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STATE OF GOOD REPAIR PREDICTIVE MODEL FOR SMALL URBAN AND RURAL TRANSIT SYSTEM'S ROLLING STOCK ASSETS

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Research Data

The data that support the findings of this research are available in the National Transit Database (NTD) Data at https://www.transit.dot.gov/ntd/ntd-data and APTA's Public Transportation Vehicle Database at https://www.apta.com/research-technical-resources/transit-statistics/vehicle-database/.

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ABSTRACT

Achieving and maintaining public transportation rolling stocks in a state of good repair is very crucial to providing safe and reliable services to riders. Transit agencies that seek federal grants must also keep their transit assets in a state of good repair. Therefore, transit agencies in small urban and rural transit systems need an intelligent predictive model for analyzing their transportation rolling stocks, determining the current conditions, predicting when they need to be replaced or rehabilitated, and determining the funding needed to replace in a future year to maintain the state of good repair. Since many transit agencies in small urban and rural transit systems do not have adequate analytical tools for predicting the service life of vehicles, this simple predictive model would be a valuable resource for their state of good repair needs and their prioritization of capital needs for replacement and rehabilitation.

The ability to accurately predict the service life of revenue vehicles is crucial in achieving the state of good repair. In this research, three unique tree-based ensemble learning methods have been applied to build three predictive models. The machine learning methods used in this research are random forest regression, gradient boosting regression, and decision tree regression. After evaluation and comparison of the performance results among all models, the gradient boosting regression model with the top 35 most important features was found to be the best fit for predicting the service life of transit vehicles. This model can be used to predict the projected retirement year for all small urban and rural vehicles in operation.

EXECUTIVE SUMMARY

This research focuses on ways to improve and maintain America's small urban and rural revenue vehicles in a good physical condition so that smaller transit systems can successfully keep their transit vehicles in a state of good repair. This research includes a method to build a machine learning predictive model (MLPM) to predict the projected replacement year of transit vehicles. Further, it develops an analytical tool to calculate backlog and yearly projected vehicle replacement costs for rural and small urban transit agencies. Finally, the detailed reports produced by these tools will be helpful for decision-makers to prioritize investment needs for rehabilitation and replacement of rural and small urban transit agencies.

The literature review conducted in this research found that the Federal Transit Administration (FTA) tried to find an intelligent way to resolve issues with the state of good repair that transit agencies were facing. Per Map-21 requirements, transit agencies require a predictive model for prioritizing capital investment for replacement and rehabilitation of transit vehicles. The FTA's study on the useful life of transit buses and vans showed that its minimum service life policy might need to be changed. NCHRP report 545 indicated that two analytical tools could be used along with existing systems to make the investment decision regarding transit vehicles. TCRP report 157 provided a framework for the state of good repair and developed tools for evaluating and prioritizing funding. TCRP project E-09 improved the state of good repair framework, which was developed in TCRP report 157. As a continuation of TCRP report 157, TCRP report 172 developed a transit asset management plan in accordance with Map-21 requirements and further improved the prioritization tools for transit agencies.

The literature reviews also discussed transit asset management systems. The development of asset management can help transit agencies optimize limited funding, estimate a state of good repair backlog, and set spending priorities. The FTA established a minimum useful life policy for transit vehicles funded with federal grants. However, the useful life benchmark by the transit providers may or may not be the same as the useful life threshold used for vehicle replacement by the FTA grant program. As per Map-21 and the FAST Act, transit agencies are required to develop a transit asset management plan to achieve the state of good repair. Therefore, the FTA developed a Transit Asset Prioritization Tool (TAPT) as well as a Transit Economic Requirements Model (TERM) analysis tool, to predict the condition of transit assets and prioritize the investment needs.

The methodology involved introducing machine learning techniques to develop a predictive model for the state of good repair to predict the service life of transit vehicles. The methodology discussed the basic concept of machine learning, the type of machine learning, and ensemble methods. The regression analysis of the supervised learning concept was utilized for the problem. The ensemble methods, which are very powerful techniques for a machine learning model, were discussed. There are three different machine learning techniques, which were introduced in the methodology: random forest regression, gradient boosting regression, and decision tree regression.

The revenue vehicle inventory data from the National Transit Database (NTD) were used to build the predictive model. The preprocessing steps of the data were discussed to format the raw data for machine learning algorithms. Data with retired vehicles were used to train and evaluate the model, and data with non-retired vehicles were used to deploy the trained model for predictions.

Three different machine learning algorithms, random forest regression, gradient boosting regression, and decision tree regression, were applied to build three different predictive models. Before building the model, the parameters for each algorithm were tuned to optimize the performance of the model. During modeling, the training data were split into the training set and the test set in these proportions: 70% of data to train the model and 30% of data to evaluate the model. As part of the evaluation, three performance metrics such as root mean squared error, mean absolute error, and R^2 score were applied to see how accurately the models were performing. After comparing the performance results, the gradient boosting regression predictive model was selected because it provided better performance results for the problem.

Sometimes a large number of features may cause problems in a generalizing a model. Therefore, the feature importance ranking method was further applied to the gradient boosting regression model to get the top 35 most important features. After applying the top 35 most important features and comparing the performance of the previous gradient boosting regression model, we found an even better performing predictive model. Finally, we applied the full dataset as a training set to train the model that further improved the performance of the predictive model. We concluded the gradient boosting regression model using the full training dataset with the top 35 most important features would be our final predictive model.

After developing the predictive model using the gradient boosting regression algorithm with the top 35 most important features, the model was applied on the deployment set for predictions. The authors deployed the predictive model on the nation's small urban and rural transit agencies' 2017 revenue vehicle data and calculated the service life of each vehicle. After the predicted service life of vehicles was acquired, the authors calculated the projected retirement year. The authors also calculated the replacement backlog from the projected retirement years, which were prior to 2019, and projected vehicle replacement cost for each year thereafter. The predicted replacement years for all revenue vehicles in small urban and rural transit agencies were calculated using the MLPM. For simplicity, automobile, ferryboat, and sport utility vehicles (SUVs) have not been included for analysis. The MLPM built in this research was applied on the North Dakota's small urban and rural transit systems revenue vehicle inventory data as a case study. The financial cost analysis tool was applied on North Dakota's transit vehicle dataset to estimate the backlog and yearly replacement costs.

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1. INTRODUCTION

Public transportation plays a vital role in providing mobility and accessibility while providing transportation alternatives and enhancement of a quality life. To maintain an efficient public transportation system, there is a need to keep the existing transit assets in proper condition. The problems of maintaining the condition of the small urban and rural transit systems in a state of good repair have become very crucial, and their transit agencies have made achieving a state of good repair a high priority. A major limitation of reaching rehabilitation and replacement needs for transit assets is under-investment, or not having a good analytical tool for investment decisions. There is growing concern that a large number of small urban and rural transit system rolling stocks are past their useful life and in need of immediate repair or replacement. Therefore, they need capital reinvestment to maintain revenue vehicles in a state of good repair. This is crucial for allowing public transportation systems to continue providing safe and reliable services (Cevallos 2016).

1.1 Background

The Moving Ahead for Progress in the 21st Century (MAP-21) bill passed by the federal government in 2012 indicates that the state of the nation's aging transit systems, particularly small urban and rural transit systems, is becoming of greater importance (iDOT 2017). The FTA implemented the MAP-21 legislation, which will mandate public transit systems to create the Transit Asset Management (TAM) system in order to get capital funding. If transit assets, most notably rolling stocks, are not in a state of good repair, the transit systems will be unsafe and unreliable and cause more maintenance cost but lower performance. Thus, the objective of the TAM system is to make sure public transit systems maintain their public transit vehicles in a state of good repair so their capital assets can perform effectively. In July 2016, FTA released the TAM Final Rule to ensure public transit agencies track the conditions of their transit assets from start to end of their life cycle. The public transit agencies with a TAM system will be able to forecast their capital needs while maintaining system reliability. The TAM Final Rule also mandates transit agencies to report a condition assessment, performance measures, and performance targets for all transit assets to the NTD (iDOT 2017).

1.2 Objective

The objective of rehabilitation and replacement is to achieve and maintain transit assets in a state of good repair (James 2010). It is important to define state of good repair in terms of transit agencies and how the definition relates to their goals and objectives. The process of defining "state of good repair" for the transit agency will allow it to set goals, progress to achieve goals over time, and provide guidelines for capital investment prioritization. As per MAP-21 requirements, the FTA creates a definition for state of good repair, and it establishes performance measures for transit agencies to use in accordance with the Transit Asset Management Plan (TAMP). Even though a transit agency uses the FTA's definition and relates the definition for its goals and objectives, it may extend and clarify the definition of state of good repair.

The FTA presented three possible approaches to define state of good repair at the 2010 State of Good Repair Roundtable. These definitions include the following (James 2010):

Option 1

A transit system is in a state of good repair when:

- The transit agency keeps a comprehensive list of capital assets and rolling stock and maintains them
- The transit agency has an asset management plan integrating with the management processes and practices of the transit agency
- The transit agency's assets are within their useful life and are performing at their designed function

Option 2

A transit system is in a state of good repair when:

- System components are well maintained regularly and replaced based on the owner's approved O&M procedures
- The system performs its design function well

Option 3

A transit system is in a state of good repair when:

- Transit assets are perfectly maintained and replaced before their condition deteriorates to an unacceptable level of a safety risk
- Transit assets meet customer expectations for comfort and reliability

The primary objective of this research is to improve and maintain America's small urban and rural revenue vehicles in a good physical condition so that smaller transit systems can successfully keep their transit vehicles in a state of good repair. Therefore, the main objective of this scope of work is to build a machine learning predictive model (MLPM) to predict the projected replacement year of transit vehicles for rural and small urban transit agencies for the purpose of obtaining a state of good repair by prioritizing rehabilitation and replacement decisions. The second objective is to build a financial analysis tool to estimate current backlog and predict yearly projected vehicle replacement costs.

The machine learning predictive tool and financial analytical tool in this scope will help transit agencies facilitate their state of good repair analysis and guide decision makers with investing rehabilitation and replacement needs. The detailed reports produced by these tools will help decision makers prioritize investment needs for rehabilitation and replacement of transit vehicles. This also includes elimination of investment backlog, replacement of transit assets reaching the end of their useful life, overall condition of their remaining service life, and projected yearly replacement costs. This tool will potentially tailor the replacement decision to a given system rather than rely solely on the FTA's useful life policies or industry-wide experiences. Better pinpointing of the boundary between "rehab and replace" will potentially allow better-informed capital decisions and perhaps better modulate capital-funding needs with available funding. Finally, this research will also offer more intuitive, softer criteria that managers and other stakeholders can use in formulating capital plans.

1.3 Organization

This report is organized as follows. It begins with the abstract that highlights the overall summary of the research and an executive summary of the key findings in each individual chapter. The main body of the report is organized into seven chapters. In Chapter 1, the introduction provides background information on state of good repair. In Chapter 2, previous studies and early research on the state of good repair and asset management practices are presented. This chapter also includes an overview of the transit asset management system and analytical tools used for the state of good repair. Chapter 3 presents the current condition of the revenue vehicles in small urban and rural transportation systems in the United States. In Chapter 4, the methodology developed for service life prediction is presented and three machine learning algorithms are introduced. Chapter 5 presents the preprocessing of data, developing training and testing sets, building the predictive model, and making predictions on the deployment set. In Chapter 6, results are analyzed on revenue vehicles in all small urban and rural transit systems. This chapter also includes a case study on North Dakota's small urban and rural transit systems' revenue vehicle data. Finally, Chapter 7 concludes the study and sets goals for further research.

2. LITERATURE REVIEW

The initial task of this research started with a review of the literature on state of good repair and an evaluation of transit capital asset rehabilitation and replacement previously published. It included, but was not limited to, FTA reports, TRB papers, related papers from other journals and conferences, and available reports from transit agencies, consultants, and vendors. The review focused on how the FTA maintains its current minimum service life policy and how it updates its policy as vehicle designs, new technologies, and new vehicle types are added to the transit fleet. It will help to understand how transit assets are inventoried, how conditions are assessed and tracked, and how transit asset management systems are used to prioritize funding for rehabilitation and replacement needs to ensure safe, reliable, and comfortable transit for riders.

2.1 Early Research on the State of Good Repair

"NCHRP Report 545: Analytical Tools for Asset Management, Reviewed Asset Management Tools and Systems," published in 2005, provided two software tools: AssetManager NT and AssetManager PT (Cambridge Systematics, 2005). These tools were intended for state departments of transportation (DOTs) and transit agencies to support tradeoff analysis for transportation asset management. The tools were developed to integrate into existing systems to help agencies analyze and predict investment decisions for their transit assets (Cambridge Systematics, 2005).

The "Useful Life of Transit Buses and Vans" research, published in 2007 by the FTA, assessed the policy on existing minimum service life for transit buses and vans (Laver, Schneck, et al., Useful life of transit buses and vans 2007). The study team interviewed transit agencies and performed engineering and economic analyses to evaluate the minimum service life policy. The engineering analysis showed that the bus life span was restricted by the bus structure, while the economic analysis showed that the optimal replacement points for various bus types were at or later than the FTA's minimum service life. The study provided details on the useful life of buses and vans, the FTA's minimum service life policy, the impact of the vehicle life expectancies, an agency's decision on retirement, vehicle maintenance, and replacement best practices. The study also showed that the actual ages when agencies were retiring buses from service exceeded the FTA's minimum service life and suggested that the minimum service life policy should be changed (Laver, et al. 2007).

In 2008, the FTA published "Transit State of Good Repair: Beginning the Dialogue." The first step was to collaborate on transit asset management practices and provide strategies to address the state of good repair needs and transit asset management for the nation's transit rail and bus rolling stock (FTA, 2008). To do this, the FTA held a workshop in the summer of 2008. Diverse stakeholders from 14 public transit providers and state DOTs addressed the state of good repair for the nation's transit inventory. The objective of the workshop was to encourage stakeholders to be proactive by raising awareness regarding the scope of the problem and exploring creative approaches to fund replacement and rehabilitation of aging transit assets. In the workshop, the FTA discussed the condition of transit capital assets, asset management practices, preventative maintenance practices, maintenance issues, and innovative financing strategies. The FTA also discussed related research work and supporting tools for transit agencies for coping with state of good repair problems (FTA, 2008).

In 2010, the FTA's "National State of Good Repair Assessment" study evaluated the level of investment required to bring all agencies in the United States to a state of good repair (FTA, 2010a). This study showed that in 2009 an estimated state of good repair backlog of $77.7 billion would be needed to achieve the state of good repair, and that an additional $14.4 billion per year would be needed to maintain the normal replacement investment for a state of good repair. The study assessed national reinvestment needs considering the condition of the existing transit assets. The study found that about one-third of the nation's overall transit assets were either in marginal or poor condition, which meant these assets were nearly or already exceeding their expected useful lives (FTA, 2010a).

The "Transit Cooperative Research Program (TCRP) Report 157: State of Good Repair - Prioritizing the Rehabilitation and Replacement of Existing Capital Assets and Evaluating the Implications for Transit" report published in 2012 provided a state of good repair framework to evaluate and prioritize the rehabilitation and replacement investment decisions for transit assets (Cohen & Barr, 2012). This state of good repair framework helps decision makers answer questions regarding transit asset replacement and rehabilitation investment decisions. The report supported the framework by presenting an analytical approach along with a set of spreadsheet tools. The tools are intended for evaluating rehabilitation and replacement investments in specific transit assets and for prioritizing them. In conclusion, transit agencies will find these models a valuable resource to plan or finance public transportation (Cohen & Barr, 2012).

The "Moving Ahead for Progress in the 21st Century (MAP-21)" law was passed July 6, 2012, and authorized $10.6 billion in fiscal year 2013 and $10.7 billion in fiscal year 2014 for federally funded transit agencies and highway programs (US Congress, 2012). Under the MAP-21 law, most of the funding was distributed through the core formula programs. MAP-21 created a state of good repair program and authorized $2.1 billion in fiscal year 2013 and $2.2 billion in fiscal year 2014 for this program. Furthermore, the program also established new asset management systems and performance measurements for transit agencies (US Congress, 2012).

In 2014, the "TCRP Report 172: Guidance for Developing a Transit Asset Management Plan" presented a method for establishing a transit asset management plan for transit agencies to achieve transit state of good repair per MAP-21 (Robert, et al. 2014). This report is associated with a Transit Asset Prioritization Tool (TAPT), which has four spreadsheet tools designed to help transit agencies forecast future condition of transit assets and prioritize them for rehabilitation and replacement. The TCRP 172 report is the second phase of developing tools for transit agencies to improve their asset management plan and achieve a state of good repair condition. However, asset management is concerned with quality data to support decisions on maintaining replacement needs and minimizing asset life cycle costs. Transit agencies can make decisions on prioritizing and investing by implementing the best practices in transit asset management and can reduce the cost of maintaining its systems over time per MAP-21 requirements (Robert, et al. 2014).

The above research reports, research studies, round tables, workshops, and the MAP-21 provision culminated in the 2015 “Fixing America’s Surface Transportation (FAST) Act.” This law reauthorized the public transportation and federal highway programs for fiscal years 2016 to 2020 (APTA, 2016). The state of good repair saw a 23.9% increase by FY 2020, beginning at $2.507 billion in FY 2016, rising to $2.684 billion by FY 2020. However, the FAST Act did not make significant changes in the state of good repair program to maintain the state of good repair on public transportation systems (APTA, 2016).

2.2 Overview of Transit Asset Management

According to Section 1103 of MAP-21, asset management is defined as a set of “actions that will achieve and sustain a desired state of good repair over the life cycle of the assets at minimum practicable cost” (Cevallos, 2016, p. 3). The FTA defines transit asset management as “a strategic and systematic process through which an organization procures, operates, maintains, rehabilitates, and replaces transit assets to manage their performance, risks, costs over their life cycle to provide cost-effective, reliable and safe service to current and future customers” (Lauren & Rose, 2012, p. 10). The FTA definition shows that asset management not only manages cost, it also handles risk and the performance across the life cycle of transit assets (Lauren & Rose, 2012).

MAP-21 requires transit agencies to establish a transit asset management system. The development of an asset management system helps transit agencies request needed funds for investments and attain a state of good repair (Cevallos, 2016). In addition, asset management systems can help transit agencies monitor their current assets’ conditions and redistribute their existing resources to more effective uses (Meyer & Cambridge Systematics, Inc., 2007). Again, asset management can help agencies prioritize capital investment, allocate limited resources to maintain current transit assets, and plan for replacement and rehabilitation of existing assets. In addition, asset management can help transit agencies optimize limited funding, estimate a state of good repair backlog, and set spending priorities (US GAO, 2013).

2.3 Service Life of Transit Asset

The FTA established a minimum useful life policy for transit vehicles funded with federal grants (Laver, et al. 2007). The policy is to ensure that federally funded vehicles have a significant service life serving transit riders. Useful life of rolling stock begins when a transit vehicle is placed in revenue service and continues until it is removed from revenue service (iDOT 2017). The FTA set guidelines for a rolling stock useful life threshold based on the vehicle type purchased by FTA funds (iDOT 2017). The FTA has assigned a threshold for years of service or total mileage accumulated during service for each type of vehicle, whichever comes first. The FTA’s default useful life benchmark is listed in Table 2.1.

Table 2.1 FTA Grant Rolling Stock Useful Life Guidelines

Transit Vehicle	Years of Service	Miles of Service
Buses - Large, heavy-duty transit buses	12	500,000
Buses - Small size, heavy-duty transit buses	10	350,000
Buses - Medium-size, medium-duty transit buses	7	200,000
Buses - Medium-size, light-duty transit buses	5	150,000
Buses - Other light-duty vehicles such as regular and specialized vans, sedans, and light-duty buses	4	100,000
Trolleys - A fixed guideway steel-wheeled "trolley"	25	
A fixed guideway electric trolley-bus with rubber tires obtaining power from overhead catenary	15	
Rail vehicles	25	
Ferries - Passenger ferries	25	
Ferries - Other ferries (without refurbishment)	30	
Ferries - Other ferries (with refurbishment)	60	
Aerial tramway	12	
Articulated bus	14	
Automated guideway vehicles	31	
Automobile	8	
Cable car	112	
Commuter rail locomotive	39	
Commuter rail passenger coach	39	
Commuter rail, Self-propelled passenger car	39	
Cutaway bus	10	

Table 2.1 FTA Grant Rolling Stock Useful Life Guidelines (Continued)

Transit Vehicle	Years of Service	Miles of Service
Double decker bus	14	
Heavy rail passenger car	31	
Inclined plane vehicle	56	
Light rail vehicle	31	
Minibus	10	
Minivan	8	
Monorail vehicle	31	
Over-the-road bus	14	
Rubber tired vintage trolley	14	
School bus	14	
Streetcar	31	
Sport utility vehicle	8	
Trolleybus	14	
Van	8	
Vintage trolley	58	

Source: Table adapted from FTA Circular 5010.1D: *Grant Management Requirements*, 2008, and 2017 Asset Inventory Module Reporting Manual, 2017

However, the FTA encouraged state DOTs and transit providers to determine their own useful life threshold based on some guidelines stated in the Grant Management Requirements circular (iDOT 2017). The acceptable methods to determine useful life threshold include (FTA 2008):

- Generally accepted accounting principles
- Independent evaluation
- Manufacturer's estimated useful life
- Internal Revenue Service guidelines
- Industry standards
- Grantee experience
- The grantee's independent auditor, who needs to concur that the useful life is reasonable for depreciation purposes
- Proven useful life developed at a federal test facility

With the TAM plan, the NTD requires transit providers to report an established useful life benchmark (ULB) for its entire vehicle fleet by vehicle type (FTA 2017). The transit provider may use either its own useful life benchmark for each vehicle type or the FTA's default useful life benchmark for each vehicle type in terms of age. However, the useful life benchmark by the transit providers may or may not be the same as the useful life threshold used for vehicle replacement by the FTA grant program. The useful life thresholds addressed in the FTA Grant Management circular only apply to vehicles funded by the FTA, while the useful life benchmark in the TAM rulemaking applies to all vehicles reported in the NTD inventory as per the TAM reporting plan. The transit provider can enter fleet information into the NTD online portal and the portal will automatically estimate the remaining useful life for each vehicle fleet and measure performance for each vehicle type (FTA 2017).

2.4 Analytical Tools for State of Good Repair

As noted, Map-21 authorized and the FAST Act reauthorized the FTA to develop a rule for the state of good repair program. This rule establishes a system to monitor performance, manage transit assets, increase safety and reliability, and estimate performance measures (WSDOT, 2016). Therefore, transit agencies need to develop a TAMP process per MAP-21 and FAST Act requirements to achieve a state of good repair. The FTA also developed a TAPT tool for transit agencies to support the TAMP process. This TAPT tool includes four spreadsheet models, which help transit agencies predict the future conditions of their transit assets and help prioritize rehabilitation and replacement needs. The FTA's TERM Lite can be used along with TAPT or without TAPT to support analysis of different investment scenarios. Furthermore, many agencies have developed their decision support tools and asset management systems, which can be used to support TAMP processes (Robert, William; Reeder, Virginia; Lauren, Katherine, 2014).

The FTA developed the TERM Lite tool in 1995 to estimate transit capital needs, and it spent about $5 million in development and updates until 2013. The TERM model measures asset conditions on a 5-point scale and considers a revenue vehicle to be in a state of good repair if the condition of the vehicle reaches or exceeds a condition rating of 2.5 (FTA, 2013; Zarembski, 2013). It estimates the state of good repair backlog, determines the capital funding levels required to achieve the state of good repair, analyzes the impact of projected future investment on capital performance, and prioritizes long-term investment (Cevallos, 2016). By using TERM, transit agencies can forecast the trend of asset maintenance, replacement, and rehabilitation costs for a 20-year period; the FTA can use it to estimate capital needs and develop various reports. The TERM model uses information obtained from the NTD. The asset age and physical condition for each asset category are considered the predictors for determining the condition (Cevallos, 2016).

Along with the TERM tool, the FTA also developed four analytical tools for transit agencies to support the TAMP process. These are (1) prioritization modeling tool, (2) vehicle modeling tool, (3) age-based modeling tool, and (4) condition-based modeling tool. The prioritization modeling tool prioritizes a series of asset rehabilitation or replacement funds and simulates the funds for 10 years. The vehicle modeling tool estimates the cost minimizing point that a bus or rail vehicle should be replaced and predicts the annual costs and prioritizes replacement of transit vehicles based on age. The age-based modeling tool assesses deteriorations on a transit asset other than a transit vehicle over time, and it forecasts the annual costs of the transit agency as well as user costs of the transit asset. The condition-based modeling tool uses non-vehicle assets that deteriorate as a function of condition of assets (Cohen & Barr, 2012).

Most transit agencies use TERM Lite as their leading practice for a state of good repair. They also use TERM Lite to collect data and develop information inventories to manage transit assets and prioritize capital investment. However, some transit agencies are using in-house assessment tools to estimate state of good repair needs, make capital investment decisions on the state of good repair backlogs, and prioritize rehabilitation and replacement needs (US GAO, 2013).

3. CONDITION OF SMALL URBAN AND RURAL TRANSIT SYSTEMS

Rolling stock is a type of passenger vehicle used for public transit service (iDOT 2017). Age and/or mileage are primary indicators of state of good repair for rolling stock assets. A manufacturer or transit provider usually establishes the expected useful life threshold for rolling stock based on the vehicle type. When the rolling stock reaches its expected useful life threshold, the asset becomes “beyond its useful life.” When rolling stocks are no longer in a state of good repair, transit providers may utilize them for revenue service, as funding is limited to replace with new vehicles. However, the maintenance costs for vehicles beyond the useful life threshold tend to increase due to the increased likelihood of mechanical failures even though transit providers want to maintain their rolling stock in a state of good repair (iDOT 2017).

3.1 Condition of the United States Small Urban and Rural Transportation System

Most transit systems in the United States report to the NTD. In 2017, 950 systems served 716 urbanized areas, which have populations greater than 50,000. In rural areas, 1,472 systems were operating. Thus, the total number of transit systems reporting to NTD in 2017 was 2,422. Of the transit agencies that submitted data to the NTD in 2017, small urban and rural systems provided both traditional fixed-route bus and demand-response services. These agencies operated 785 bus systems, with 1,398 demand-response services, 61 demand taxi services, 29 transit vanpool systems, nine ferryboat systems, and one aerial tramway. These agencies reported 129 million (128,725,878) unlinked passenger trips and 497 million (496,838,698) vehicle revenue miles. They reported 33,824 vehicles in 2017. Figure 3.1 shows the number of rural transit vehicles in service in 2017.

