous Vehicle Fleet Management

Predictive analytics in fleet management is an effective solution to make the best of the rich historical data through proactive analysis for planning or operations. Taking help from historical data on similar patterns for better decision-making in the future can result in savings and allow managers to make informed decisions in managing their fleets. Some use cases could be vehicle maintenance forecasting, route optimization, demand prediction, and battery state of charge forecasting. The early maintenance indicator may be helpful in planning the maintenance of components in advance, reducing a vehicle's downtime to a huge extent and increasing operational revenue. In alignment with predictive maintenance, route optimization is another effective preventive measure that can save energy and cut operating costs. The mixed use of predictive models could save costs on fleet operations, as shown by the high order of experienced staff failing with some guesswork by operating buses with empty seats and others running late when long queues are gathering.

The use of predictive analytics for this has been shown in similar case studies or real-world cases where increasing the frequency of those less-in-demand routes and buses ensures no high-density traffic piles up that could cause a potential accident. This increases fleet safety management and could also have a positive image transfer commercially for the company's standing. Allocated resources of skilled bus drivers and their buses can also be of reduced shortage in infrequent services like those of late and early hours at destinations and origins. One of the major objectives in anticipation of after Covid-19 is to limit passenger congestion, and more fleet will be needed. Trips could also have seen a complete overhaul with a lot of new routes and route frequencies re-planned, new population hotspots, or industrial revolutions of interest. Sentinel usage could easily see demand as much as passenger numbers newly predicted with predictive analytics. Having a seamless network of operational fleet backing up your ticket system and the support of optimization models ensures award-winning customer satisfaction for a new normal.

4.1. Maintenance Optimization

Maintenance optimization is among the use cases where predictive analytics has been implemented across various fleets. An internal report gives an account of the main systems that private operators have been experimenting with during the last years. In urban public transport, maintenance accounts for around 30% of a fleet's operational costs. Early detection of off-nominal behavior and rapid intervention lead to improved service delivery, lower operational costs, extended vehicle lifespan, and increased return on assets. Previous research has investigated predictive analytics as a maintenance-oriented technique but is largely limited to the analysis of data from bus telemetry only. The maintenance of a public transit bus fleet could yield substantial benefits in the form of decreased costs and improved vehicle availability. An operator performing maintenance on a properly operating vehicle can have higher efficiency. Unfortunately, data-related costs have still restricted the application. Some interest is emerging in high-dimensional data analytics, but most of the involved research projects aim at systems health assessment and diagnostic insights that help low-level maintenance tasks.

In road haulage, however, maintenance is the third biggest logistics cost, generating up to one third of downtime in operation and needing up to 70% of the available budget. Connecting predictive maintenance at the product level with predictive analytics at the operational level could potentially allow the operator to implement a more risk-oriented and proactive approach to fleet management. Through a case study of waste collection vehicles, research has identified the interplay between interventions at both the product and operational levels as a critical factor in asset management. Investment costs versus long-term cost savings and fleet availability, together with life cycle management from design to operational level, are recurring arguments. Legislation and environmental concerns have influenced the trucking industry significantly over recent years, steering towards more focus on the management of customer-level service from the headquarters rather than on the operational management of the fleet. Through a case study, it has been shown that there is a 20–30% cost savings potential, alongside lifetime prediction for built assets and performance prediction in the affected subsystems.

5. Challenges and Future Directions in Implementing Predictive Analytics in Autonomous Vehicle Fleet Management

Adding predictive analytics within the AV fleet management workflow involves addressing several system-level challenges. First, there may be quality issues with available data. Additionally, the predictive element of the analysis must be integrated with the data infrastructure used for historical analytics that has been leveraged heretofore. Making these two computational worlds coexist within a parallel pipeline can be a considerable technical headache, one in which much of the software industry is still stuck. Furthermore, many are still working on the creation of robust data infrastructures that can be relied upon for making decisions.

Besides the technical challenges, there are also organizational issues that need to be considered. In order to yield actionable insights, predictive analytics require a number of expertise, ranging from statisticians to database architects to domain experts. Also, an organization that leverages predictive analytics allows data—not only intuition—to guide its decision-making process. This way of working might involve considerable resistance and organizational change. Many organizations still have a long way to foster organizational elements and a corporate culture that could be data-driven. Finally, the mainstream use of predictive analytics in the LMAV field is poised to be initially checked by the increasing difficulty of obtaining and using data due to regulatory compliance and ethical issues associated with data use and collection. This might be an impediment for wider LMAV implementation over the next decade, unless there are clear regulatory frameworks that can offer some leeway for firms when it comes to data usage. To address these barriers and accelerate AI maturity, a key strategy must involve collaboration among multiple stakeholders, including technology providers, AV fleet operators, regulators, road authorities, and the public. By doing so, predictive analytics tools can be designed to be extensively tested and, if possible, integrated in occasions where the vehicles become operational.

Predictive models are developed to make appropriate decisions that yield the most favored outcome. However, in operation, the effectiveness of a model may degrade as the operational context changes. One must continuously recalibrate and adapt the model to ensure reliability. Future directions for predictive analytics advancements are exciting, driven by challenges of managing large-scale intelligent networks, such as the advancing use of the Internet of Things in monitoring tens of billions of connected devices. In addition to these challenges, while classic statistical models and algorithms have thus far enabled us to begin these first steps for autonomous vehicles, AI and machine learning are anticipated as future tools in predictive analytics to tackle these challenges. The most critical stage of this predictive model is the transition where we start to build the models based on some initial available data. Many have called this near-AI and AI.

6. Conclusion

Conclusion: Key takeaways

Predictive analytics has been proven to have substantial benefits for both improving the decision-making process in fleet operations management and for horizontally and vertically optimizing the overall operations. Machine learning needed to advance.

The implementation of predictive analytics has come a long way in a short period, but it is a constantly evolving practice. It is important for different organizations – fleet managers, EAMs or third-party suppliers who are servicing various industries – to keep pace and be flexible and open to improvements and updates. It can be quite challenging to implement change, but the process is necessary – technology and data-driven decision-making is the future, and people are and need to be the driving force behind it.

Conclusions

Today's fast-paced, high-tech world provides us with an enormous amount of data at every turn. Entire industries have been created because of our impregnable relationship and reliance on data and technology. As we live and work in this hyper-connected age, embracing a wider range of data and algorithms in an effort to extend our understanding of operations seems logical and beneficial. Using state-of-the-art machine learning techniques to make predictions about how AMs will behave could help fleet operations to make critical operational decisions, such as deciding when to best conduct vehicle maintenance in order to minimize the risk of unwanted AM downtime.

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