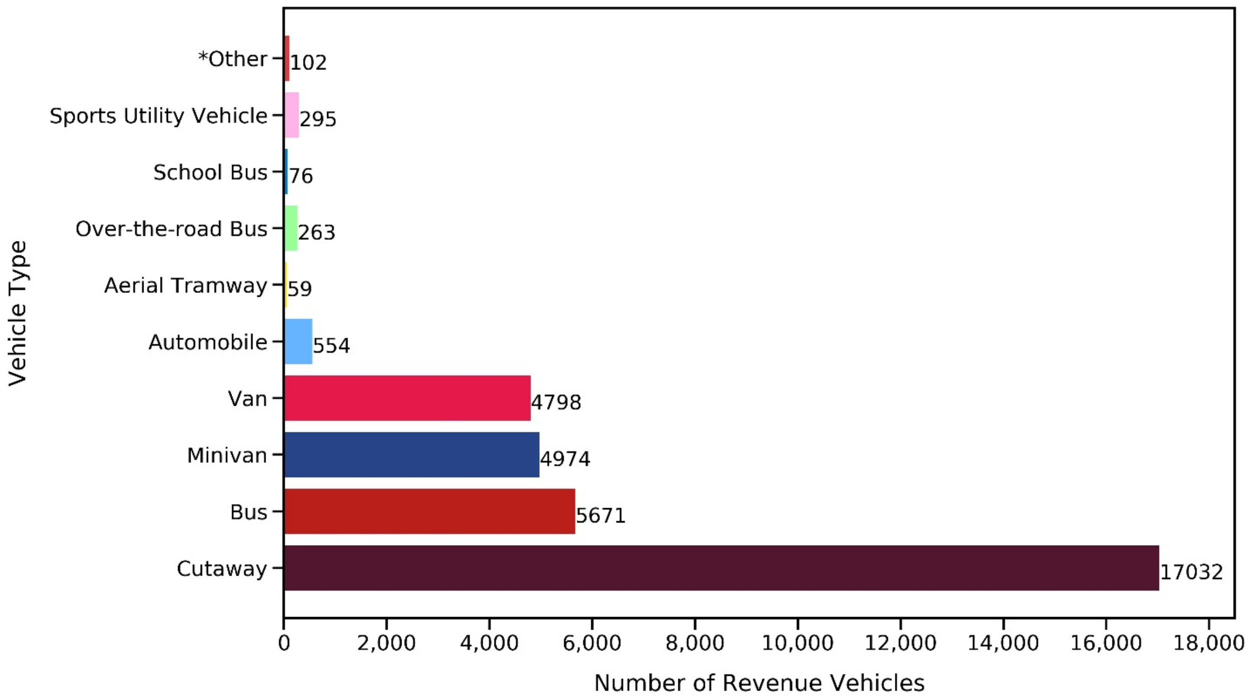


Figure 3.1 Small Urban and Rural Transit Vehicles by Vehicle Type, 2017
Note: *Other includes Articulated Bus, Double Decker Bus, Ferryboat, and Other similar vehicles.
Source: National Transit Database, 2017

Large buses carry more than 35 passengers, small buses carry 16–24 passengers, and cutaways carry 25–35 passengers. As seen in Figure 3.2, rural transit operators mostly use small cutaway buses (49.6%). In comparison, buses account for 17.1%, minivans for 15.5%, and vans for 14.8 % of the rural fleet.

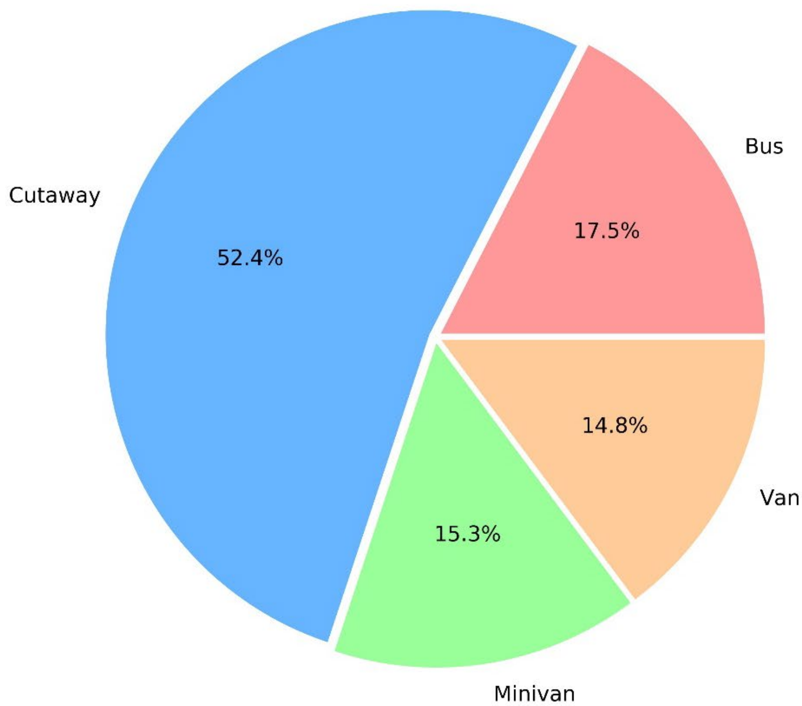


Figure 3.2 Percent of Bus, Cutaway, Minivan, and Van in Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

3.2 Age Distribution of Small Urban and Rural Transit Vehicles

Figure 3.3 presents the age distribution of small urban and rural transit buses, cutaways, over-the-road buses, ferries, vans, and minivans, respectively. Cutaways account for 49% of the small urban and rural transit fleets, whereas bus fleets account for 17% of total vehicles. Although most buses are retired by age 12 and most cutaways by age 10, roughly 9% to 17% of these fleets remain in service well after their typical retirement ages.

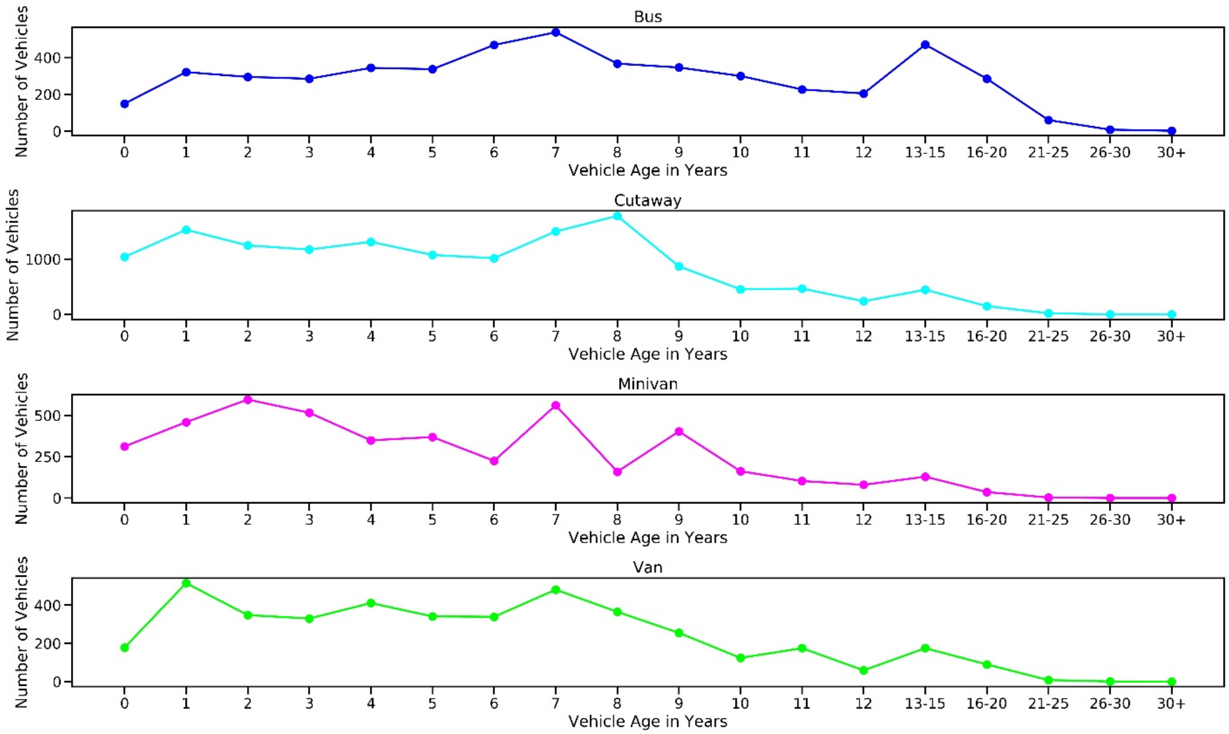


Figure 3.3 Age Distribution of Small Urban and Rural Transit Vehicles
Source: National Transit Database, 2017

3.3 Average Age and FTA Minimum Useful Life for Small Urban and Rural Transit Vehicles

The FTA establishes a minimum useful life that a vehicle must exceed before federal financial assistance can be used to replace the vehicle. Many vehicles are rehabilitated, thereby extending their useful lives and reducing maintenance costs. Figure 3.4 details how the age of vehicles by vehicle type compares with the stated minimum useful life for small urban and rural transit assets. The rural transit fleet had an average age of 5.94 years in 2017; buses, with an average age of 7.71 years, were older than cutaways, which each had an average age of 5.48 years. In 2017, data reported to NTD indicated that 16.53% of rural buses, 9.22% of cutaways, and 21.14% of rural vans were past their FTA minimum life expectancy.

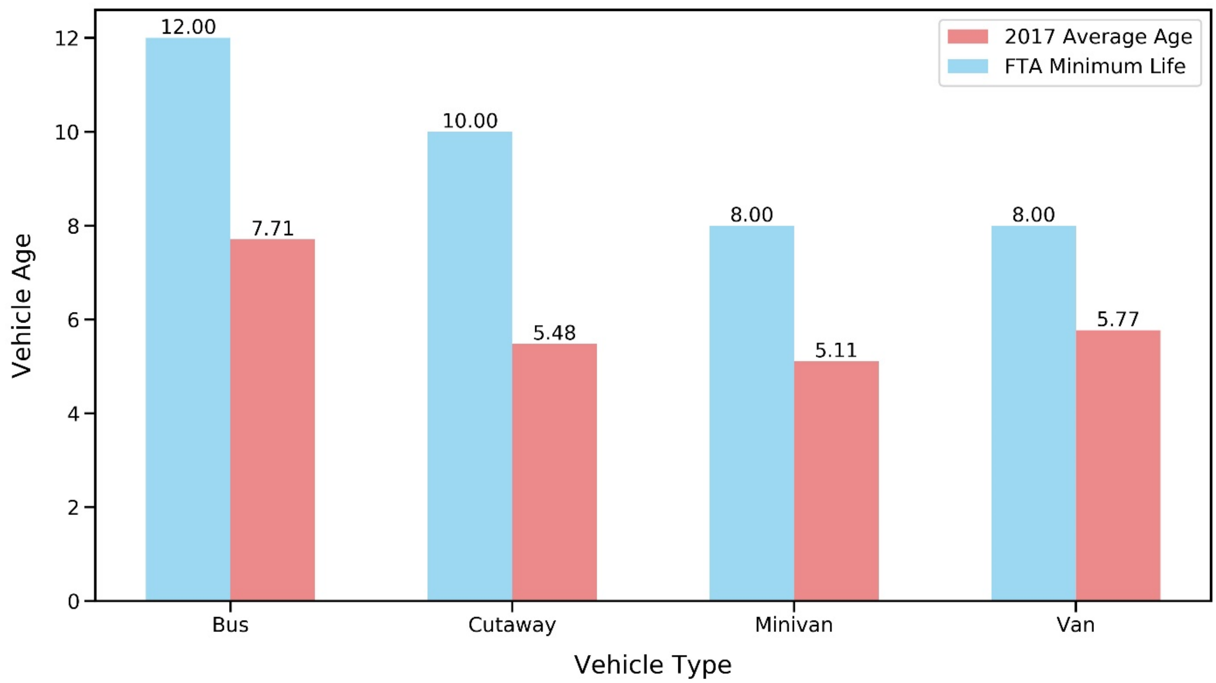


Figure 3.4 Comparison of Average Age and FTA Minimum Useful Life for Small Urban and Rural Transit Vehicles
Source: National Transit Database, 2017

Figure 3.5 shows the three-year (2015–2017) statistics of operating expenses, vehicle revenue miles, vehicle revenue hours, and unlinked passenger trips in small urban and rural transit systems. Small urban and rural transit operators reported 128.73 million (128,725,878) unlinked passenger trips on 496.84 million (496,838,698) vehicle revenue miles in 2017. Public transit passenger trips dropped 1% from 2015 to 2017 (130.36 million trips to 128.73 million trips). In response to reduced trip demand, transit operating expenses increased, while transit service hours increased 3% from 27.25 million revenue hours in 2015 to 28.05 million revenue hours in 2017. Vehicle revenue miles increased 3% from 482.50 million miles in 2010 to 496.84 million miles in 2017.

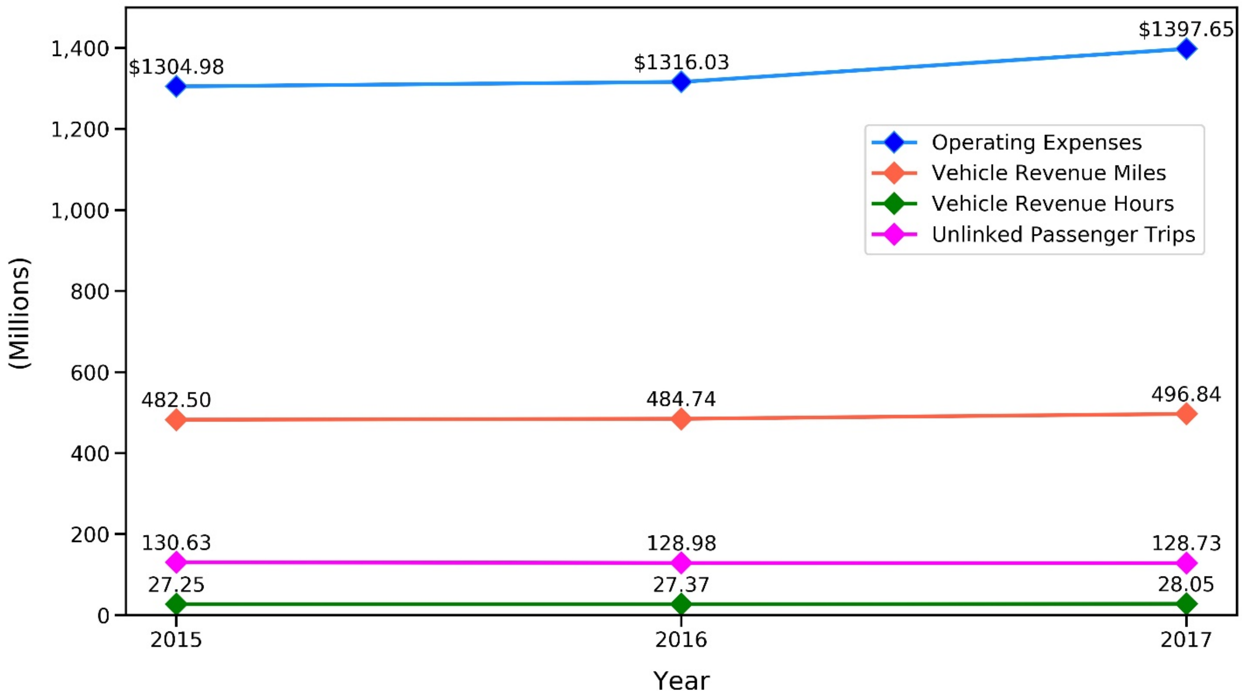


Figure 3.5 Operating Expenses, Vehicle Revenue Miles, Vehicle Revenue Hours, Unlinked Passenger Trips in Small Urban and Rural Transit Systems: Time Series
Source: National Transit Database, 2017

4. METHODOLOGY

Based on the state of good repair information from transit agencies and the literature review, a machine learning predictive model was developed to address the state of good repair for small urban and rural transit systems. The predictive model will predict the projected service life of transit vehicles. Next, a financial analytical tool was built to calculate the replacement backlog and yearly replacement cost for revenue vehicles to keep them in a state of good repair. This will help evaluate long-term capital funding and help decision makers evaluate replacement and rehabilitation needs for transit vehicles and allocate available funds across small urban and rural transit rolling stocks. It is the intention of this research to use existing data as may be found in the NTD.

4.1 Basic Concept of Machine Learning Techniques

The field of machine learning builds a computer program that can automatically improve with experience (Jordan & Mitchell, 2015). As one of the rapidly growing technologies, it uses the core concept of artificial intelligent (AI), data science, computer science, and statistics. The development of new machine learning algorithms and the availability of online data made the machine learning techniques more effective. Since machine learning methods are data intensive, the application of machine learning is an evidence-based decision-making process in the field of science, technology, medicine, education, manufacturing, finance, and marketing (Jordan & Mitchell, 2015).

Machine learning algorithms have been developed to solve data and machine learning related problems (Jordan & Mitchell, 2015). In the past decade, scientists and engineers collected a vast amount of data through networking and mobile computing systems that are referred to as "big data." They used machine learning to convert these data for a solution to the problem. Machine learning algorithms learn from large amounts of data and customize the output based on business requirements. The trend of capturing and mining large amounts of diverse datasets can improve services and productivity across many fields of science. For example, historical medical records can be used to identify a patient with similar symptoms and provide the best treatment; historical traffic data can be used to control traffic perfectly and reduce congestion; historical crime data can be used to dispatch police to a specific location and reduce the crime rate. Therefore, many organizations are capturing large datasets and analyzing them through machine learning techniques to automate decision-making processes across many aspects of data-intensive sciences (Jordan & Mitchell, 2015).

The objective of developing a machine learning predictive model in this research was to choose the learning algorithm and train the model from several past retired revenue vehicles inventory data from the NTD and deploy the model to predict the projected retired years on current non-retired revenue vehicles. Before feeding the data into the model, a variety of new features were created, missing data were fixed, and outliers were handled for the machine learning algorithm.

4.2 Machine Learning Algorithms

In this research, the machine learning technique was used for estimating the service life of revenue vehicles. There are many methods of machine learning available for building predictive models. In this problem, the ensemble method was used to build the state of good repair predictive model.

4.2.1 Ensemble Methods

Ensemble methods are very powerful techniques, and the basic idea is to train multiple learners to solve the same problem and then combine them by averaging the output of models to calculate the final prediction. Therefore, ensemble methods are significantly more accurate than a single learner (Zhou, 2012). The idea of ensemble methods is used in many daily decision-making situations (Zhang & Haghani, 2015). For example, when we have problems, we seek others' opinions. By combining the weighted ideas, we can make a better decision. Therefore, the success of the ensemble method depends on the combination of base models. If individual base models generate different outputs, then combining several base models is useful. The ensemble methods minimize errors on the predictions by correcting mistakes on the predictions made by the individual base model. If individual base models produce similar mistakes, combining base models becomes worthless. There are two techniques, such as bagging and boosting, which use various resampling methods to achieve diverse base models (Zhang & Haghani, 2015).

Ensemble methods can handle extremely complicated behavior, but they are very simple to use and can rank features based on the predictive performance. Ensemble methods became successful in many real-world problems and provided nearly optimum performance among all major predictive analytics (Bowles, 2015; Zhou, 2012). The most popular ensemble algorithms are adaBoost, boosting, bootstrapped aggregation (bagging), gradient boosting machines (GBM), stacked generalization (blending), gradient boosted regression trees (GBRT), and random forest (Brownlee, 2013). The gradient boosting regression method uses a forward stage-wise modeling approach, which fits additional models to minimize the gap between the prediction value and the true value using the loss functions, such as squared error or absolute error (Zhang and Haghani 2015).

4.2.1.1 Random Forest Regression

Random forest is a predictive algorithm that is a representative of ensemble methods (Kumar, 2016). The algorithm creates predictions on individual trees randomly and then averages predictions of all trees. The random forest does not use the cross-validation process; instead, the method uses bagging. Suppose there are m number of variables and n number of observations in training dataset T. S number of trees need to be grown in the forest, and each tree will be grown from the separate training dataset. Each training dataset from S number of training datasets is created from sampling n observation randomly; therefore, some datasets might get duplicate observations, and some observations might be missing from all the S training datasets. These datasets are called bootstrap samples or bagging. The observations that are not part of the bag are “out of the bag” (Kumar, 2016). A random forest model has better generalization performance than an individual decision tree because of its randomness, and it helps the model decrease the variance. Another advantage of random forests is that they are good at handling outliers in the dataset and do not need much parameter optimization (Raschka, 2015).

4.2.1.2 Gradient Boosting Regression

Gradient boosting regression trees are stage-wise ensemble trees where weak models are fit sequentially to minimize the errors on the training set, and predictions are made by the previous model in the sequence (Gagne, McGovern, Haupt, & Williams, 2017). These weak models are considered as decision trees in gradient boosting trees. In the beginning, the initial model is fit directly to the training labels, and the additional weak models are fit sequentially to the negative gradient of the loss function to optimize the predictive model. The difference between the actual observation and the prediction from the previous model is called a residual, which is also the mean squared error of the loss function. The predicted residual is added to the sum of the previous residuals. A learning rate is multiplied by each tree’s prediction to minimize the residual of the prediction, and a smaller learning rate can be used to correct the prediction and minimize the risk to fit to noise. The base gradient boosting regression model uses the default parameters of learning rate 0.1, 500 trees, a maximum depth of 5, and least absolute deviance loss function (Gagne, McGovern, Haupt, & Williams, 2017).

Several parameters can be tuned by the grid search method to optimize the performance of the predictive model (Johnson, et al., 2017). One of the parameters is the number of trees that grows sequentially, and another parameter is the depth of the tree that indicates the depth of interaction between features. The learning rate, which is another important parameter of the model, can be tuned to determine how much each tree contributes to the overall performance of the model (Johnson, et al., 2017).

4.2.1.3 Decision Tree Regression

The decision tree regression is a regression model built on a form of tree-based structures. The model generates predictions on the dependent variable in numeric form (Rathore & Kumar, 2016). The decision tree method can build models with complex variables without having many assumptions on the modeling (Zhao & Zhang, 2008). The method can isolate important independent features by basis function when many variables are used in the model. The decision tree regression can be unstable; for example, a change in the training data can change the output and different attributes for the model need to be selected (Zhao & Zhang, 2008). In this research, the decision tree regression was also applied as it could handle datasets with high dimensionality and could predict a dependent variable in a numeric form (Rathore & Kumar, 2016).

4.3 Parameter Optimization

The regression algorithm requires parameter values to be set up before applying the algorithm. Appropriate parameter settings in the algorithm will provide the best model while bad parameter settings will produce poor results. The best model with the tuned parameter will provide good performance on making predictions on new data with previously unseen values (Ma, 2012). The random forest model works very well without optimizing parameters. However, the performance of the model can be improved by removing redundant variables, fixing a minimum leaf size, and defining a random state number (Mueller & Massaron, 2015).

In this research, a simple parameter optimization method was used to find the optimal parameters for the random forest regression model. In addition, the grid search methodology was used in the gradient boosting and decision tree regression models to find the optimal parameter values where the points are situated on the grid within the parameter space. The grid search does a complete search starting from the minimum point of the grid in the parameter space to the maximum points and finds the optimal parameters. In short, the grid search chooses the best point after evaluating every point in the grid, and the best value on the best point is considered to be the optimum solution (Ma, 2012).

4.4 Evaluation of Predictive Model

After setting the best parameter values in the model, training the model with regressor objects, and fitting the model with the training set of data, the test dataset was used to calculate the performance of the model on the unseen data. The performance of the machine learning model was tested by measuring the R^2 score, root mean squared error (RMSE), and mean absolute error (MAE) (Raschka, 2015). Once the evaluation of each model was complete, the performance of each model was compared with each other, and the best performing predictive model was chosen to predict on new data.

RMSE calculates the measure of the model's performance, which is simply the square root of the average of the sum of squared error function. In regression problems, RMSE is the primary performance indicator over the other measures for regression problems (Aurlien, 2017). Another performance measure is called mean absolute error (MAE), which was used to check the accuracy of the model's predictions. MAE looks at every prediction the model makes, and it provides an average mistake across all the predictions (Geitgey, 2017). Another performance measure, the coefficient of determination (R^2), which is the fraction of the response variance, was also used to measure the model performance. The value of R^2 is between 0 and 1, and the model fits the data perfectly if the value is equal to 1.

4.5 A Roadmap for Building Machine Learning Predictive Model

Previously, the basic concepts of machine learning, supervised learning, and learning algorithms were discussed. In this section, Figure 4.1 depicts a workflow diagram for machine learning predictive modeling, which will be discussed below. After acquiring the revenue vehicle inventory data from the NTD, the initial raw data from FY 2002 to FY 2016 were combined and preprocessed for the machine learning algorithm. The preprocessed data were separated into training data with retired vehicles to build the predictive model and deployment data for predictions for retirement. The training dataset was split into the training set and the test set. The learning algorithms were applied to the training set to build the predictive model, and various performance measures were applied to the testing set to evaluate the model. After getting the best predictive model, the model was deployed on deployment data for predictions.

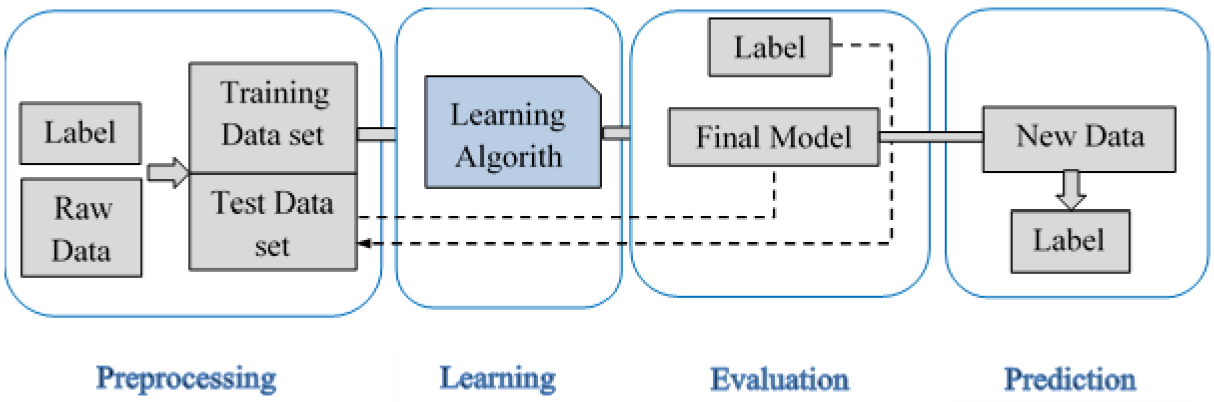


Figure 4.6 Roadmap for Machine Learning Predictive Model (Adapted from Raschka, Sebastian. 2015. Python machine learning. First Edition. Edited by Roshni Banerjee. Birmingham: Packt Publishing Ltd.)

5. PREPARE TRAINING, TESTING, AND DEPLOYMENT SETS FOR PREDICTIVE MODEL

5.1 Preprocessing of Data

The quality of data and the information they contain are key factors of how well a machine learning algorithm can learn. Most of the time, raw data from the source do not come in the form and shape to use in the machine learning algorithm. Therefore, the preprocessing of the data is a critical step before feeding the data to any machine learning application (Raschka, 2015). The NTD contains the revenue vehicle inventory data in an Excel format, which has many general problems related to how transit agencies entered their data and maintained the data structures. In this research, the revenue vehicle inventory data from FY 2002 to FY 2016 were processed for a machine learning predictive model to solve the transit state of good repair.

In the real-world application it is common to have errors in the data collection process. Therefore, items such as data quality, missing records, misspelling of different fuel types or vehicle types, extra whitespace at the end of columns, and inconsistencies of a column naming in the legacy datasets were taken into consideration to ensure the data's accuracy. The most common problem is missing values. Some fields are sometimes left blank as NaN (not a number) in the database. Unfortunately, machine learning algorithms cannot handle missing values. Thus, it is very important to take care of the missing values before analyzing and modeling. The missing values were handled either by removing missing entries from the unique vehicle inventory ID or filling missing values in the non-unique attributes with the value calculated by different methods based on data types. In addition, there were misspellings of categorical names or alternate names present in the Fuel Type or Vehicle Type categories. These categorical names were replaced with a normalized form of name to maintain data consistency throughout all the historical data. All the other issues of the column names in the historical data were fixed either by replacing or renaming with correct attribute names.

If the Retired column had a Flag Y present, a new column, Retired Year, was created with the value of the year the vehicle was retired. Another new column, Service Life, was created with the historical data for training the model. The value of Service Life was generated by subtracting Manufacturing Year from the Retired Year. Since Revenue Vehicle Inventory ID was unique for vehicle identification, it was used for indexing the datasets; and in that way duplication was avoided. The retired vehicle data were used for training and evaluating the model, and the data with the current vehicles in operation were used for predicting the projected service life of the transit vehicles.

The reason behind the data preprocessing was to transform RAW data to useful ones; in this case we need to do the following:

5.1.1 Data Cleansing

- Remove white spaces from Fuel Type, Vehicle Type, Funding Source, and Ownership Type.

- Drop rows if data are missing from 'Manufacture Year' column.
- Because inconsistent names such as Buses, Bus, and bus exist for vehicle type, rename these categorical names for consistency.
- Because inconsistent names such as Diesel fuel, Bio-diesel(BD), and Diesel Fuel exist for Fuel Type, rename these categorical names for consistency.
- Fill missing values for Fuel Type column for all vehicle modes based on vehicle model. For example, fill missing column for Fuel Type with "Electric Propulsion Power" for model TR – Aerial Tramway.
- Rename categorical names for Funding Source for consistency.
- Rename categorical names for Ownership Type for consistency.
- Remove whitespaces from Dedicated Fleet column.
- Fill missing values with 0 (zero) for Total Fleet Vehicles column.
- Fill missing values by copying values from Total Fleet Vehicles.
- Fill missing values with 0 (zero) for ADA Fleet Vehicles column.
- Fill missing values with 0 (zero) for Emergency Contingency Vehicles column.
- Filling missing values by applying forward filling along a series for Reporter Type and rename Reduced Asset Reporter with Reduced Reporter for consistency.
- Fill missing values for Reporting Module based on Reporter Type. For example, if Reporter Type is Full Reporter, fill missing values with "Urban." Rename category names Asset and Tribe with Tribal for Reporting Module.
- Remove white spaces from the Seating Capacity column and fill missing values with the mean value of Seating Capacity based on Vehicle Type. For example, if missing values for Seating Capacity exist for Bus, fill missing values with the mean value of the Seating Capacity for Bus.
- Remove white spaces from the Standing Capacity column and fill missing values with the mean value of Standing Capacity based on Vehicle Type.
- Remove white spaces from the Vehicle Length column and fill missing values with the mean value of Vehicle Length based on Vehicle Type.
- Fill missing values for Supports Model with the value of Mode.
- Fill missing values for Supports Service with the value of TOS.
- Fill missing values with 0 (zero) for Rebuild Year.
- Fill missing values with 0 (zero) for Average Lifetime Miles per Active Vehicles.
- Fill missing values with 0 (zero) for Total Miles on Active Vehicles During Period.

5.1.2 Drop Unwanted Columns

Some variables from the datasets were not required for either data analysis or modeling. Therefore, we do not need some columns, such as Agency Name, NTD ID, Legacy NTD ID, Manufacturer, Other Manufacturer Description, Retired, and Model, so we end up dropping them from the data frame.

5.1.3 Dealing with Categorical Features

For the moment we still have several categorical features, which are Vehicle Type, Fuel Type, Funding Source, Ownership Type, Reporter Type, Reporting Module, Supports Mode, Support Service, and TOS. The aim is to preprocess those features in order to make them numerical so they will fit into the predictive model. In the literature, there are two well-known kinds of categorical variable transformation; the first one is label encoding, and the second one is the one hot encoding. In this case, we will use the one hot encoding; we choose this kind of data labeling is because we will not need any kind of data normalization later.

5.2 Data Exploration and Visualization

Exploratory data analysis is the first step in analysis before creating a training dataset for a machine learning model (McKinney, 2017). As we built a training set using revenue vehicle inventory data for the predictive model, it was also important to visualize these data to see the significant value of the model and how data are distributed.

Since we are looking to express the service life by different features, one of the important plots is to visualize how service life differs among vehicle types.

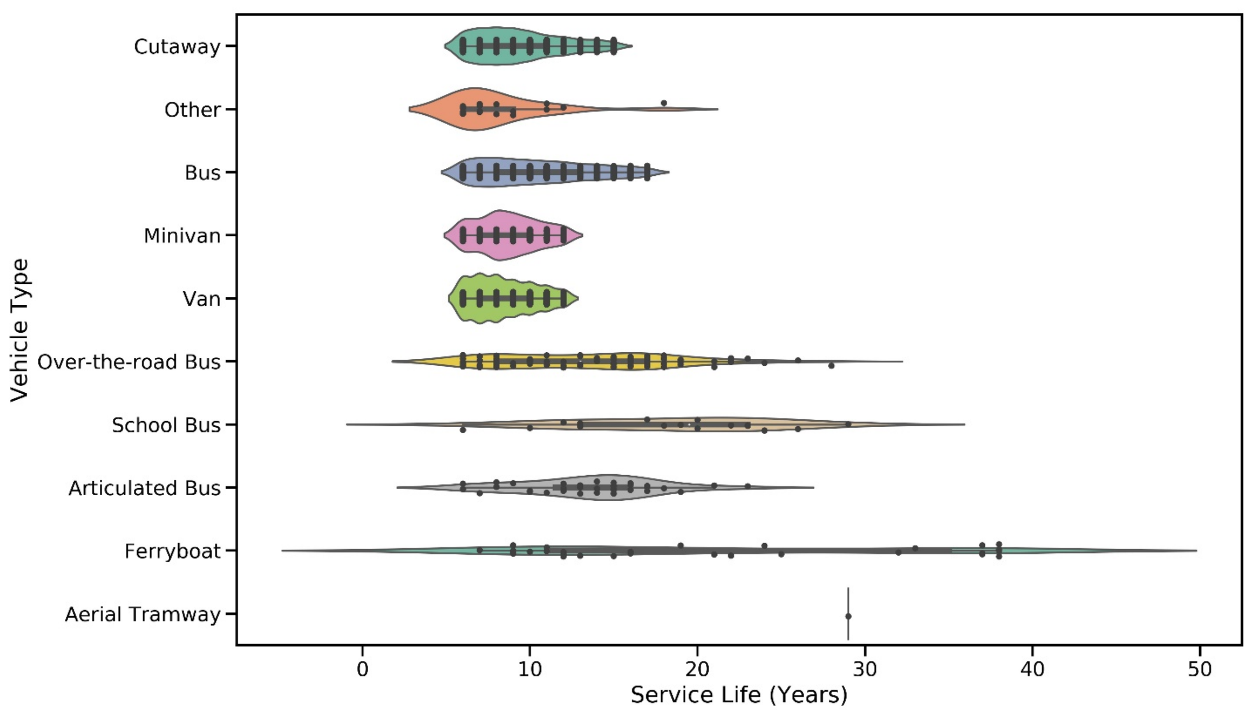


Figure 5.7 Service Life Distribution by Vehicle Type in Retired Revenue Vehicle Inventory Data for Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

From the plot above, we can see that cutaway, bus, minivan, and van had a stable service life. On the other side, over-the-road bus, school bus, articulated bus, and ferryboat had a long range of service life.

In the following plot (Figure 5.2), we will visualize the service life distribution by fuel type.

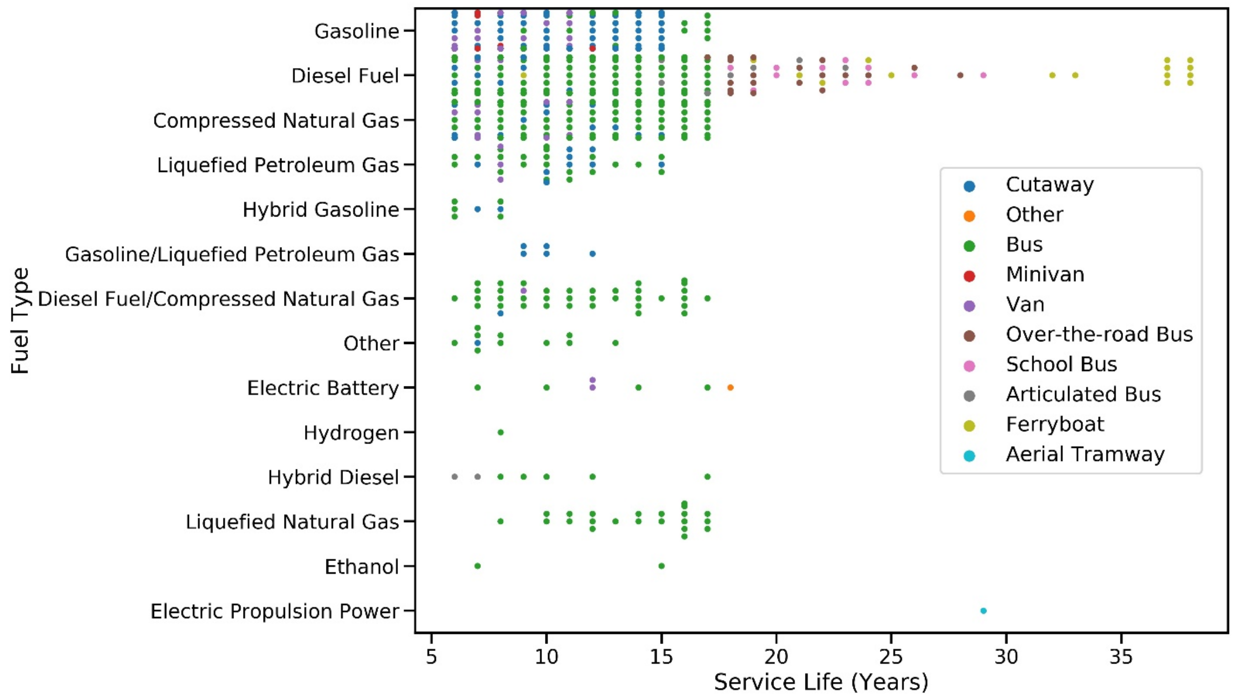


Figure 5.8 Service Life Distribution by Fuel Type on Retired Revenue Vehicles for Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

As we can see from the plot above, most of the revenue vehicles use gasoline, diesel fuel, and compressed natural gas as fuel. Most of the van vehicles use gasoline as fuel, and their average service life was about seven years. Bus vehicles use almost all kinds of fuels, and their average service life was about 10 years. Ferryboats use diesel fuel, and they had a wide range of service life. Aerial tramway uses electric propulsion power.

There seems to be positive relationships between vehicle type and service life as well as fuel type and service life. We will look at what is the actual correlation between service life and the other data points in two ways: heatmap for visualization and the correlation coefficient score.

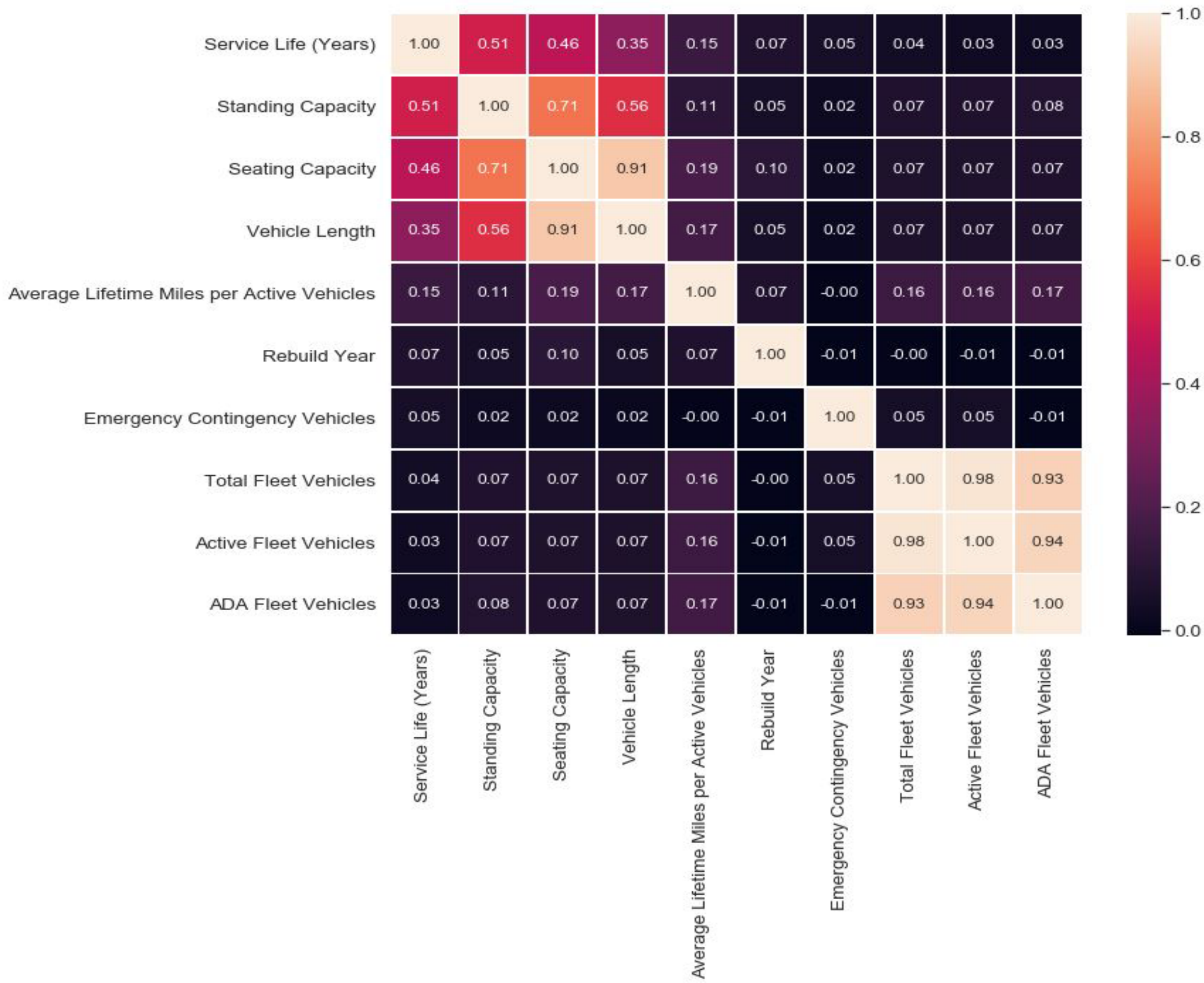


Figure 5.9 Correlation Matrix with Heatmap Visualization for Service Life with Other Data Points

Source: National Transit Database, 2017

As we can see from Figure 5.3, there is a strong correlation between service life and standing capacity, seating capacity, and vehicle length features, with the largest correlation score of 0.51 for standing capacity. The strong correlation scores validate the relationship between the service life and those columns.

5.3 Development of Training Dataset

The development of the algorithm starts with building a training set, which consists of two types of data, such as the target data, and the features for making the prediction (Bowles, 2015). In order to create the training set, the retired vehicles from revenue vehicle inventory datasets from the NTD from 2002 to 2016 were filtered out. After preprocessing and cleaning the data, the initial training dataset was built by creating the target column Service Life by subtracting Manufacture Year from Retired Year. Since the target column was created from Retired Year and Manufacture Year, which were no longer needed in the training set, the columns were removed from the training set. At this stage, features of the training dataset need to be engineered before building a machine learning model.

The feature engineering process involves determining what features need to be used, what iterative processes need to be required for feature selection, and what combination of features need to be added for making predictions (Downey, 2014). A convenient way to create dummy features for machine learning applications is to transform a categorical variable into a dummy matrix. If a string column in a data frame has *n* values, the *get_dummies()* function will convert *n* columns into 1's or 0's (McKinney, 2017). In this training dataset, the categorical string columns Fuel Type, Vehicle Type, Funding Source, Reporting Module, Mode, Supports Mode, Supports Service, Ownership Type, TOS, and Dedicated Fleet were converted into dummy variables by get_dummies.

5.4 Development of Deployment Dataset

The revenue vehicle deployment dataset includes the data where all vehicles are in operation. Since the 2017 revenue vehicle inventory data, the NTD has the most up-to-date data, which will be considered as the non-retired revenue vehicles data. The 2017 revenue vehicle inventory data include nationwide rolling stock data. However, in order to build the deployment dataset for small urban and rural transit systems, we need to remove the urban data. Therefore, we removed urban data by filtering out full reporter data by reporter type as well as Automobiles and Sport Utility Vehicles by vehicle type. The main purpose of creating the deployment dataset was to predict the target feature. In this case, the model will generate predictions as Predicted Service Life. Since the machine learning method works only when the X features in the training dataset exactly match with the deployment dataset, we needed to process the deployment dataset in the same general fashion as processing the training dataset. After building the model with training data, the model was applied to this deployment data to predict the service life of vehicles.

5.5 Development of Predictive Model

The main task in this process is data modeling. We used three machine learning models dedicated for regression problems, and at the end we created a benchmarking table to compare each model r2_score and select the best one. The models used are Random Forest Regression, Decision Tree Regression, and Gradient Boosting Regression.

Before building any predictive model, it is important to test the model on unseen data to evaluate the performance of the model. Therefore, at first, the training data were split into train and test set where the model was fit to the train set and evaluated on the test set (Raschka, 2015). In this case, we used a test with 30% in test size, and the rest for training. After having fitted the model with the training data, the model was evaluated on test set as well as on train set by applying the performance measures of RMSE, MAE, and R^2 score to see how well the model was working on the unseen data. If the performance results are satisfied on generalization errors, the model can be used to predict the future data. The performance measures will be further compared with the performance measures of the other algorithm used in this research, and the best performing algorithm will be chosen to build the predictive model.

5.5.1 Random Forest Regression Model

The random forest regression is an ensemble technique that combines multiple decision trees. Due to randomness, the random forest has a better generalization than an individual decision tree, and it decreases the variance of the model (Mirjalili & Raschka, 2017).

Scikit-learn follows four-step modeling patterns for building a machine learning model. In step one, the random forest regression class was imported. In step two, the model was instantiated with the estimator by setting hyper-parameters. In step three, the model was fit on the training data and stored the information learned from the data. In step four, the fitted model was applied to predict the response to the test set for evaluation. The performance results of predictive model on train set and test set are listed in Table 5.1.

Table 5.1 Comparison of Performance Results on Training Set and Test Set using Random Forest Regression Method

Method	Training Set			Hold-Out Set (Test Set)		
	RMSE	MAE	R^2 Score	RMSE	MAE	R^2 Score
RFR	1.04	0.73	0.92	2.64	2.02	0.36

From the above comparison results between the test set and the train set, we saw that the RMSE on the test set was 2.64, which was much larger than the RMSE on the train set value of 1.04. This difference is an indicator that the current model is overfitting the train data. In a machine learning problem, overfitting is common where the model performs well on train data but does not generalize well on the test or unseen data. Due to overfitting, we also assume that the model may have a high variance. Many parameters in the model might make the model too complex and overfit.

5.5.2 Gradient Boosting Regression Model

Tree-based ensemble methods combine simple regression trees with poor results, fit complex non-linear relationships, and produce the high-performance prediction. In this problem, the gradient boosting regression tree method was applied to build the model for service life on revenue vehicle inventory data, and it was hoped to improve prediction accuracy over the random forest regression model. The gradient boosting regression method corrects the prediction made by previous base models and tries to improve prediction accuracy (Zhang & Haghani, 2015).

The gradient boosting regression has many parameters that were tuned, such as learning_rate, n_features, max_features, min_samples_split, max_depth, and min_samples_leaf, before building the predictive model with the revenue vehicle inventory training data. The training data were split into the train set and the test set, and then train the model with the train set by setting tuned hyperparameters and fit it. In order to test the performance of the model on unseen data, the performance results of the predictive model on the train set and test set are shown in Table 5.2.

Table 5.2 Comparison of Performance Results on Training Set and Test Set with Gradient Boosting Regression Method

Method	Train Set			Hold-Out Set (Test Set)		
	RMSE	MAE	R^2 Score	RMSE	MAE	R^2 Score
GBR	1.52	1.05	0.95	1.37	0.94	0.96

The above table shows that the RMSE score on the train set is very close to the RMSE score on the test set. It seems there is no indication of overfitting in the model and generalizes it very well. This model can be used for predictions; however, the full training set with limited important features can be used to train the model, which will further improve the performance as data contain more training data.

5.5.3 Decision Tree Regression Predictive Model

A decision tree builds a regression model in the form of a tree-like structure to solve regression problems, and is a good fit to handle the complex nonlinear relationship between feature variables and target variable. A decision tree is a top-down approach where the processing breaks down a dataset into smaller subsets while simultaneously the tree moves down into the leaf node. The basic idea is to break down a complex decision into the smaller subset of the simpler decision so it is easier to get a solution. In a regression problem, the decision tree considers features of data as predictor variables and a continuous variable as the target variable. The features with important information are chosen for the model, and features with no information are rejected automatically from the model, which increases the computational efficiency (Xu, Watanachaturaporn, Varshney, & Arora, 2005).

The four-step scikit-learn modeling was used on the decision tree regression model in the same way the previous models were built with the training set. The performance results of the predictive model on the train set and test set are listed in Table 5.3 for comparison.

Table 5.3 Comparison of Performance Results on Training Set and Test Set with Decision Tree Regression

Method	Train Set			Hold-Out Set (Test Set)		
	RMSE	MAE	R^2 Score	RMSE	MAE	R^2 Score
DTR	2.68	2.10	0.49	2.92	2.23	0.21

The high performance scores on the train and test sets indicate that the decision tree regression model is not a good fit for the problem on the revenue vehicle inventory dataset and will not predict perfectly on unseen data. Therefore, we will not consider the decision tree regression model as our predictive model.

5.6 Comparison between Random Forest Regression and Gradient Boosting Regression Model

Since the decision tree regression model was not considered due to overfitting, we compared the following two methods for selection of the predictive model for service life on revenue vehicle inventory data. Table 5.4 shows the performance metric for both models.

Table 5.4 Comparisons of Performance Measures between Random Forest Regression and Gradient Boosting Regression

Method	Full Training Dataset		
	RMSE	MAE	R^2 Score
Random Forest Regression	1.02	0.72	0.92
Gradient Boosting Regression	0.88	0.50	0.94

From the above comparison results, we can conclude that the gradient boosting regression model is a better fit for this problem. The RMSE score of 0.88 indicates that the prediction will fall within one year below or above the standard deviation at 94% accuracy with a mean absolute error of 0.50 years of prediction difference from the actual service life of vehicles.

5.7 Building Gradient Boosting Regression Model for Service Life Prediction

In the previous gradient boosting regression predictive model, we used every useful feature available in the data and some combined features in the training dataset. It seemed reasonable, as we wanted to use as much information as available to build the model. However, some features may sometimes add redundant information, which may lead to poor generalization, and some irrelevant features may cause overfitting the model. Some poor features may return poor results. Sometimes, a large number of features may increase computation time without improving the regression model and may cause the problem on generalizing to train a model on a dataset. As a result, a smaller set of the most important features may produce better results. Therefore, we found a way to get important features algorithmically. This process of selecting features is called feature selection, which is very important to get better performance for any machine learning algorithms (Garreta & Moncecchi, 2013).

In addition, since the model was trained and tested, and the out-of-sample test dataset already provided a good estimate of prediction errors, the model can perform even better if a larger training dataset can be used. The model generalizes and performs better if it is trained on the combined large dataset (Downey, 2014). Therefore, the predictive model was created on an overall training dataset with the 35 most important features and saved for unseen revenue vehicle inventory data for prediction.

The gradient boosting regression generates a rank among the important features on a scale between 0 and 1 (Downey, 2014). After ranking the 35 most important features, the scikit-learn modeling patterns were applied to build the predictive model with the 35 most important features. Finally, the performance results of predictive model on the train set are listed in Table 5.5.

Table 5.5 The Performance Measures by Gradient Boosting Regression with 35 Most Important Features on Full Dataset

Performance Measures	Performance Scores
Root Mean Squared Error (RMSE)	0.77
Root Mean Squared Error (MAE)	0.38
R^2 Score	0.96

In the above result, the root mean squared error of 0.77 and the R^2 score of 0.96 indicate that the predictions will fall less than one year below or above the standard deviation with a 99% accuracy rate and a mean absolute error of 0.38 for predictions. The results show that the model is performing well enough, using a gradient boosting regression model to predict the future service life of vehicles.

6. RESULTS

In this research, the authors deployed the predictive model on the nation's small urban and rural transit agencies' 2017 revenue vehicle data and calculated the service life of each vehicle. The service life of each vehicle depends on many important features such as vehicle type, vehicle length, fuel type, seating capacity, standing capacity, and mode. The predictive model built in this research learns the importance of such features and predicts the service life of vehicles in the nation's small urban and rural transit agencies' revenue vehicles. After the predicted service life of vehicles was acquired, the authors calculated the projected retirement year. The authors also calculated the replacement backlog from the projected retirement years, which were prior to 2020 and projected vehicle replacement cost for each year thereafter.

6.1 Backlog and Predicted Year Retirement for Revenue Vehicles in Small Urban and Rural Transit Systems

The predicted replacement years for all revenue vehicles in small urban and rural transit agencies were calculated using the machine learning predictive model (MPLM). For simplicity, automobiles, ferryboats, and sport utility vehicles have not been included for analysis. If vehicles are replaced according to MLPM, then 8,394 out of 29,251 of the revenue vehicles have reached or surpassed that benchmark and would need to be replaced to bring the revenue vehicles into a state of good repair, as shown by the red bar in Figure 6.1. Then a corresponding number of vehicles would need to be replaced each year to maintain a state of good repair in providing a 12-year long-range plan, as indicated by the year in Figure 6.1. The figure includes vehicles that may be replaced more than once during the period and assumes vehicles will be replaced with similar types of vehicles and total fleet size will not change.

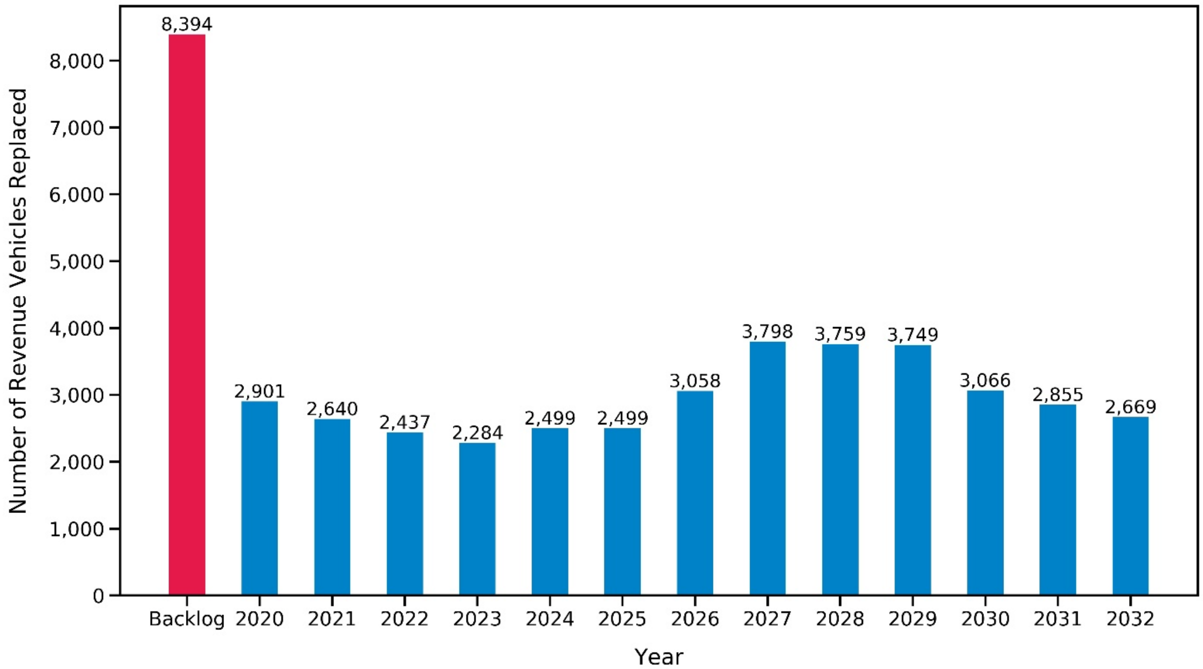


Figure 6.10 Backlog and Projected Replacement of Revenue Vehicles in Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

6.2 Backlog by Vehicle Type in Small Urban and Rural Transit Systems

The number of revenue vehicles indicated as backlog was further categorized by vehicle type, shown as a bar chart in Figure 6.2 and as a pie chart in Figure 6.3. The bar chart plot in Figure 6.2 shows that the cutaway vehicles have more backlog than any other vehicle type, and they account for about 49% of all vehicle types, as shown in Figure 6.3.

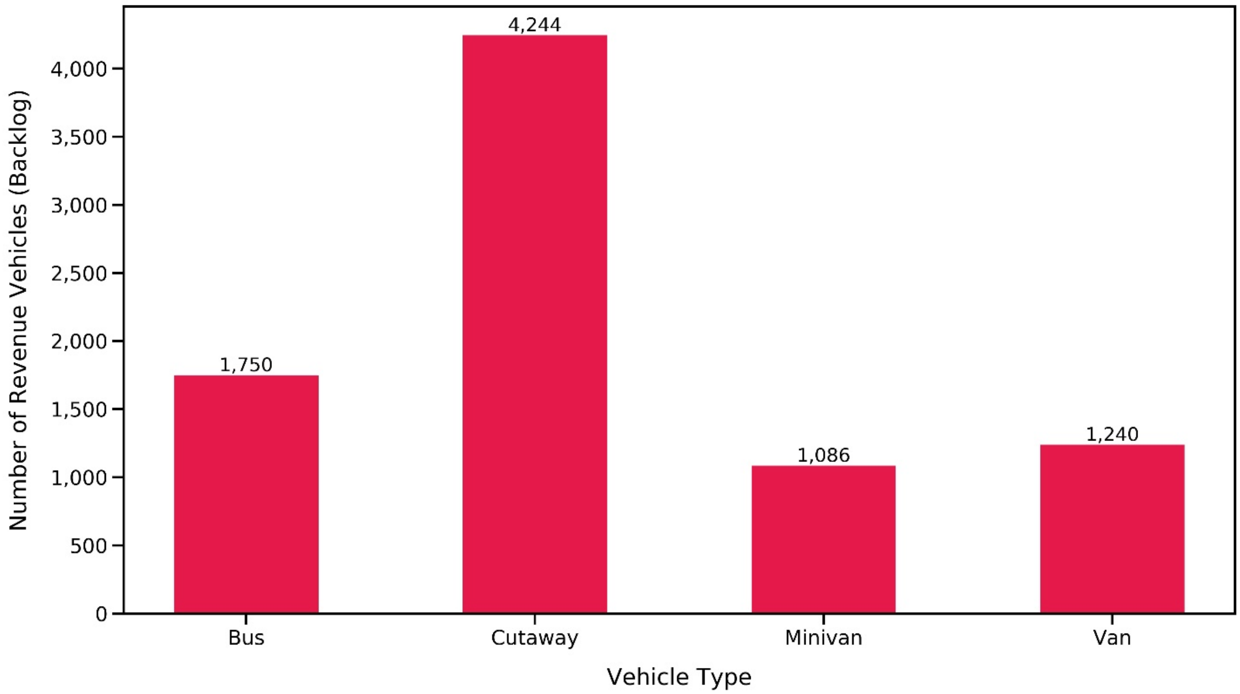


Figure 6.11 Backlog of the Revenue Vehicles by Vehicle Type in Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

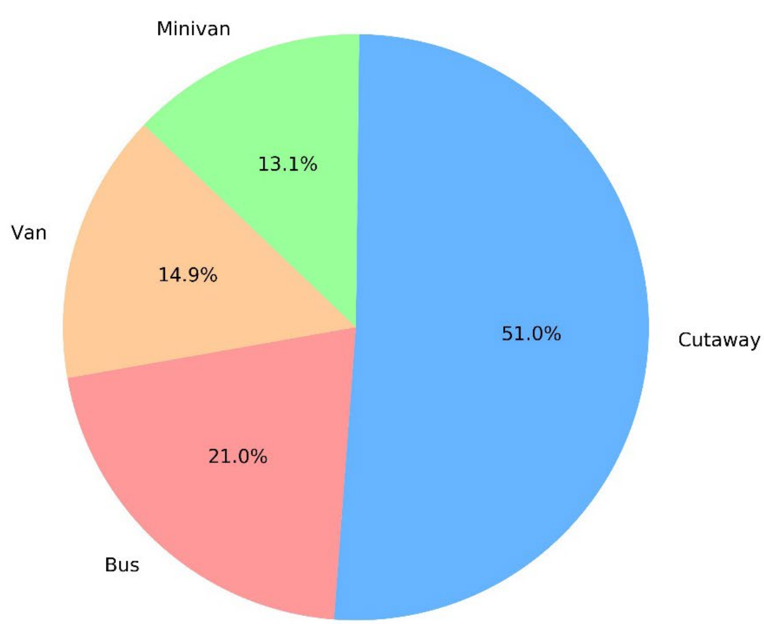


Figure 6.12 Percentage of Backlog of the Revenue Vehicles by Vehicle Type in Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

6.3 Backlog and Predicted Replacement Cost of Revenue Vehicles

The replacement costs of revenue vehicles are calculated considering fleet characteristics, including date of manufacture, manufacturer, model, length, and equipment for U.S. transit agencies, which are acquired from American Public Transportation Association's (APTA) Public Transportation Vehicle Database. The replacement backlog of revenue vehicles for Small Urban and Rural Transit Systems is calculated using service life predicted by the MLPM on revenue vehicles. The revenue vehicle inventory data from the NTD were used for fleet information, and the U.S. fleet data from APTA's Public Transportation Vehicle Database were used to estimate the cost of the vehicles.

In addition, with the MLPM, a financial cost analysis tool was developed and applied on the deployment dataset to estimate the backlog and yearly replacement costs. Figure 6.4 shows a backlog of $1.212 billion for small urban and rural transit systems to achieve a state of good repair, and the replacement cost in each year after the backlog shows the funds needed for replacement to maintain the state of good repair.

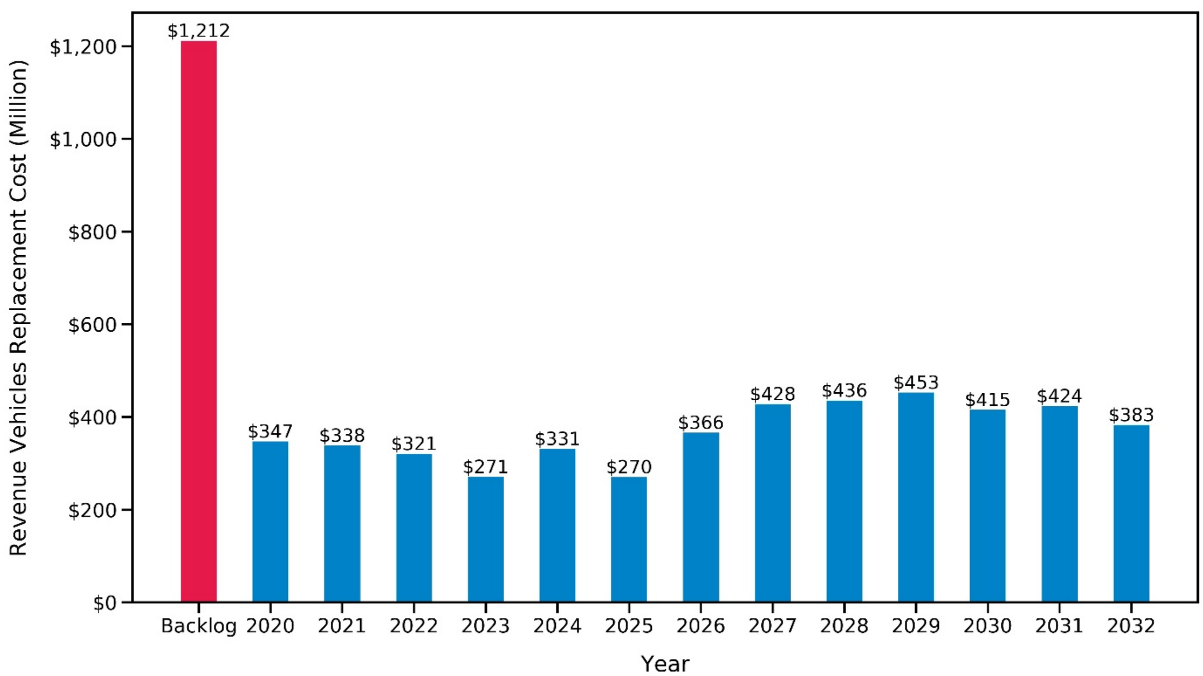


Figure 6.13 Backlog and Projected Replacement Cost for Revenue Vehicles in Small Urban and Rural Transit Systems (NTD 2017)

Source: 2017 Revenue Vehicle Inventory Data, the National Transit Database (NTD); U.S. Fleet Data, APTA 2018 Vehicle Database

6.4 Funds Needed for Backlog by Vehicle Type for Small Urban and Rural Transit System

The bar chart plot in Figure 6.5 shows the funds needed for backlog by vehicle type to achieve a state of good repair. For example, the backlog for replacing buses that have exceeded their useful lives would be nearly $644 million to achieve a state of good repair.

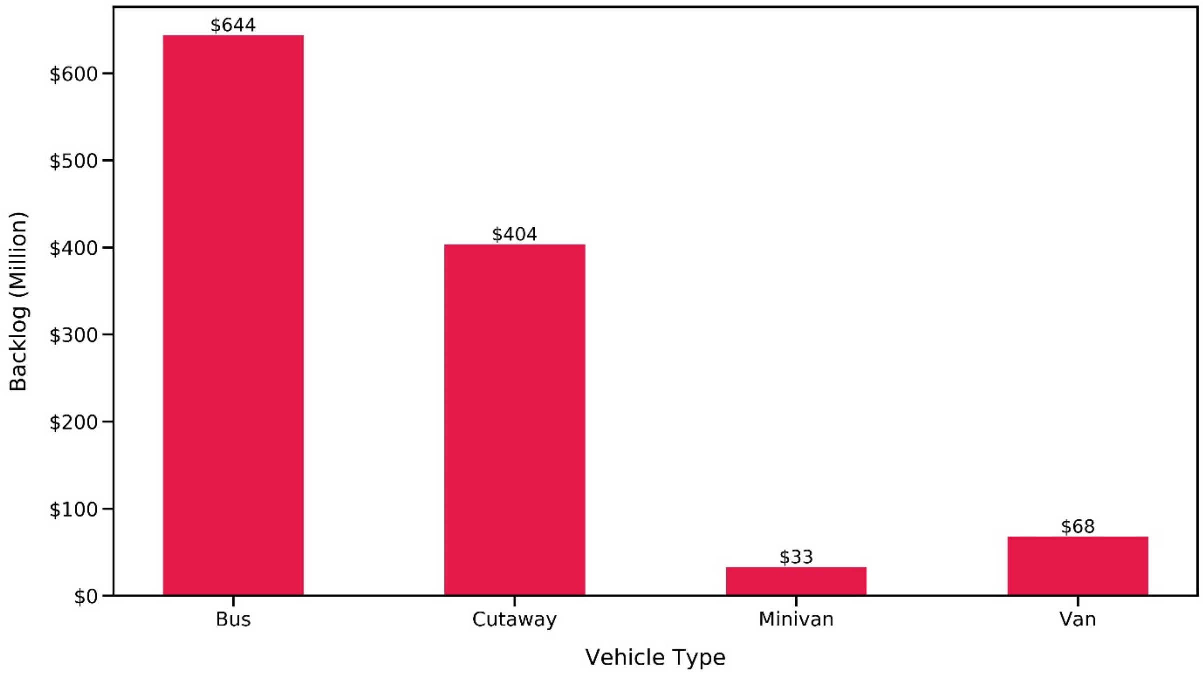


Figure 6.14 Funds Needed for Backlog by Vehicle Type in Small Urban and Rural Transit Systems (NTD 2017)
Source: 2017 Revenue Vehicle Inventory data, the National Transit Database (NTD); U.S. Fleet Data, APTA 2018 Vehicle Database

6.5 Backlog and Projected Replacement Cost by Vehicle Type in Small Urban and Rural Transit Systems

The replacement years for buses, cutaways, minivans, and vans were predicted according to the MLPM. Based on the predicted service life of each vehicle, the number of vehicles in each category that would need to be replaced each year was calculated. The number of vehicles predicted to be retired before 2020 were considered as backlog. The replacement costs also were calculated by vehicle type similar to the calculation of replacement costs for all revenue vehicles. The backlog and replacement costs for buses, cutaways, minivans, and vans by predicted replacement year are shown in Figure 6.6 to Figure 6.13.

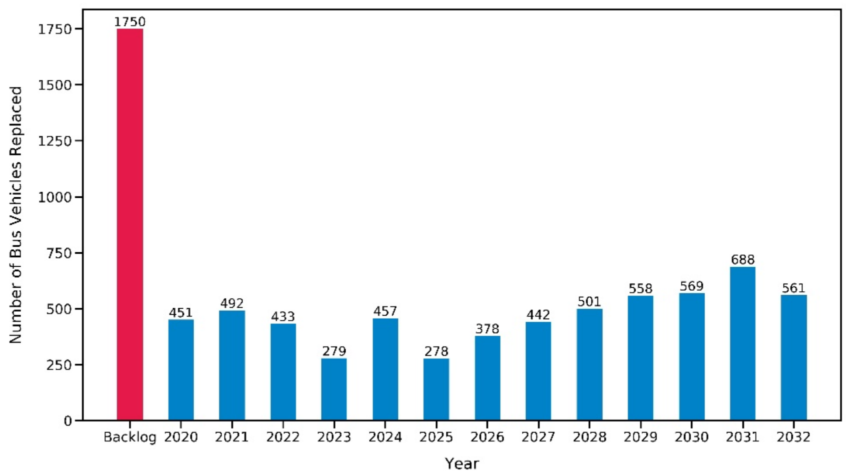


Figure 6.15 Backlog and Projected Replacement of Buses in Small Urban and Rural Transit Systems

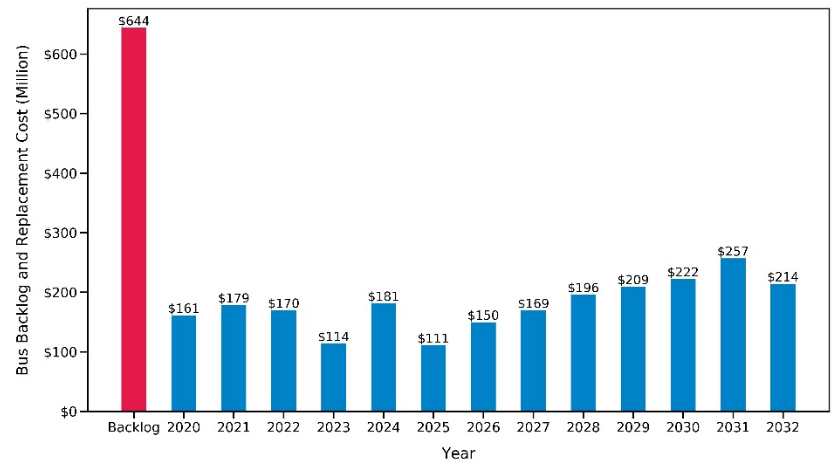


Figure 6.16 Backlog and Projected Replacement Cost for Buses in Small Urban and Rural Transit Systems

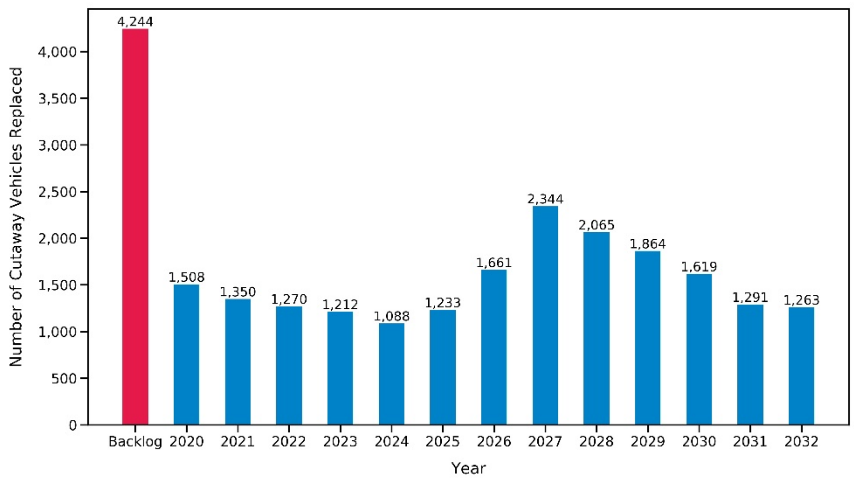


Figure 6.17 Backlog and Projected Replacement of Cutaways in Small Urban and Rural Transit Systems

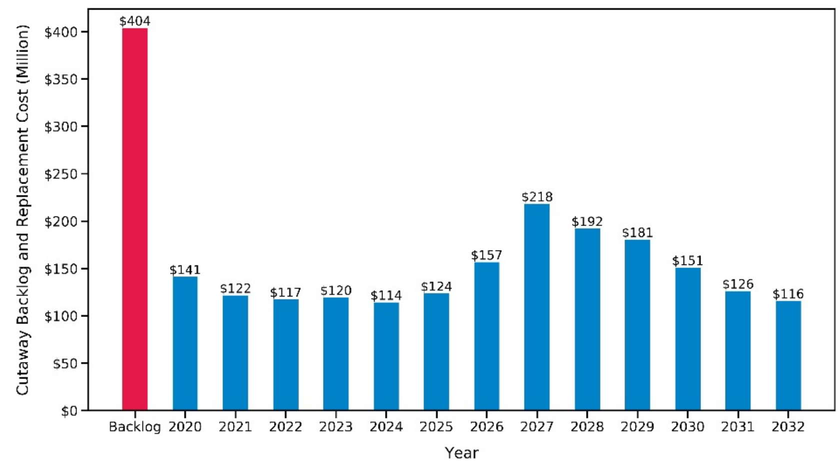


Figure 6.18 Backlog and Projected Replacement Cost for Cutaways in Small Urban and Rural Transit Systems

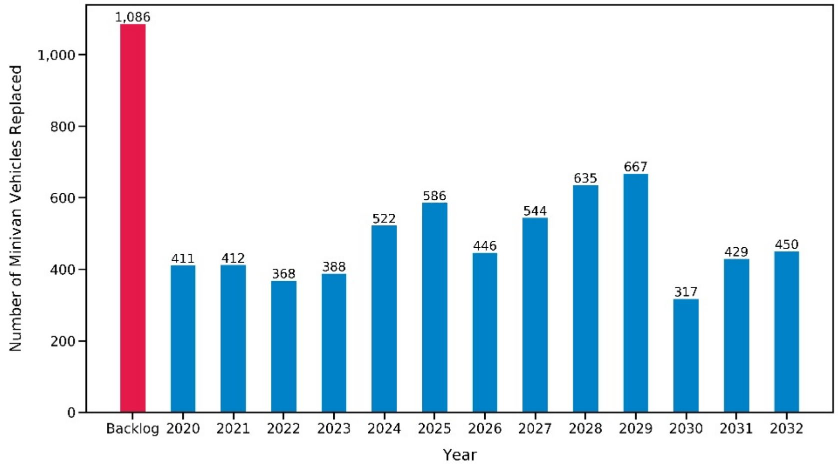


Figure 6.19 Backlog and Projected Replacement of Minivans in Small Urban and Rural Transit Systems

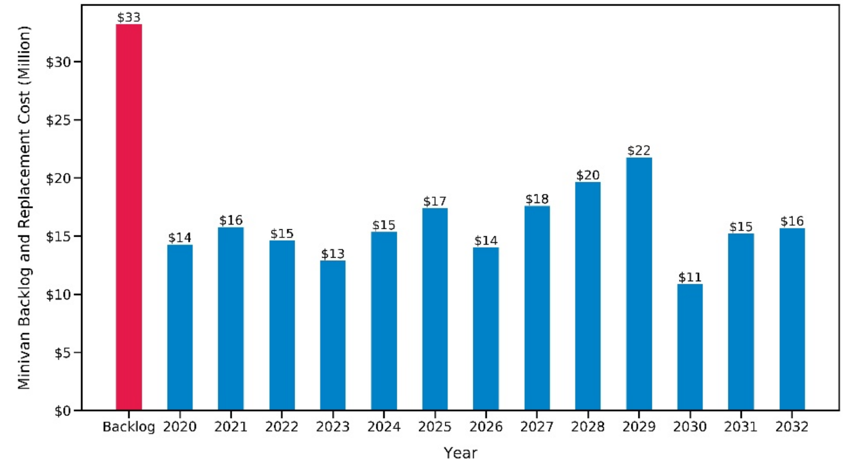


Figure 6.20 Backlog and Projected Replacement Cost for Minivans in Small Urban and Rural Transit Systems

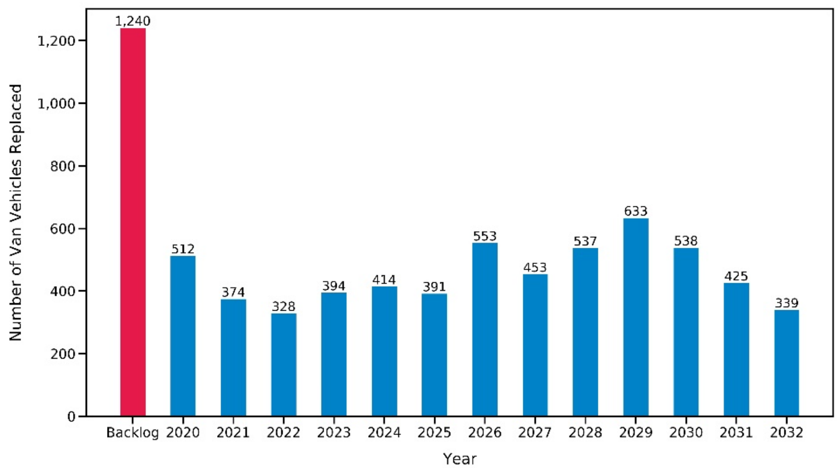


Figure 6.21 Backlog and Projected Replacement of Vans in Small Urban and Rural Transit Systems

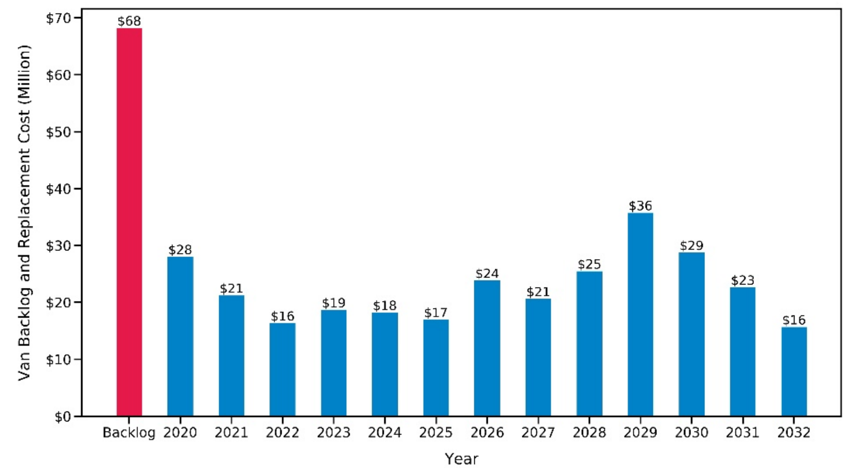


Figure 6.22 Backlog and Projected Replacement Cost for Vans in Small Urban and Rural Transit Systems

6.6 Case Study on North Dakota's Small Urban and Rural Transit Systems Revenue Vehicles Data

Next, we will provide an example using the state of North Dakota to illustrate how the DOT may benefit from using the model. The revenue vehicle inventory data are reported for North Dakota for 28 transit agencies, including 261 total fleet vehicles. The number of revenue vehicles by vehicle type is shown in Figure 6.14, and the percentage of revenue vehicles by vehicle type is shown Figure 6.15. Minivans comprise 41.4% of total fleet vehicles while cutaways, buses and vans account for 35.6%, 14.2%, and 8.8%, respectively.

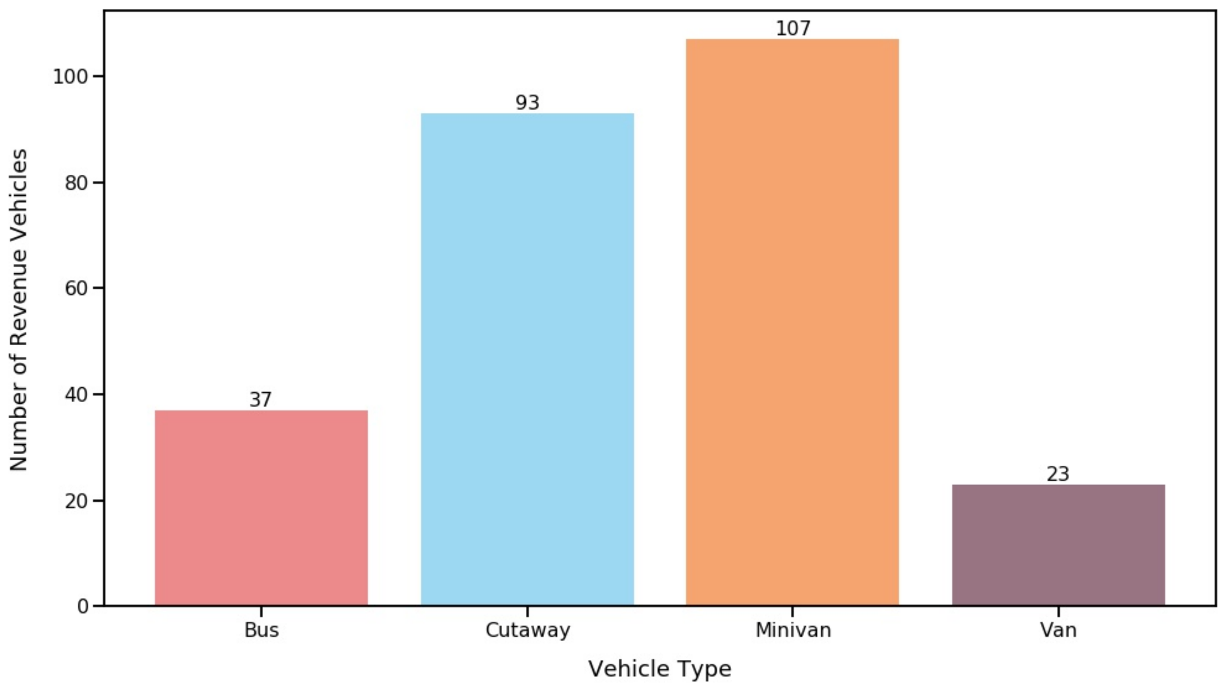


Figure 6.14 Number of Revenue Vehicles by Vehicle Type in North Dakota's Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

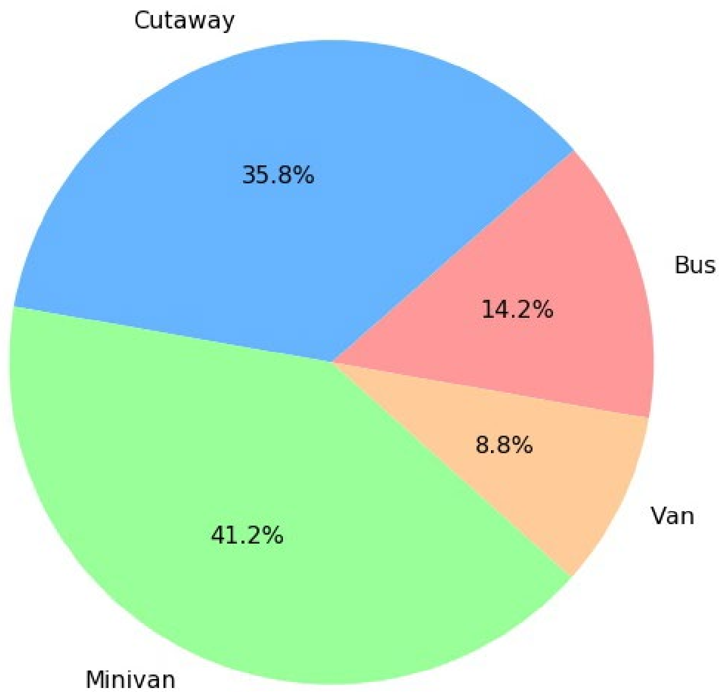


Figure 6.23 Number of Revenue Vehicles by Vehicle Type in North Dakota's Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

The machine learning predictive model built in this research was applied on North Dakota's small urban and rural transit systems revenue vehicle inventory data (NTD, 2017). The number of revenue vehicles the model predicted to be retired before year 2020 will be considered as backlog. The model shows 51 revenue vehicles, shown in Figure 6.16, exceeded their service life before 2020 in North Dakota's small urban and rural transit systems, and would need to be replaced to bring the revenue vehicles into a state of good repair. The corresponding number of vehicles, as shown by the number above each year (Figure 6.16), would then need to be replaced in that year to maintain a state of good repair.

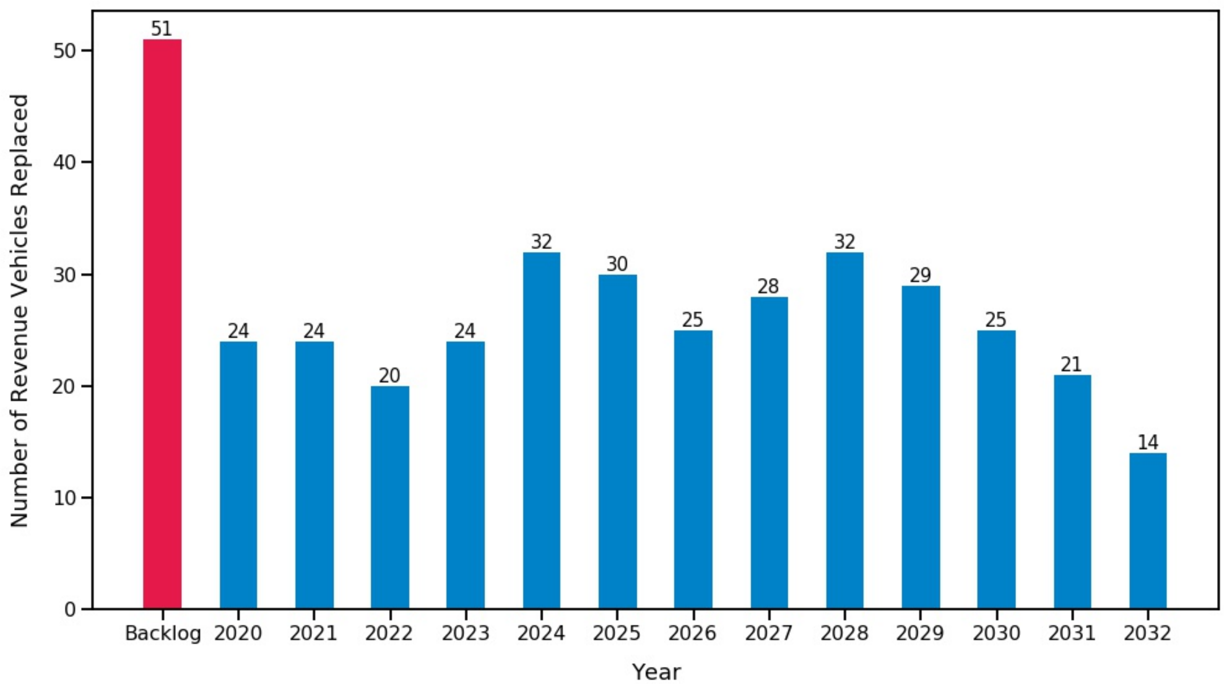


Figure 6.24 Backlog and Projected Replacement of Revenue Vehicles in North Dakota's Small Urban and Rural Transit Systems
Source: National Transit Database, 2017

The financial cost analysis tool was applied on North Dakota's small urban and rural dataset and estimated the yearly replacement costs. The plot in Figure 6.17 shows a backlog of $5.58 million to achieve a state of good repair for the vehicles, and the replacement cost in each year thereafter the backlog shows the funds needed for replacement to maintain the state of good repair.

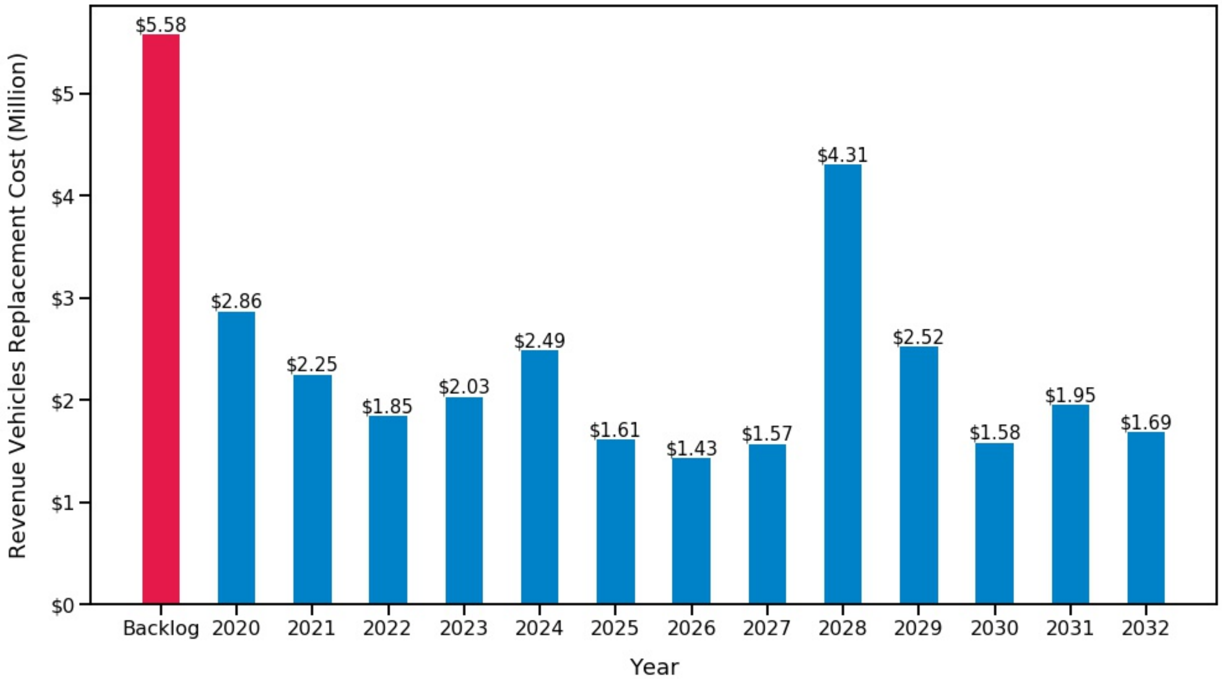


Figure 6.25 Backlog and Projected Replacement Costs for Revenue Vehicles in North Dakota's Small Urban and Rural Transit Systems

Source: 2017 Revenue Vehicle Inventory Data, the National Transit Database (NTD); U.S. Fleet Data, APTA 2018 Vehicle Database

The number of revenue vehicles indicated as backlog was further categorized by vehicle type, shown as a bar chart in Figure 6.18. It shows that cutaway vehicles indicate more backlog than any other vehicle types, and they require a fund of $1.81 million to eliminate backlog, as shown in Figure 6.19. Even though fewer buses indicate backlog, as shown in Figure 6.18, they require more funds ($3.02 million) than the backlog of other vehicle types to eliminate backlog, as shown in Figure 6.19.

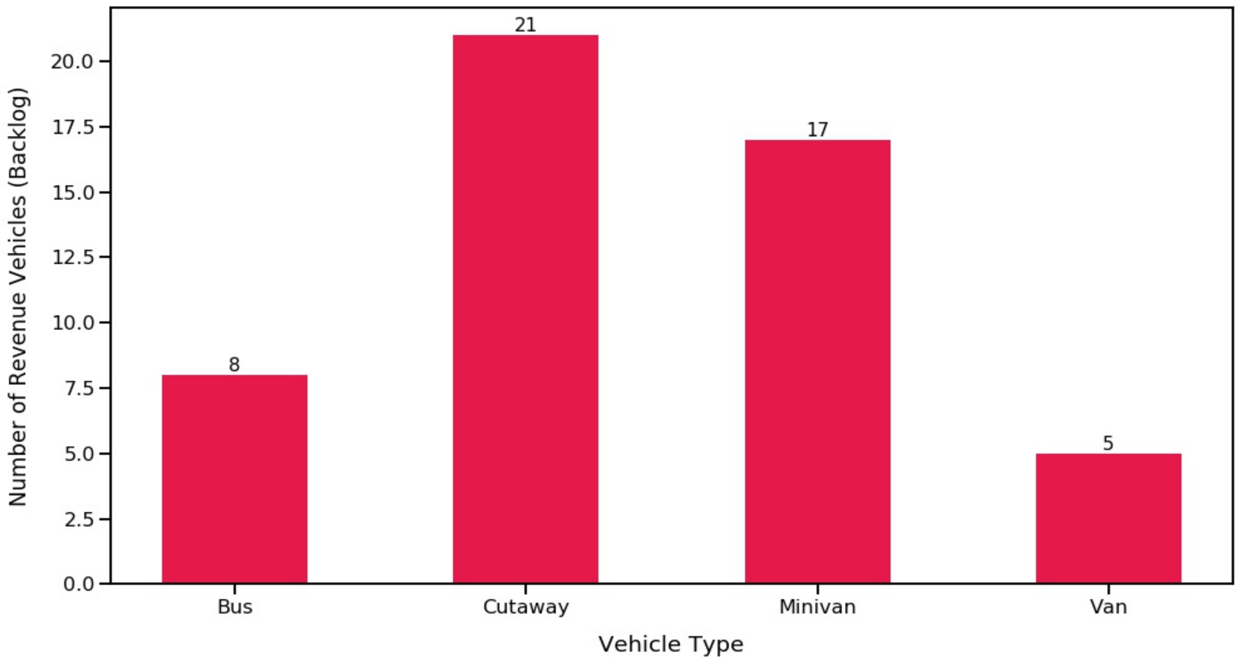


Figure 6.26 Backlog by Vehicle Type in North Dakota's Small Urban and Rural Transit Systems (NTD 2017)

Source: National Transit Database, 2017

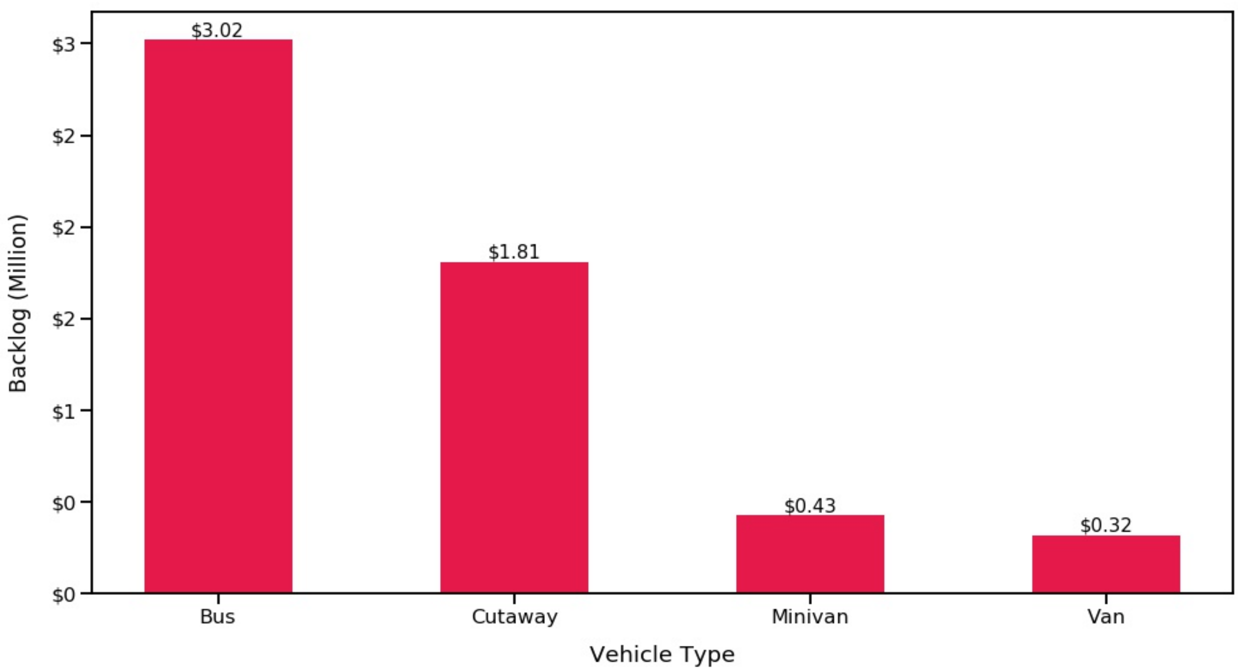


Figure 6.27 Fund Needed for Backlog by Vehicle Type in North Dakota's Small Urban and Rural Transit Systems (NTD 2017)

Source: 2017 Revenue Vehicle Inventory Data, the National Transit Database (NTD); U.S. Fleet Data, APTA 2018 Vehicle Database

The backlog for replacement costs were calculated by vehicle type in a way similar to the calculation of replacement costs for all revenue vehicles. The projected replacement costs were also calculated by vehicle type on a yearly basis. The backlog and replacement costs for North Dakota's small urban and rural transit systems by vehicle category are shown in Figure 6.20 to Figure 6.27. The cutaway category indicates more backlog (21 vehicles) than any other vehicle category; however, the bus category indicates more replacement cost for backlog ($3.02 million) than any other vehicle category. Again, the backlog and replacement costs for the nation's statewide small urban and rural transit systems by vehicle category are shown in Appendix A.

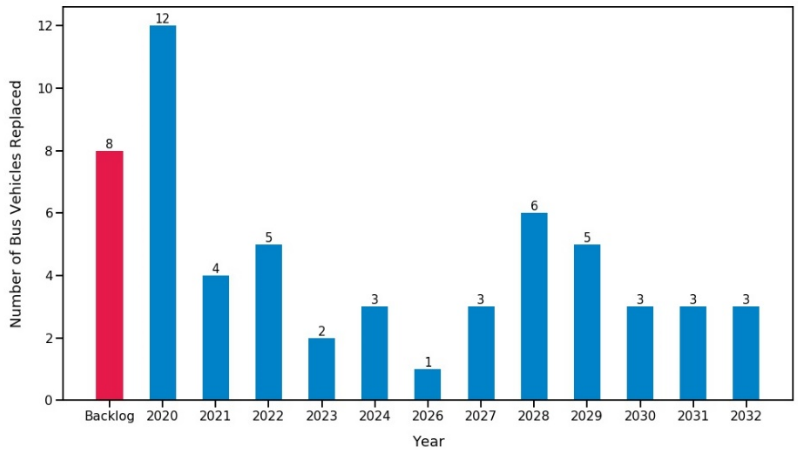


Figure 6.28 Backlog and Projected Replacement of Buses in North Dakota's Small Urban and Rural Transit Systems

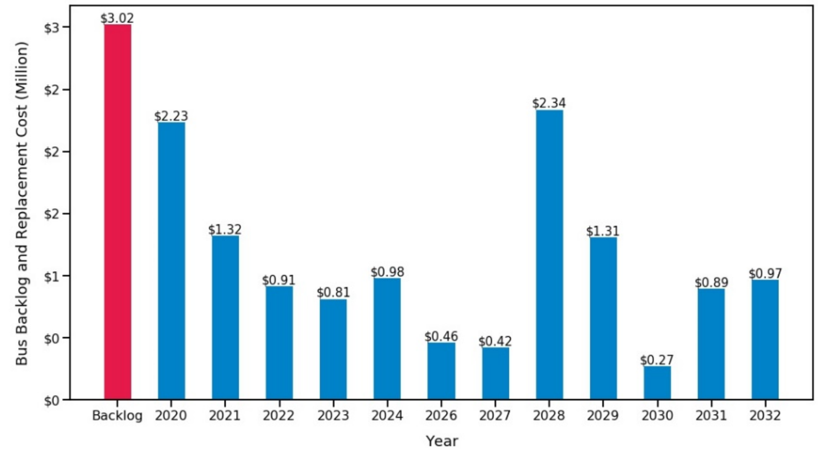


Figure 6.29 Backlog and Projected Replacement Cost for Buses in North Dakota's Small Urban and Rural Transit Systems

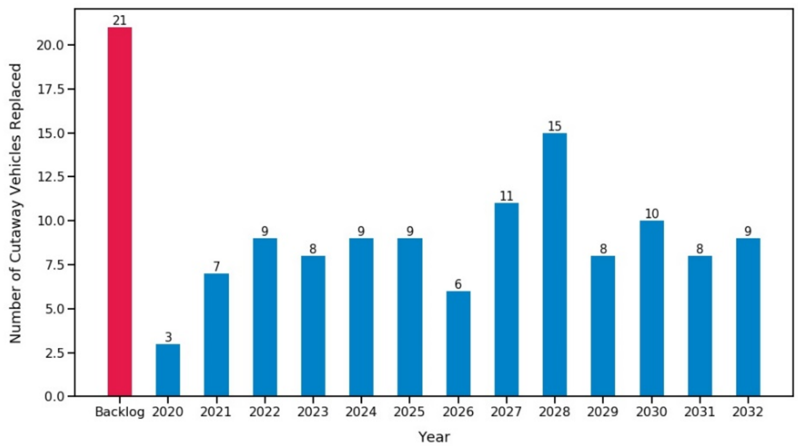


Figure 6.30 Backlog and Projected Replacement of Cutaways in North Dakota's Small Urban and Rural Transit Systems

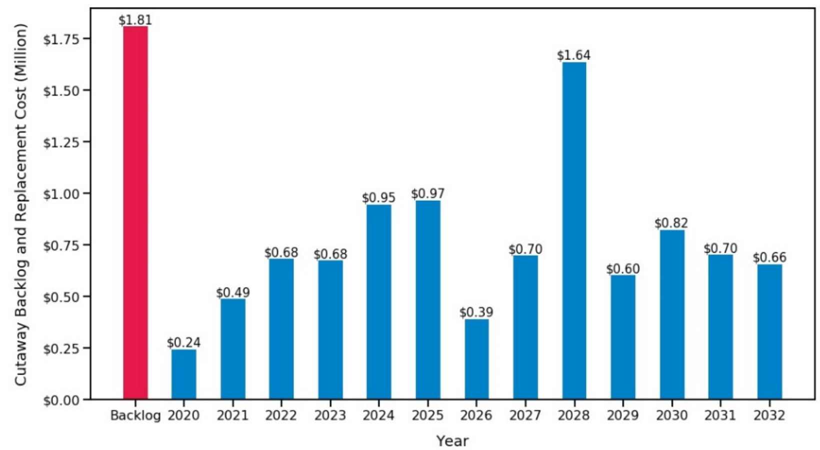


Figure 6.31 Backlog and Projected Replacement Cost for Cutaways in North Dakota's Small Urban and Rural Transit Systems

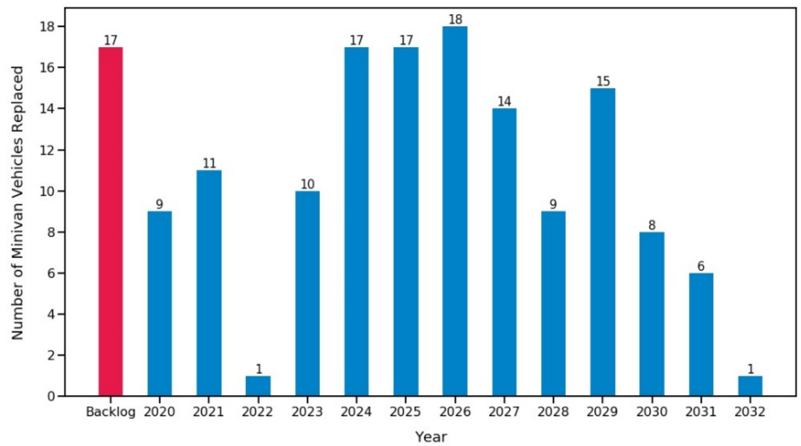


Figure 6.32 Backlog and Projected Replacement of Minivans in North Dakota's Small Urban and Rural Transit Systems

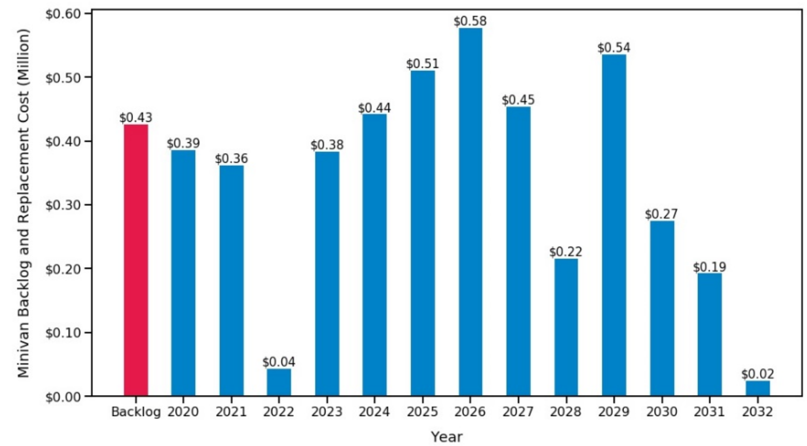


Figure 6.33 Backlog and Projected Replacement Cost for Minivans in North Dakota's Small Urban and Rural Transit Systems

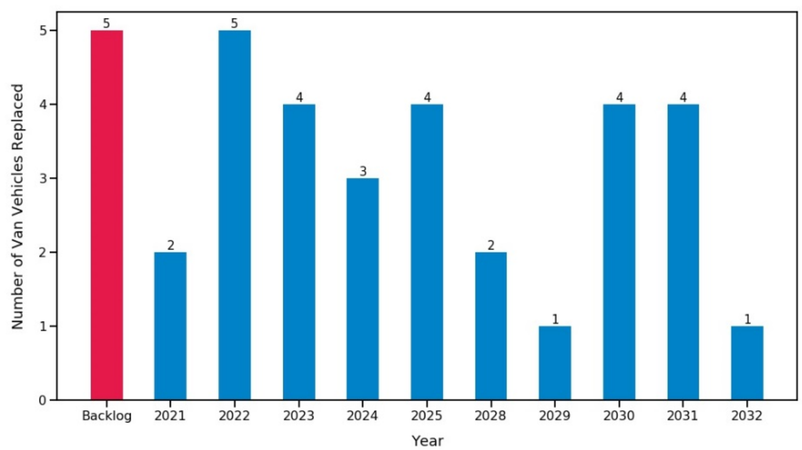


Figure 6.34 Backlog and Projected Replacement of Vans in North Dakota's Small Urban and Rural Transit Systems

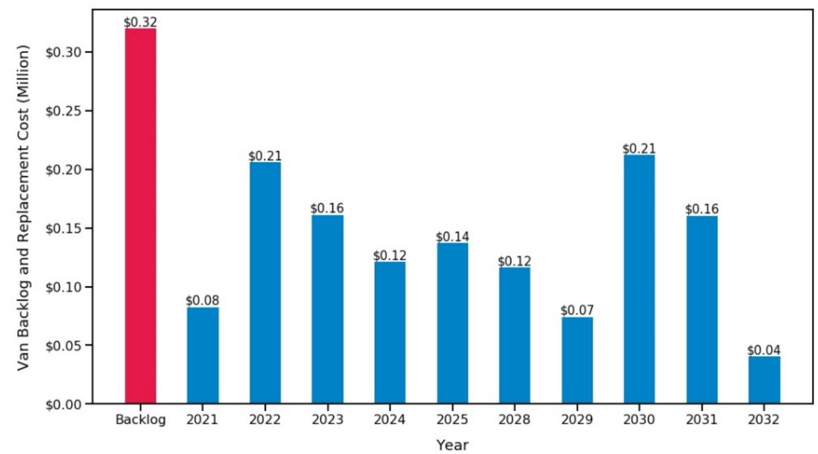


Figure 6.35 Backlog and Projected Replacement Cost for Vans in North Dakota's Small Urban and Rural Transit Systems

7. CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusion

The predictive model developed in this study provides a tool to conduct an analysis to predict the service life of small urban and rural transit agency revenue vehicles and evaluate the state of good repair for the agency rolling stocks. Because the machine learning predictive model learns from data, it gives accurate and realistic information regarding the predicted service life of revenue vehicles. Therefore, the predictive model developed in this research will allow transit agencies to utilize their revenue vehicles for maximum service and reduce overall long-term replacement costs to achieve and maintain a state of good repair. Furthermore, the FTA, US DOT, and researchers can use this tool to identify the overall condition of the nation's small urban and rural revenue vehicles.

A financial analytical tool developed as part of this research, used the predicted service life data from MLPM to calculate the backlog and project replacement costs for revenue vehicles for small urban and rural transit systems. The financial analytical tool may help rural and small urban transit agencies to facilitate their state of good repair analysis and guide DOTs and decision makers to determine investment, rehabilitation, and replacement needs. This tool will potentially tailor the replacement decision to a given system rather than solely rely on the FTA's useful life policies or industry-wide experiences. Better pinpointing the boundary between "rehab and replace" will potentially allow better-informed capital decisions and, perhaps, better modulate capital-funding needs with available funding.

The detailed reports produced by these tools will be helpful for decision makers to prioritize investment needs for rehabilitation and replacement of rural and small urban transit agencies. This includes elimination of investment backlog, replacement of transit assets reaching the end of their useful life, overall condition of their remaining service life, and projected yearly replacement costs. Therefore, the machine learning predictive model would be a more cost-effective approach to replacing revenue vehicles and achieving a state of good repair for small urban and rural transit systems. Finally, this research offers a more intuitive, softer criteria that managers and other stakeholders can use in formulating capital plans.

7.2 Limitation

The FTA releases NTD data each year from the previous year's most recent data on transit revenue vehicles. For example, in 2018, FTA released its 2017 NTD data. Therefore, reports produced with the deployment data may not match with the current data.

The model did not take manufacturer issues into consideration. The FTA does not track systematic problems with certain manufacturers into the NTD. In order to make this worth the time, an agency would need to be able to report its preventive maintenance issues into the NTD's revenue vehicle inventory database.

7.3 Recommendation

Even though the performance of the predictive tool is very good, it could be further improved by implementing some recommendations. Data are the most important part of developing any predictive model. Lack of good quality data or lack of sufficient data may not produce a good predictive model. Therefore, in the future, the authors recommend adding more retired data to the training set to train the model considering vehicles will be retiring in future years. Adding more training data to train the predictive model may improve the performance of the model in the future.

This model did not take factors not reported to NTD's revenue vehicle inventory data into consideration. The authors recommend that the FTA should take an initiative to add crucial columns in the revenue vehicles inventory database. For example, the FTA can instruct transit agencies to add "operating start date," "retired date," "cost of vehicles," and "agency zone" columns in the database.

The exploratory data analysis showed that some extreme values in the data were causing outliers in the data. For example, in some cases, the retired year was earlier than the manufacture year, which was creating negative service life of vehicles. The authors recommend that the FTA take actions to improve the quality of the revenue vehicle inventory data by correcting manufacture year in the NTD.

The above information will improve the predictive performance for the model. The authors suggest that further analysis of revenue vehicle inventory data should be an essential step to resolve issues in the state of good repair. Even though the performance of the predictive tool is good enough to predict the service life of an agency's revenue vehicles, the agency may not retire them because of the good condition of their vehicles. In addition, there could be some safety risks if vehicles are kept in service too long according to MLPM's predicted service life.

7.4 Further Research

As this is a relatively new field, the authors suggest that the research of machine learning algorithms on the state of good repair problem opens many opportunities for further research. It has enormous potential for further analysis, development of tools, and other areas that can be used by agencies to efficiently prioritize investments and keep rolling stocks in a state of good repair. Adding features as suggested earlier and selecting better features for the model may produce optimum results. Further improvement of this predictive model will help transit agencies predict the service life of their vehicles accurately so that the agency can plan and prioritize to replace or rehabilitate their assets accordingly.

8. REFERENCES

APTA. 2016. *A Guide to Public Transportation and Rail-Related Provisions: Fixing America's Surface Transportation Act (FAST ACT).* Washington, D.C.: American Public Transportation Association.

Aurlien, Gron. 2017. *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems.* O'Reilly Media, Inc.

Bowles, Michael. 2015. *Machine Learning in Python: Essential Techniques for Predictive Analysis.* Indianapolis, IN: John Wiley & Sons, Inc.

Brownlee, Jason. 2013. *A tour of machine learning algorithms: Machine Learning Mastery.*

Cambridge Systematics. 2005. *Analytical tools for Asset Management.* NCHRP Report: 545, Washington, D.C.: Transportation Research Board.

Cevallos, Fabian. 2016. *State of Good Repair Performance Measures: Assessing Asset Condition, Age, and Performance Data.* Lehman Center for Transportation Research (LCTR), University of South Florida, National Center for Transit Research.

Cevallos, Fabian. 2016. *State of Good Repair Performance Measures: Assessing Asset Condition, Age, and Performance Data.* Project No. 2117-9060-02-B, National Center for Transit Research.

Cohen, Harry, and Joseph Barr. 2012. *State of Good Repair: Prioritizing the Rehabilitation and Replacement of Existing Capital Assets and Evaluating the Implications for Transit.* TCRP Report 157, Transportation Research Board.

Downey, Allen B. 2014. *Think stats: exploratory data analysis.* O'Reilly Media, Inc.

FTA. 2017. *Asset Inventory Module Reporting Manual.* National Transit Database, Federal Transit Administration. https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/2017%20Asset%20Inventory%20Module%20Reporting%20Manual.pdf.

FTA. 2008. *Grant Management Requirements.* FTA C 5010.1D, U.S. Department of Transportation, Federal Transit Administration. https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/C_5010_1D_Finalpub.pdf.

FTA. 2010a. *National State of Good Repair Assessment.* Report to Congress, U.S. Department of Transportation, Washington, D.C.: Federal Transit Administration.

FTA. 2013. *Transit Economic Requirements Model.* User Training Overview, U.S. Department of Transportation, Washington, D.C.: Federal Transit Administration.

FTA. 2008. *Transit State of Good Repair: Beginning the Dialogue.* U.S. Department of Transportation, Washington, D.C: Federal Transit Administration.

Gagne, David John, Amy McGovern, Sue Ellen Haupt, and John K Williams. 2017. "Evaluation of statistical learning configurations for gridded solar irradiance forecasting." *Solar Energy 150* (Elsevier) 383-393.

Garreta, Raúl, and Guillermo Moncecchi. 2013. *Learning scikit-learn: Machine Learning in Python.* Birmingham: Packt Publishing Ltd.

Geitgey, Adam. 2017. "Machine Learning & AI Foundations: Value Estimations." *Lynda.com.* Lynda. https://www.lynda.com/Data-Science-tutorials/Machine-Learning-Essential-Training-Value-Estimations/548594-2.html.

iDOT. 2017. "Capital Asset State of Good Repair Report: Illinois Statewide Public Transportation Plan."

James, Aaron C. 2010. *Addressing the Challenge: Formulating a Definition of SGR for a Federal Program.* Presented at the 2nd State of Good Repair Roundtable, U.S. Dept. of Transportation, Federal Transit Administration.

Johnson, Nicholas E, Olga Ianiuk, Daniel Cazap, Linglan Liu, Daniel Starobin, Gregory Dobler, and Masoud Ghandehari. 2017. "Patterns of waste generation: A gradient boosting model for short-term waste prediction in New York City." *Waste Management* V 62: 3-11. doi:10.1016/j.wasman.2017.01.037.

Jordan, Michael, and Tom Mitchell. 2015. "Machine Learning: Trends, perspectives, and prospects." *Science* 349 (6245): 255-260. doi:10.1126/science.aaa8415.

Kumar, Ashish. 2016. *Learning Predictive Analytics with Python.* Edited by Nikhil Amey. Vol. First Edition. Birmingham: Packt Publishing Ltd.

Lauren, Isaac, and David Rose. 2012. "Transit Asset Management Manual - Overview." *4th State of Good Repair Roundtable.* Philadelphia, PA: Federal Transit Administration.

Laver, Richard, Donald Schneck, Douglas Skorupski, and Laura Cham. 2007. *Useful life of transit buses and vans.* No. FTA-VA-26-7229-07.1, U.S. Department of Transportation, Washington, D.C.: Federal Transit Administration.

Ma, Jinjin. 2012. "Parameter tuning using gaussian processes." *Ph.D. Dissertation.* University of Waikato. Hamilton. https://hdl.handle.net/10289/6497.

McKinney, Wes. 2017. *Python for data analysis: Data wrangling with Pandas, NumPy, and IPython.* 2nd. Sebastopol, CA: O'Reilly Media, Inc.

Meyer, Michael D., and Cambridge Systematics, Inc. 2007. *US Domestic Scan Program: Best Practices in Transportation Asset Management.* NCHRP Project 20-68, Federal Highway

Administration; National Cooperative Highway Research Program; The American Association of State Highway and Transportation Officials.

Mirjalili, Vahid, and Sebastian Raschka. 2017. *Python Machine Learning. Second Edition.* 2nd. Birmingham: Packt Publishing Ltd.

Mueller, John P., and Luca Massaron. 2015. *Python for Data Science for Dummies.* Hoboken, New Jersey: John Wiley & Sons, Inc.

Raschka, Sebastian. 2015. *Python machine learning.* First. Edited by Roshni Banerjee. Birmingham: Packt Publishing Ltd.

Rathore, Santosh Singh, and Sandeep Kumar. 2016. "A decision tree regression based approach for the number of software faults prediction." *ACM SIGSOFT Software Engineering Notes* v. 41 (no. 1): 1-6.

Robert, William, Virginia Reeder, Katherine Lawren, Harry Cohen, and Katherine O'Neil. 2014. *Guidance for Developing a Transit Asset Management Plan.* TCRP Report 172, Transportation Research Board, Washington, D.C.: Federal Transit Administration in cooperation with the Transit Development Corporation. doi:10.17226/22306.

Robert, William; Reeder, Virginia; Lauren, Katherine. 2014. *Guidance for Developing the State of Good Repair Prioritization Framework and Tools.* TCRP Project E-09A Report, Transit Cooperative Research Program, Arlington, MA: Spy Pond Partners, LLC.

US Congress. 2012. "Moving Ahead for Progress in the 21st Century (MAP-21)." 112th Congress Public Law, Washington, D.C., vol 141.

US GAO. 2013. *Transit Asset Management: Additional Research on Capital Investment Effects Could Help Transit Agencies Optimize Funding.* GAO-13-571, U.S. Government Accountability Office. www.gao.gov/products/gao-13 - 571.

Xu, Min, Pakorn Watanachaturaporn, Pramod K Varshney, and Manoj K Arora. 2005. "Decision tree regression for soft classification of remote sensing data." *Remote Sensing of Environment* 97 (3): 322-336.

Zarembski, Allan M. 2013. *Analysis of Transit 20 Year Capital Forecasts: FTA TERM Model vs. Transit Estimates.* Washington, D.C.: Transportation Research Board of the National Academies. http://onlinepubs.trb.org/onlinepubs/reports/TERM_March_2013Zarembski.pdf.

Zhang, Yanru, and Ali Haghani. 2015. "A gradient boosting method to improve travel time prediction." *Transportation Research Part C: Emerging Technologies* 308-324.

Zhao, Yongheng, and Yanxia Zhang. 2008. "Comparison of decision tree methods for finding active objects." *Advances in Space Research* 41 (no. 12): 1955-1959.

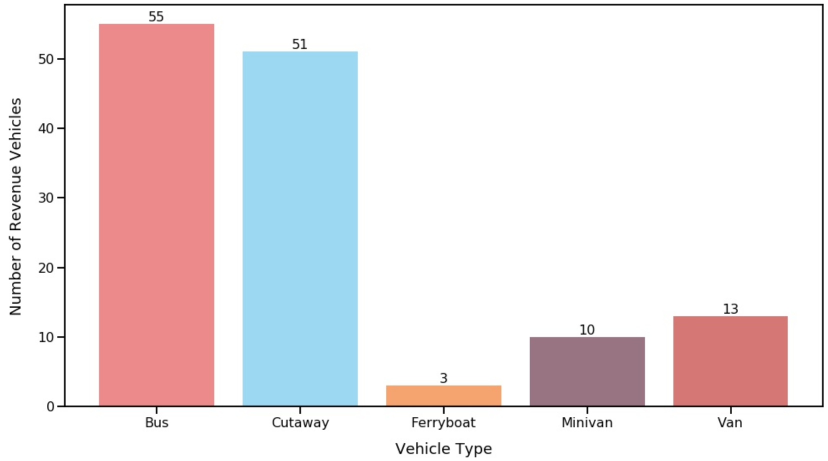
Zhou, Zhi-Hua. 2012. *Ensemble Methods: Foundations and Algorithms.* Edited by Ralf Herbrich and Thore Graepel. Boca Raton, FL: Chapman & Hall/CRC.

APPENDIX A

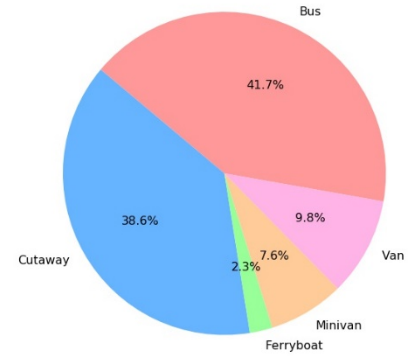
THE BACKLOG AND PREDICTED REPLACEMENT YEAR OF REVENUE VEHICLES IN SMALL URBAN AND RURAL TRANSIT SYSTEMS

The details report of backlog and replacement costs for Nation’s statewide small urban and rural transit systems by vehicle category are shown in the following figures:

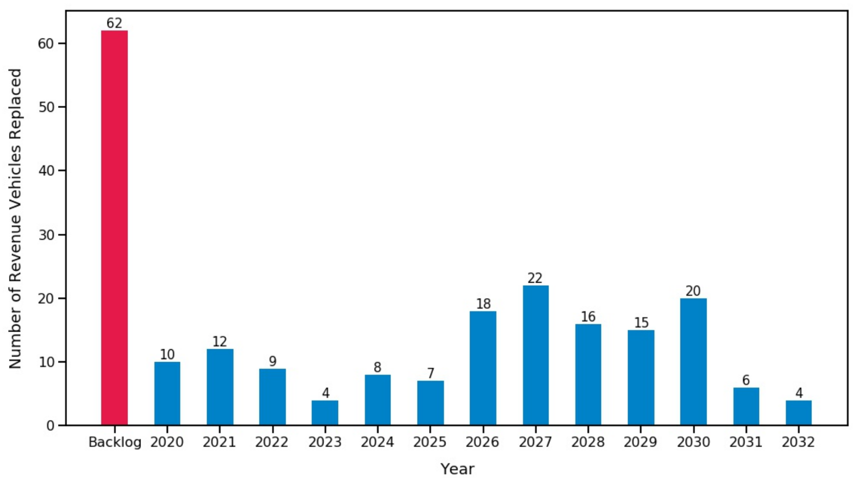
01 AK – Revenue Vehicles Information for Alaska's Small Urban and Rural Transit Systems (NTD 2017)



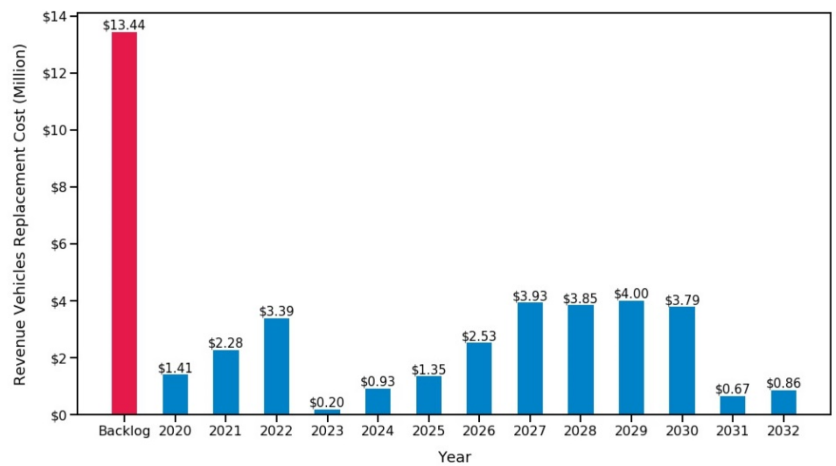
Number of Revenue Vehicles by Vehicle Type



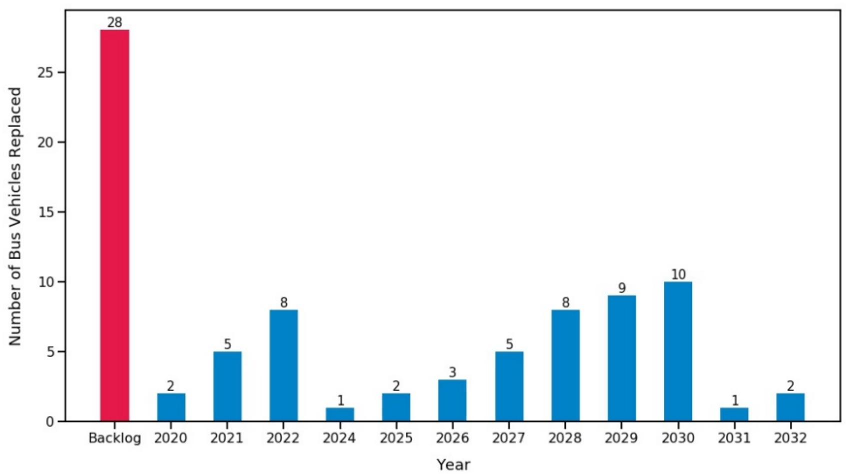
Percentage of Revenue Vehicles



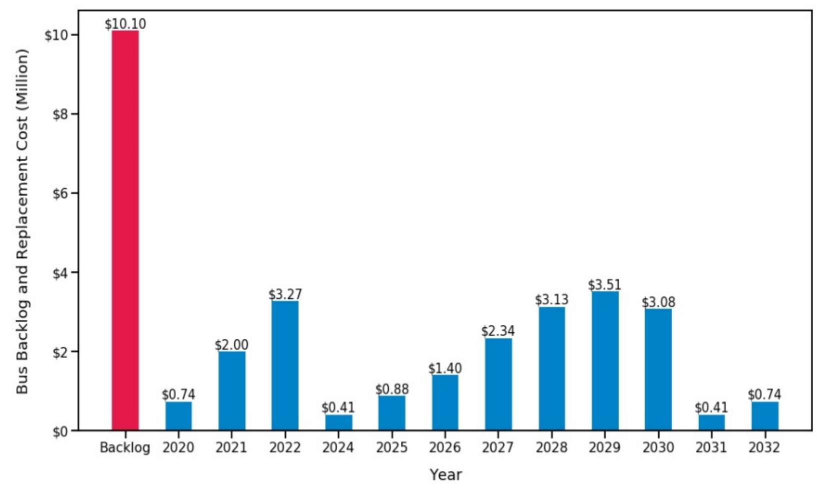
Backlog and Projected Replacement of Revenue Vehicles



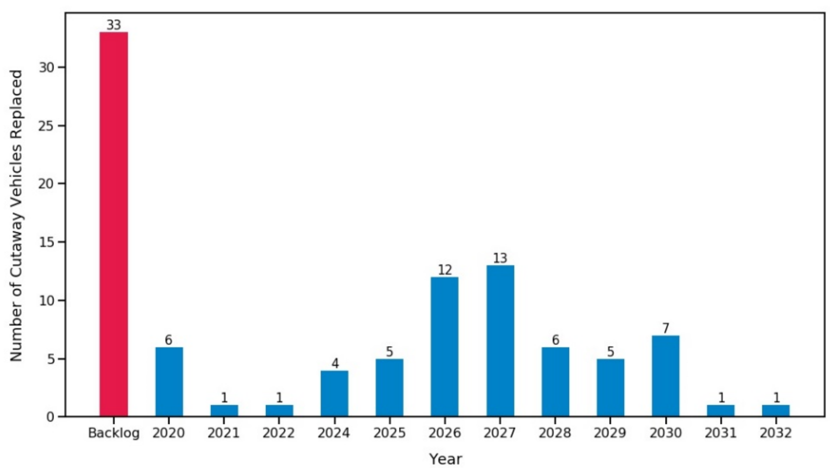
Backlog and Projected Replacement Costs for Revenue Vehicles



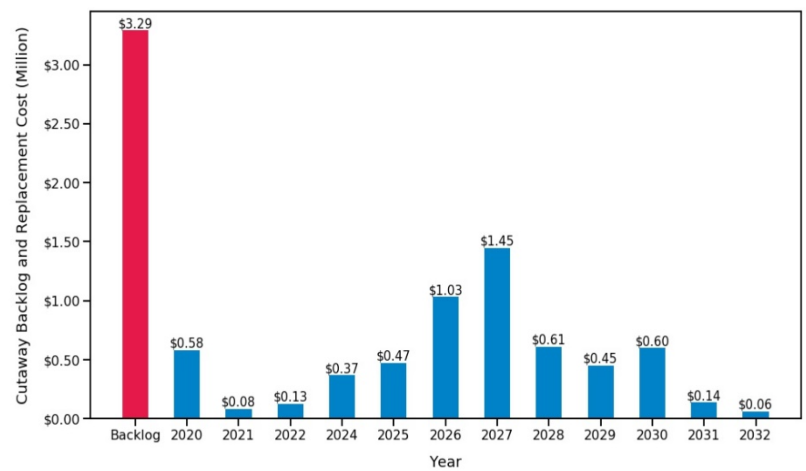
Backlog and Projected Replacement of Buses



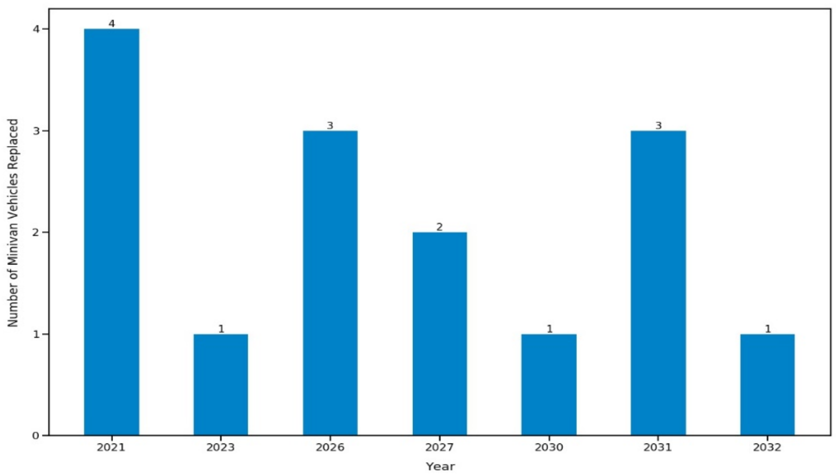
Backlog and Projected Replacement Cost for Buses

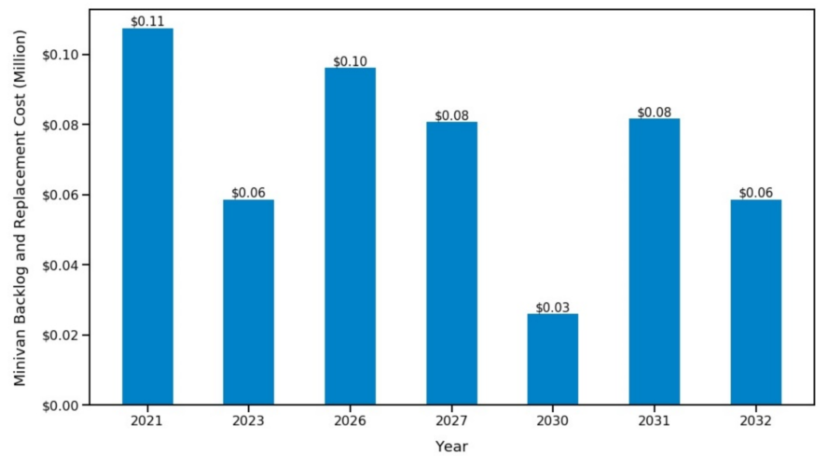


Backlog and Projected Replacement of Cutaways



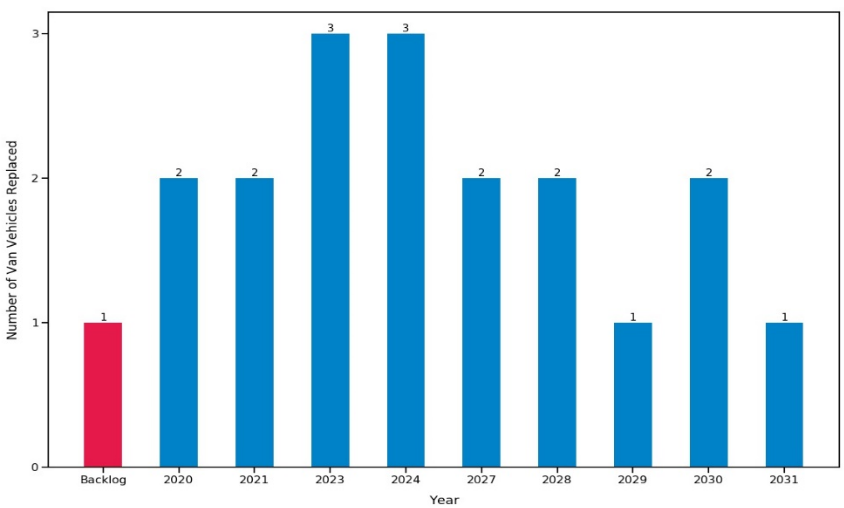
Backlog and Projected Replacement Cost for Cutaways

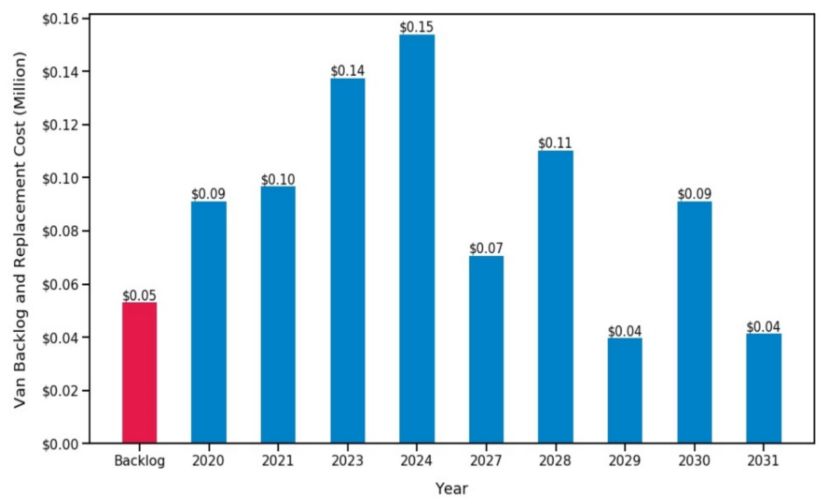




Backlog and Projected Replacement of Minivans

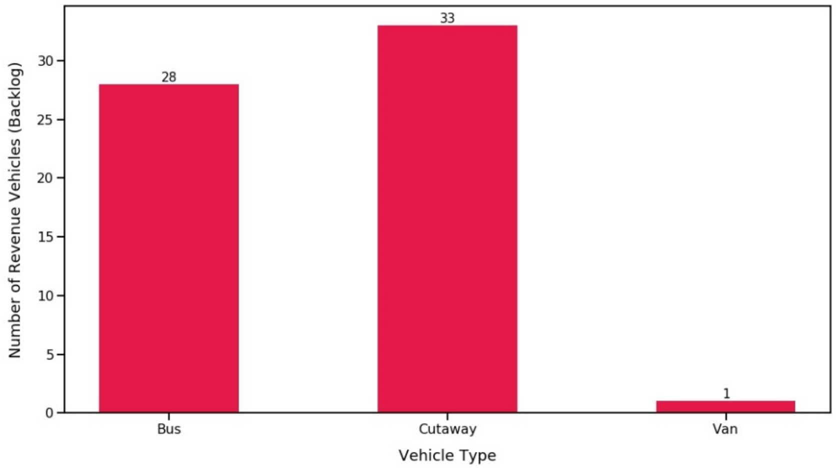
Backlog and Projected Replacement Cost for Minivans



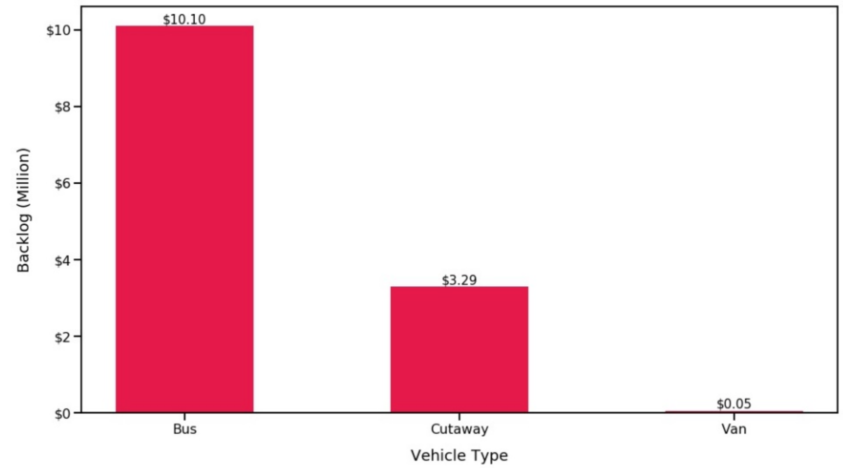


Backlog and Projected Replacement of Vans

Backlog and Projected Replacement Cost for Vans

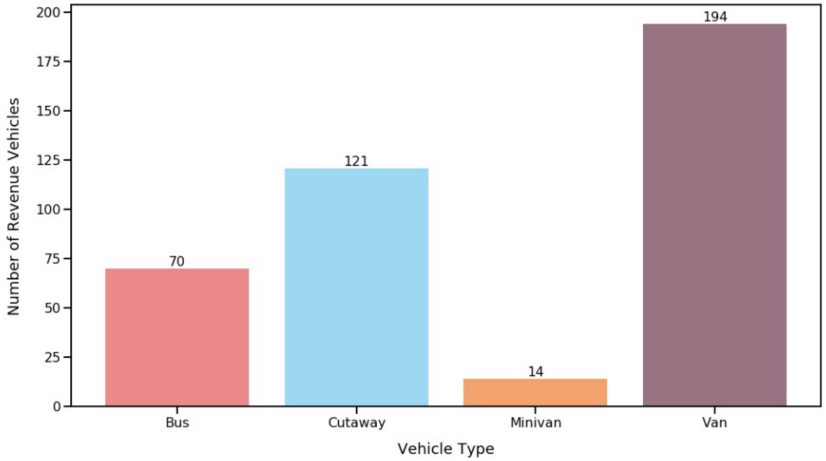


Backlog of the Revenue Vehicles by Vehicle Type

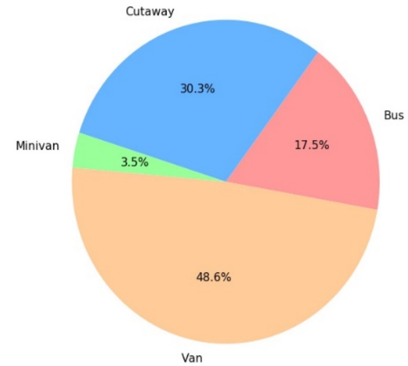


Funds Needed for Backlog by Vehicle Type

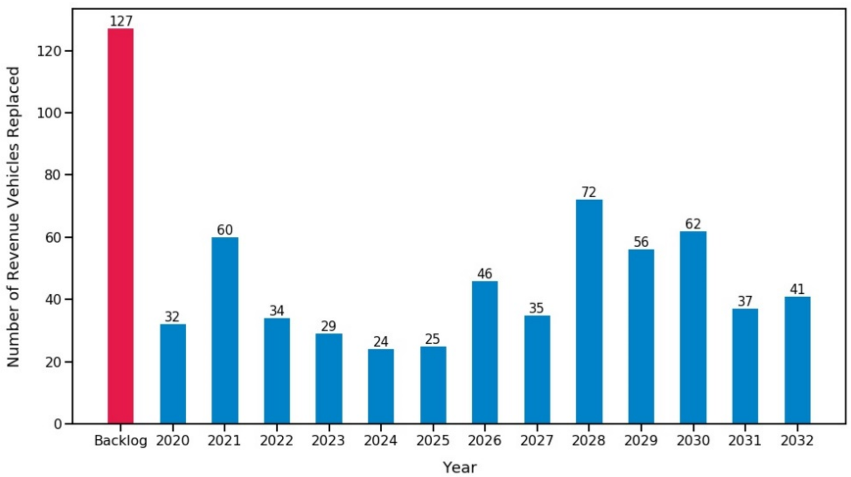
02 AL – Revenue Vehicles Information for Alabama’s Small Urban and Rural Transit Systems (NTD 2017)



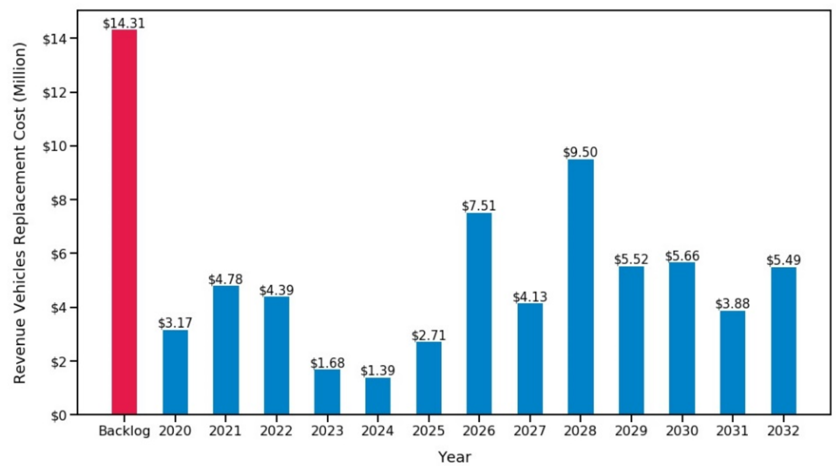
Number of Revenue Vehicles by Vehicle Type



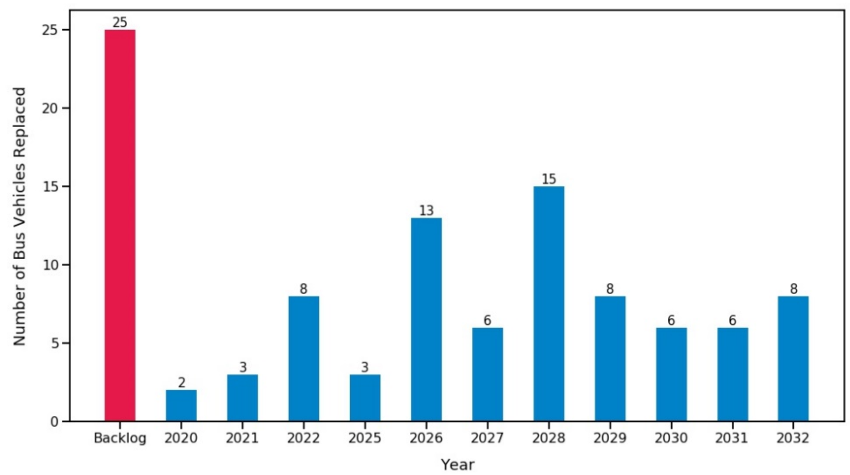
Percentage of Revenue Vehicles



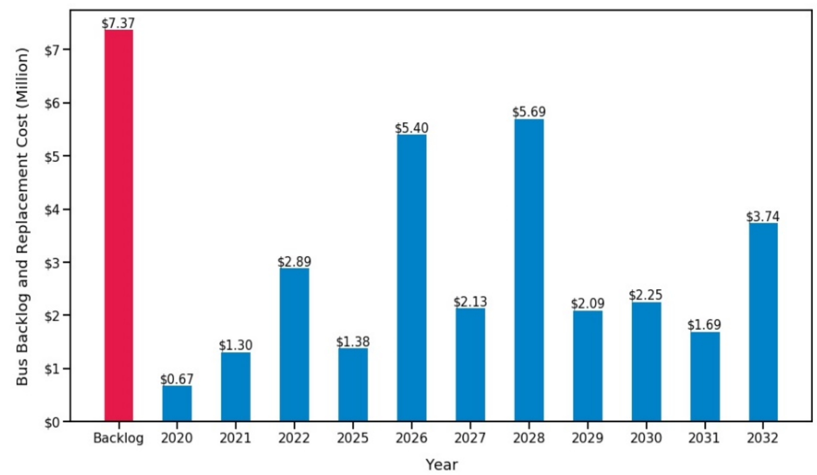
Backlog and Projected Replacement of Revenue Vehicles



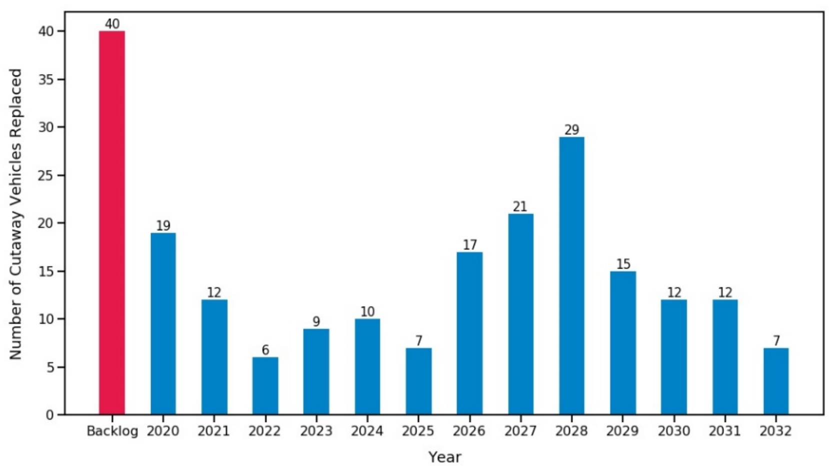
Backlog and Projected Replacement Costs for Revenue Vehicles



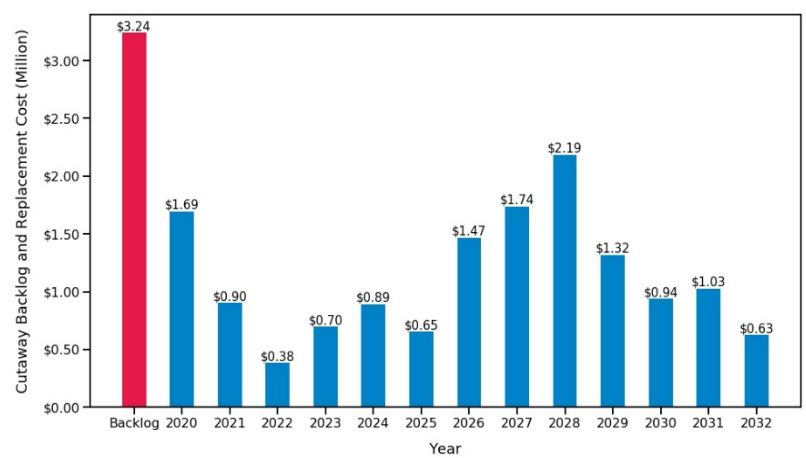
Backlog and Projected Replacement of Buses



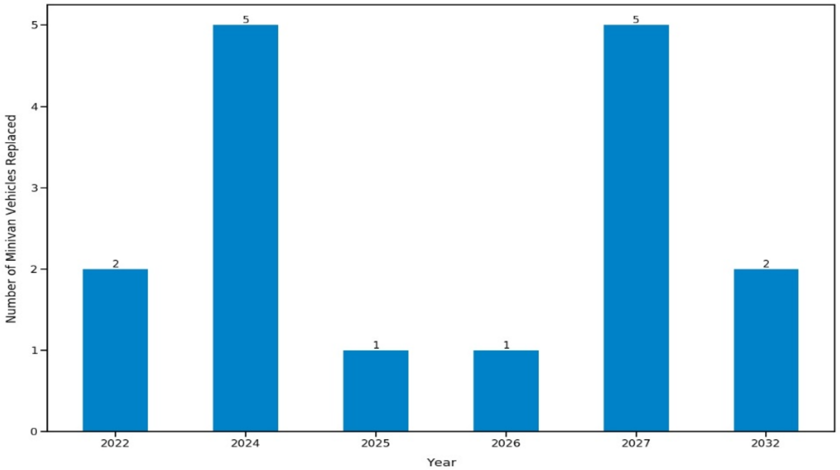
Backlog and Projected Replacement Cost for Buses



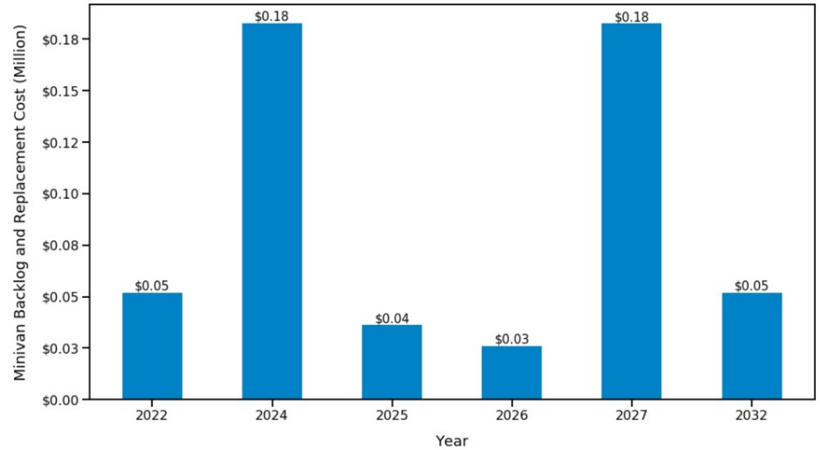
Backlog and Projected Replacement of Cutaways



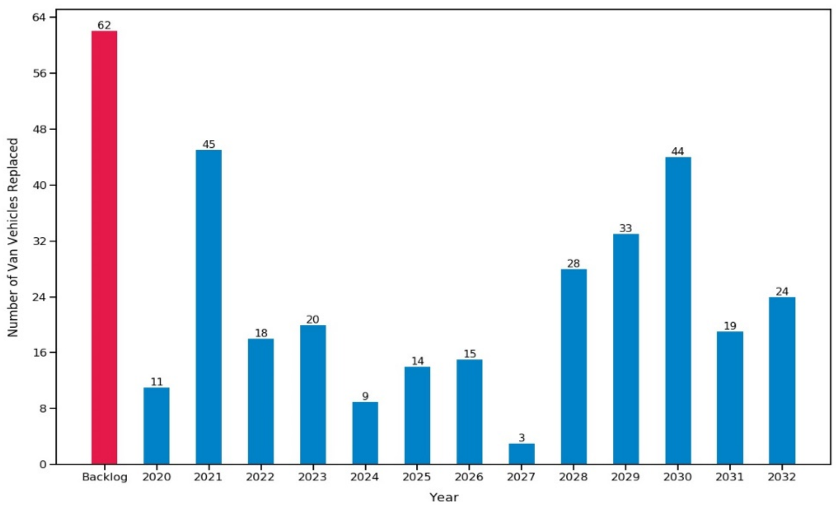
Backlog and Projected Replacement Cost for Cutaways



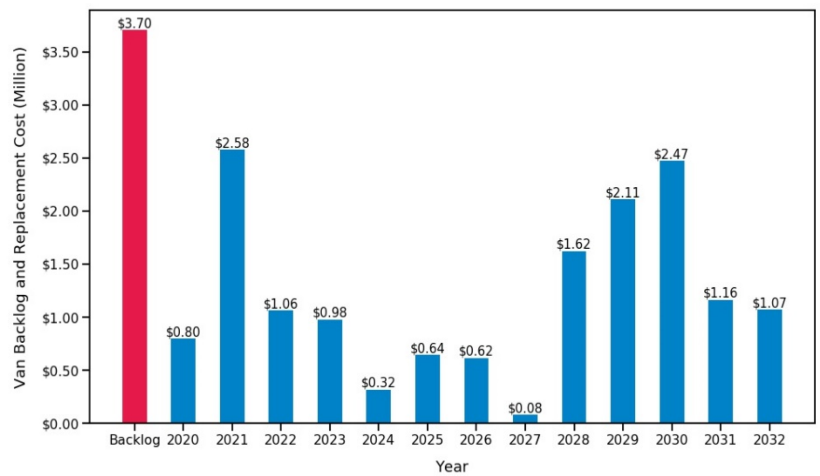
Backlog and Projected Replacement of Minivans



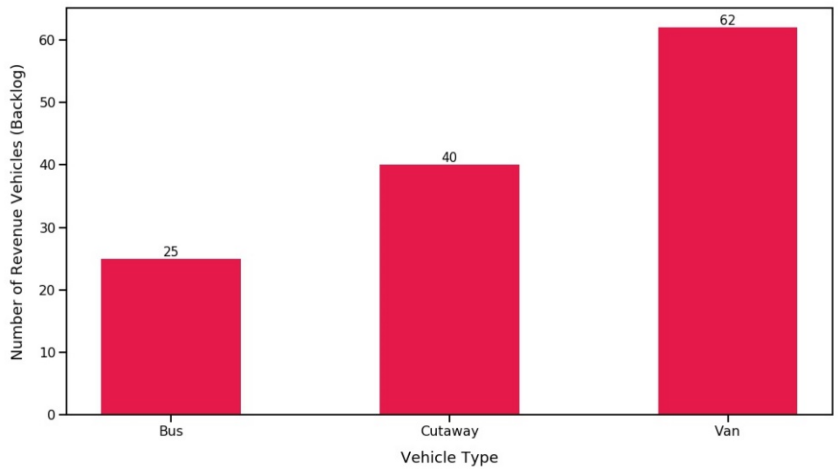
Backlog and Projected Replacement Cost for Minivans



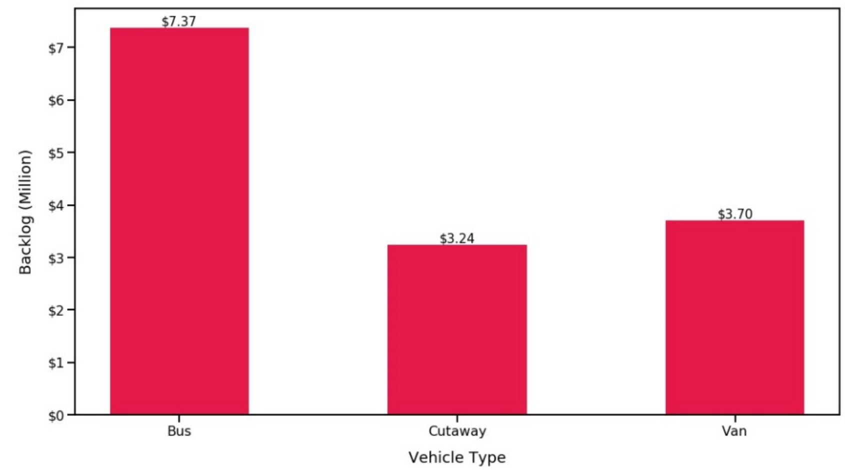
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

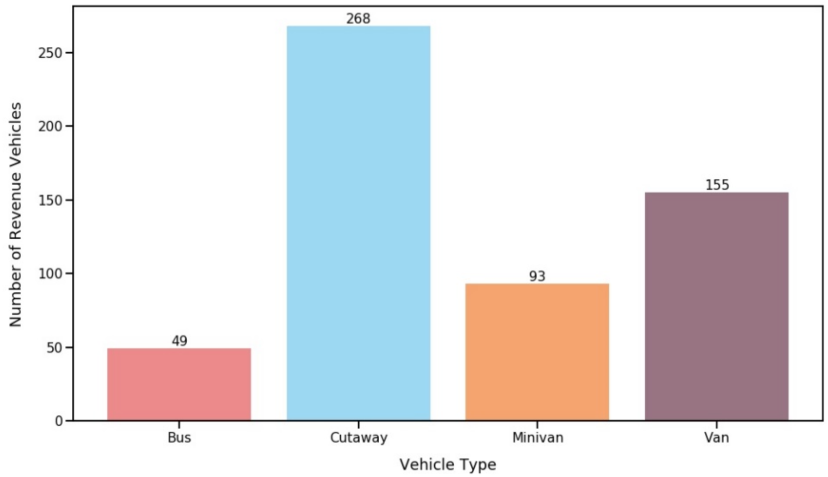


Backlog of the Revenue Vehicles by Vehicle Type

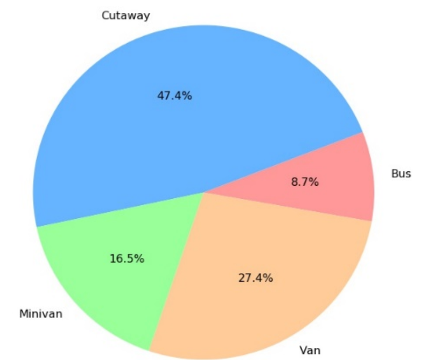


Funds Needed for Backlog by Vehicle Type

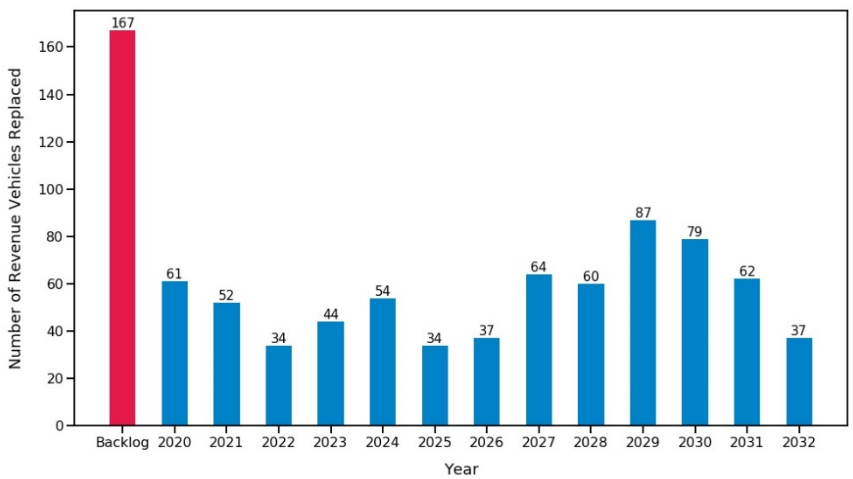
03 AR – Revenue Vehicles Information for Arkansas's Small Urban and Rural Transit Systems (NTD 2017)



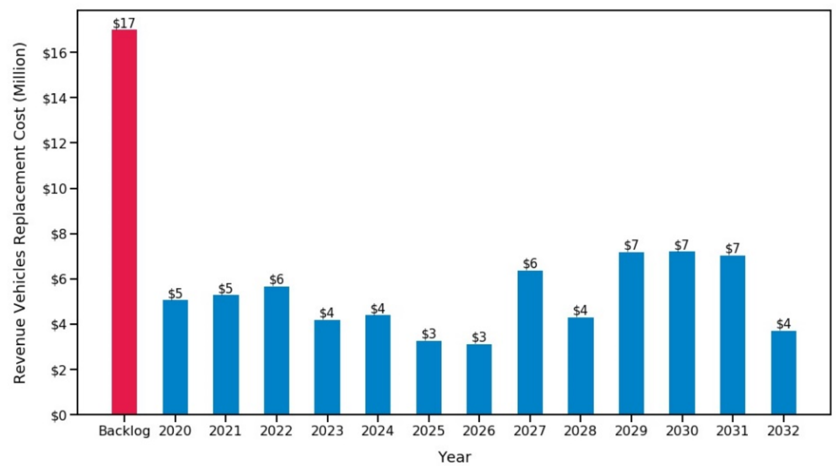
Number of Revenue Vehicles by Vehicle Type



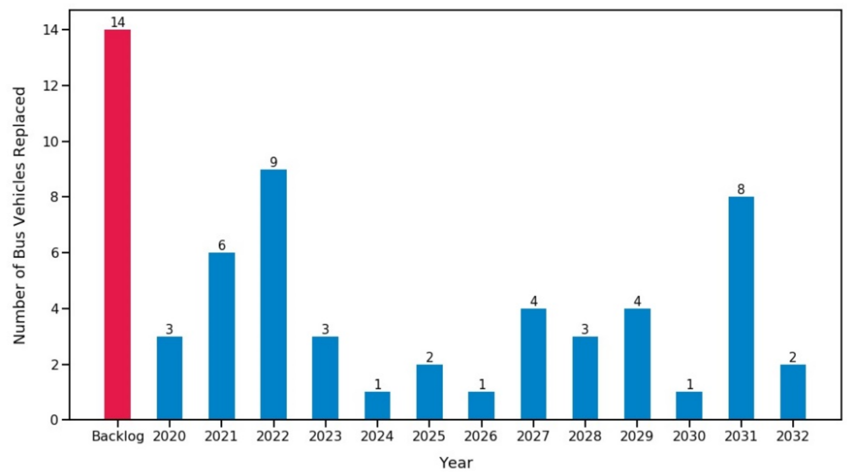
Percentage of Revenue Vehicles



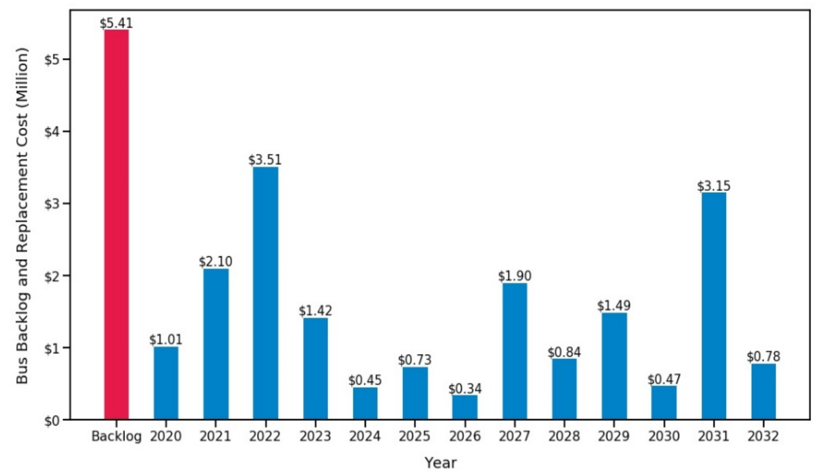
Backlog and Projected Replacement of Revenue Vehicles



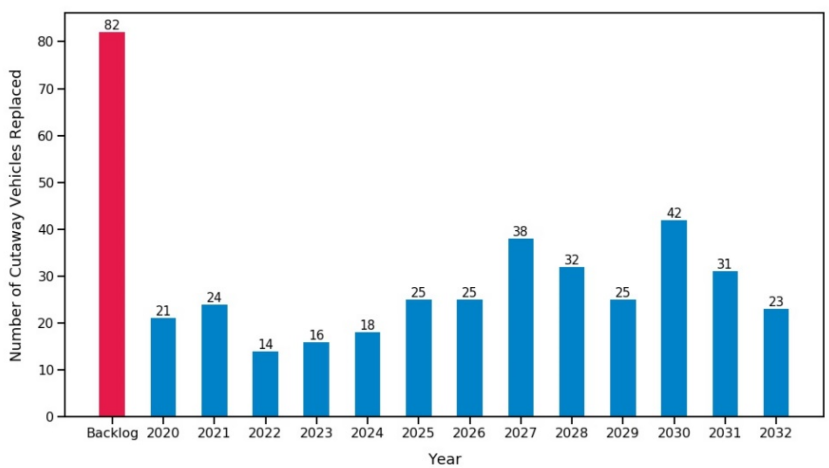
Backlog and Projected Replacement Costs for Revenue Vehicles



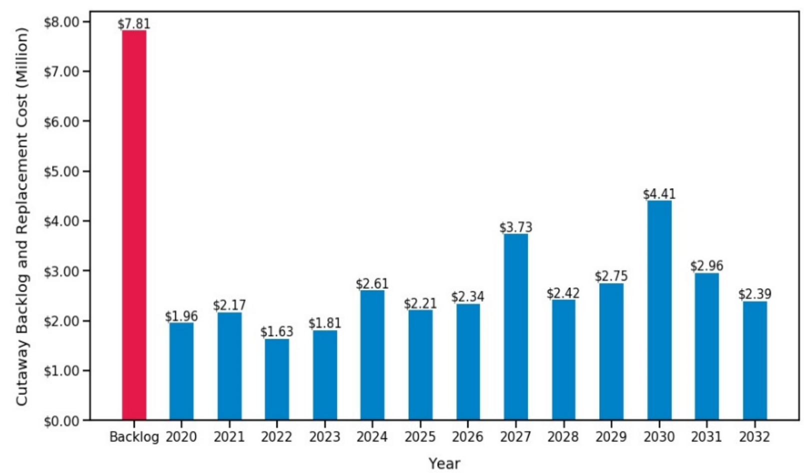
Backlog and Projected Replacement of Buses



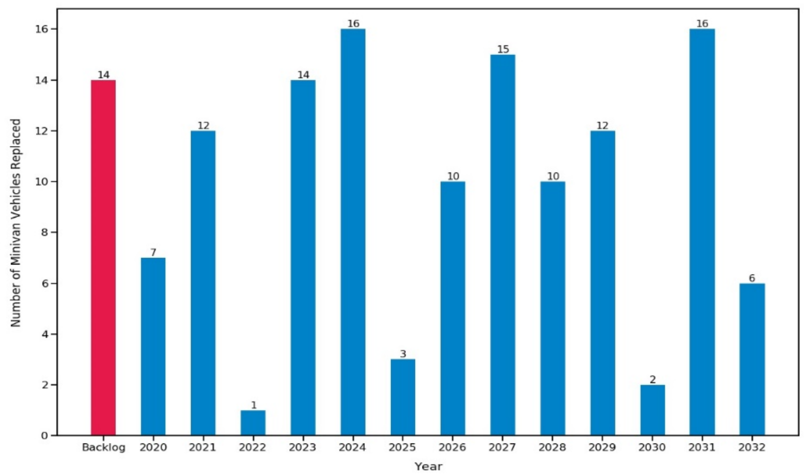
Backlog and Projected Replacement Cost for Buses



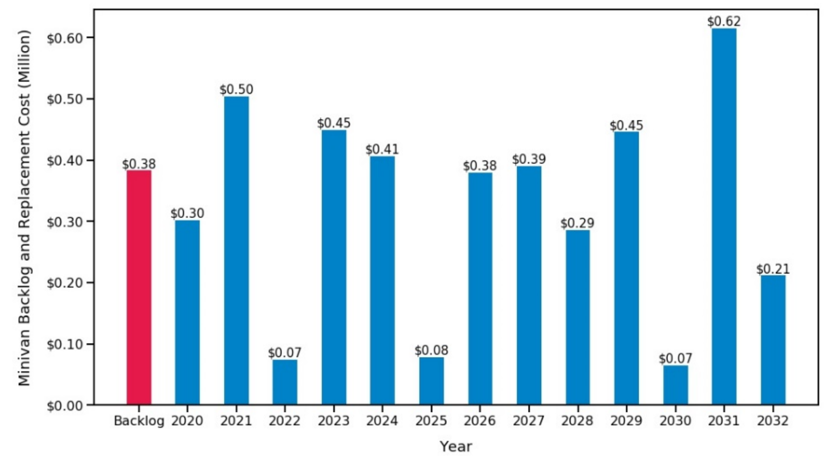
Backlog and Projected Replacement of Cutaways



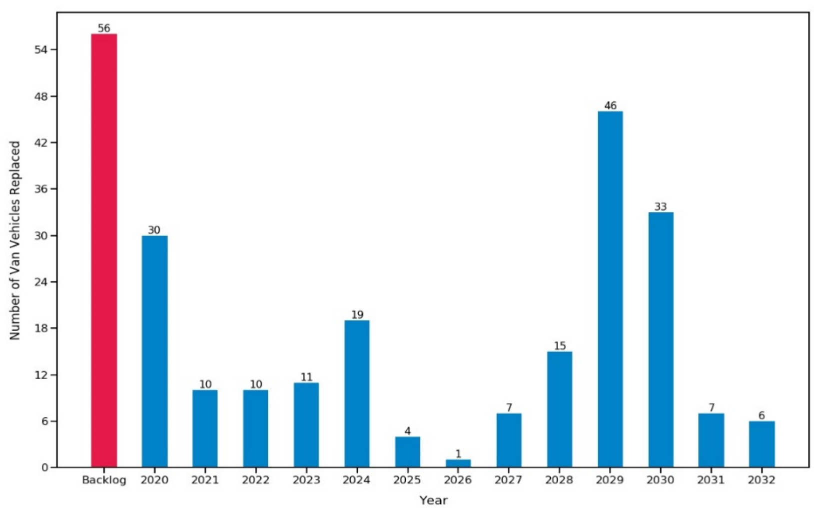
Backlog and Projected Replacement Cost for Cutaways



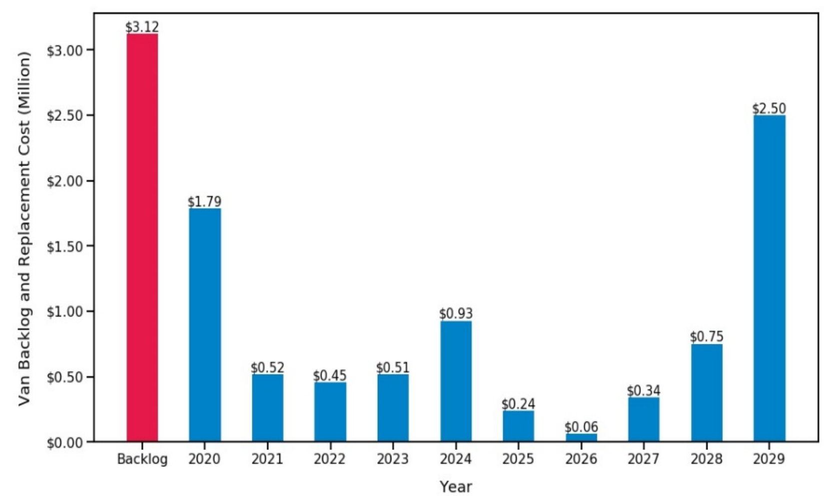
Backlog and Projected Replacement of Minivans



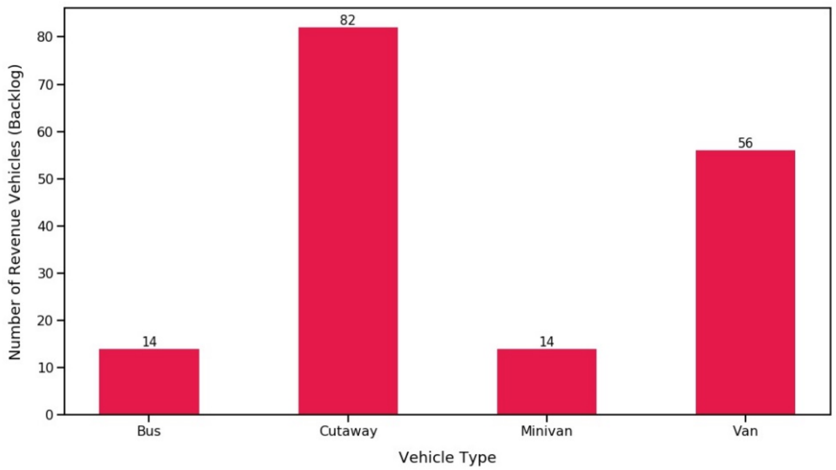
Backlog and Projected Replacement Cost for Minivans



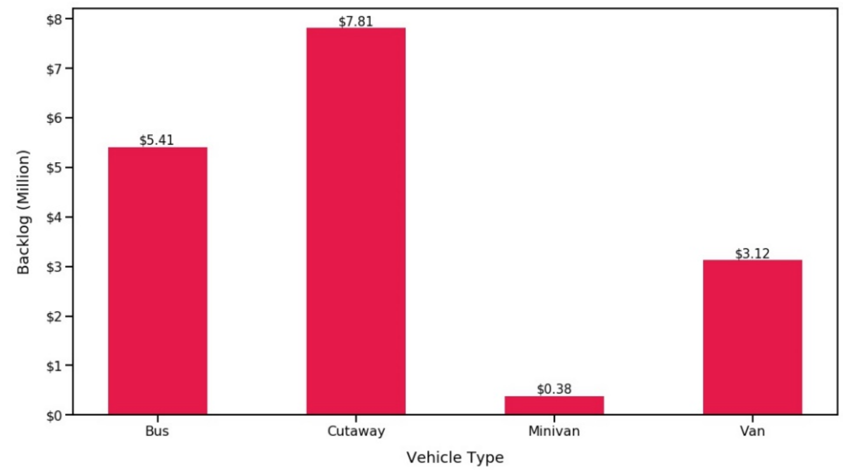
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

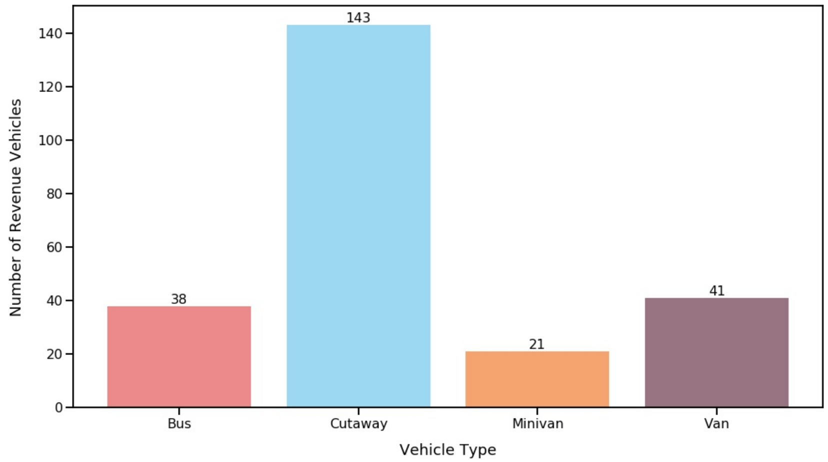


Backlog of the Revenue Vehicles by Vehicle Type

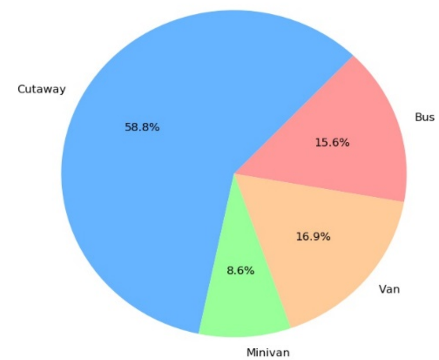


Funds Needed for Backlog by Vehicle Type

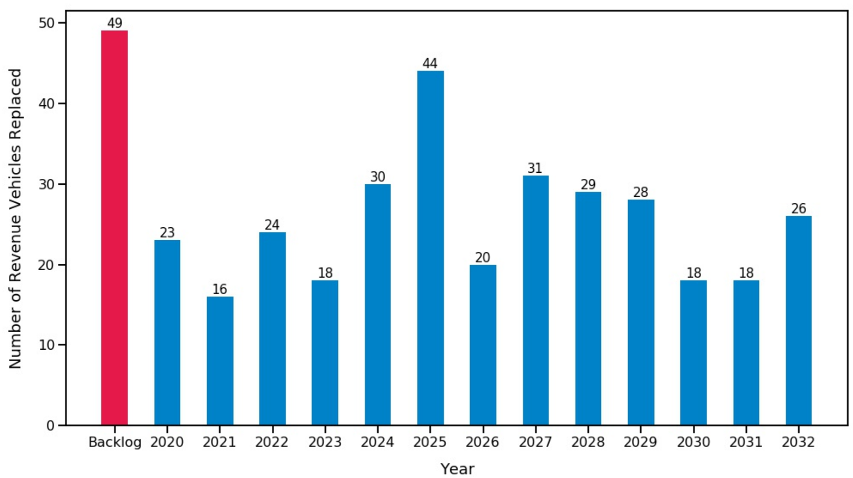
04 AZ – Revenue Vehicles Information for Arizona's Small Urban and Rural Transit Systems (NTD 2017)



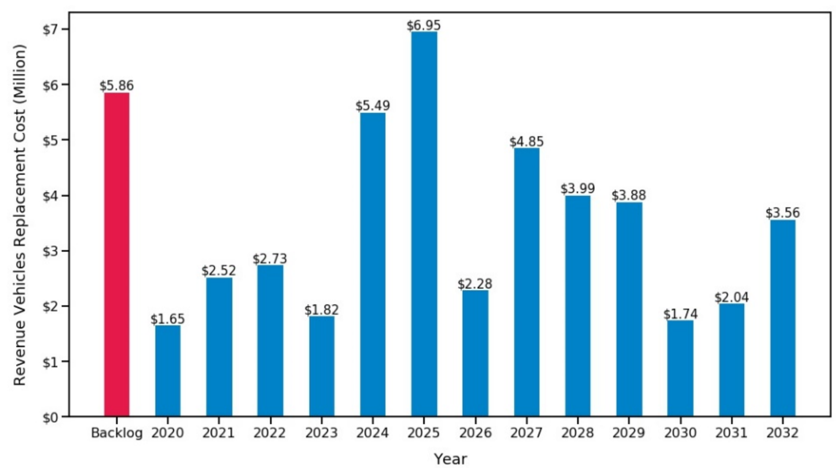
Number of Revenue Vehicles by Vehicle Type



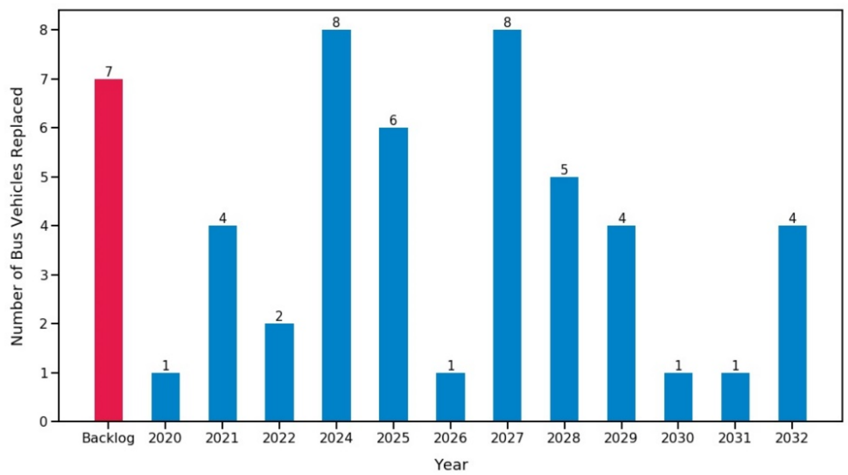
Percentage of Revenue Vehicles



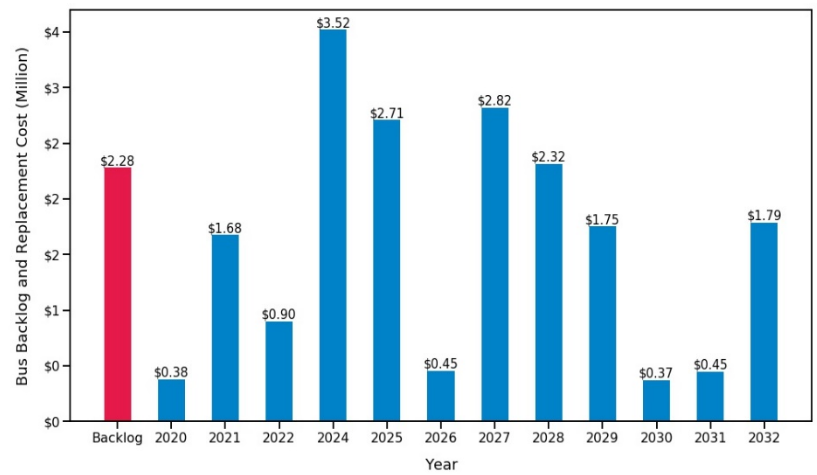
Backlog and Projected Replacement of Revenue Vehicles



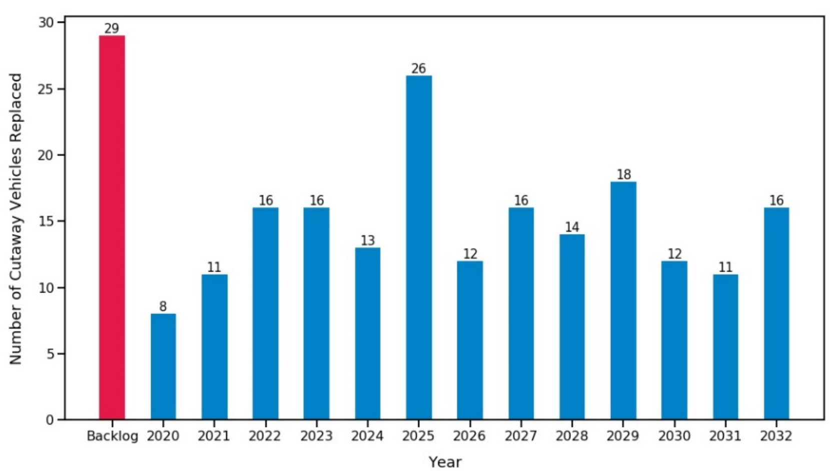
Backlog and Projected Replacement Costs for Revenue Vehicles



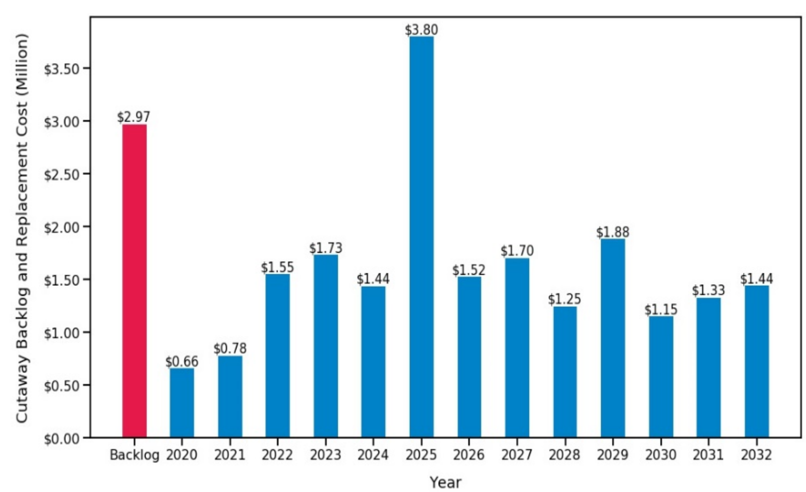
Backlog and Projected Replacement of Buses



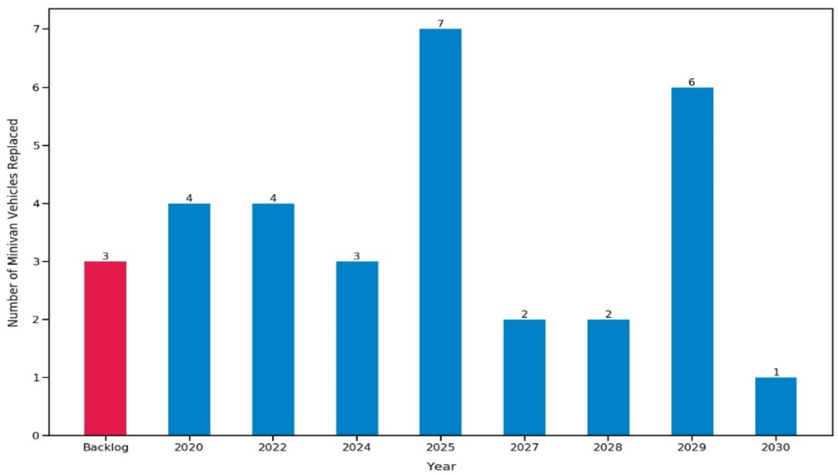
Backlog and Projected Replacement Cost for Buses



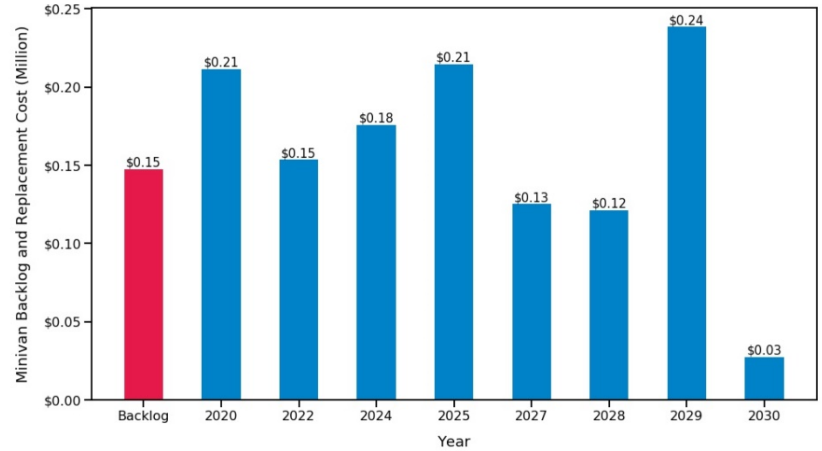
Backlog and Projected Replacement of Cutaways



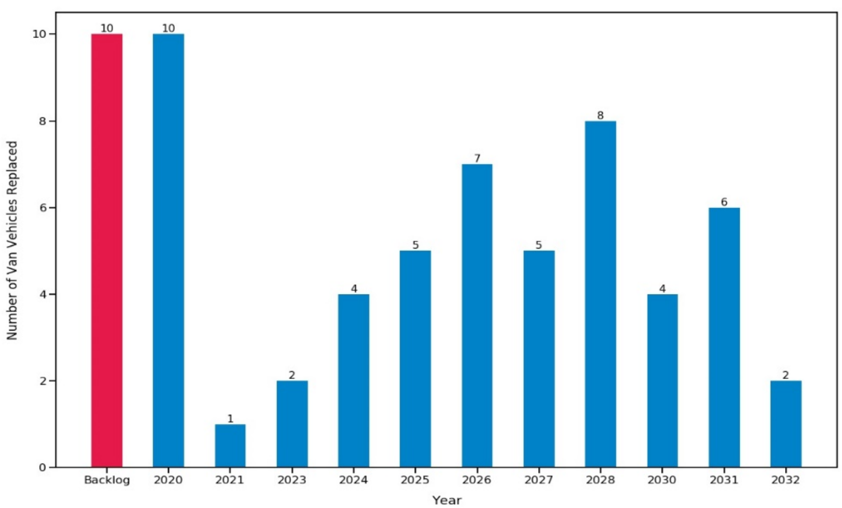
Backlog and Projected Replacement Cost for Cutaways



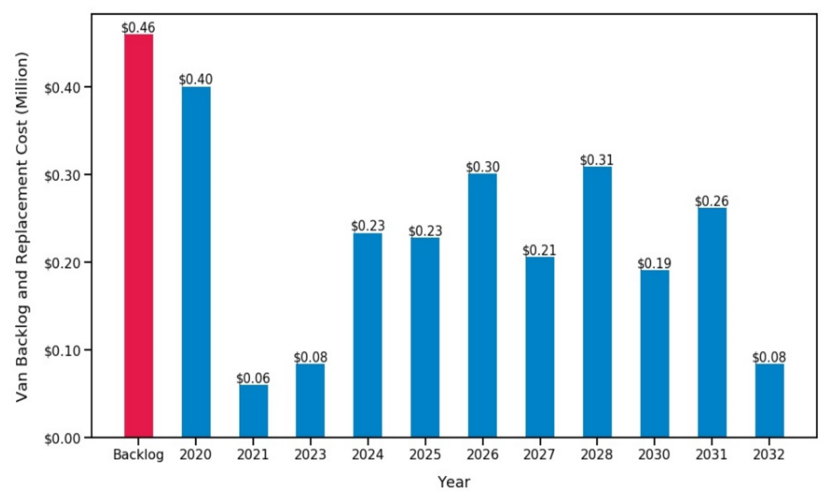
Backlog and Projected Replacement of Minivans



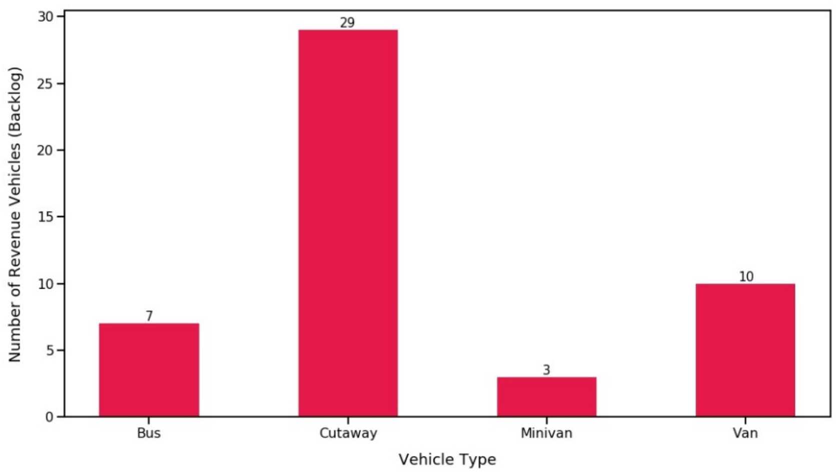
Backlog and Projected Replacement Cost for Minivans



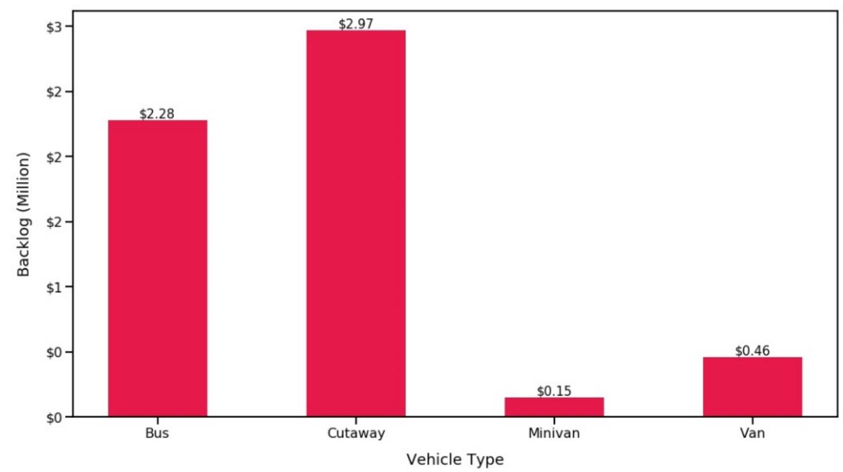
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

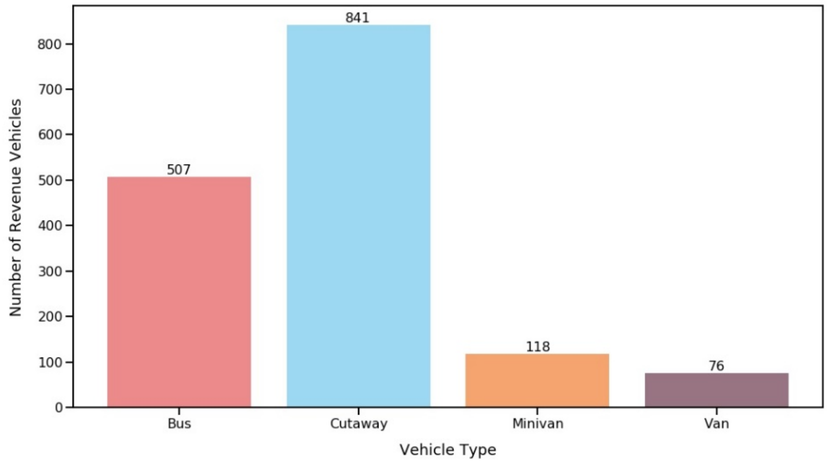


Backlog of the Revenue Vehicles by Vehicle Type

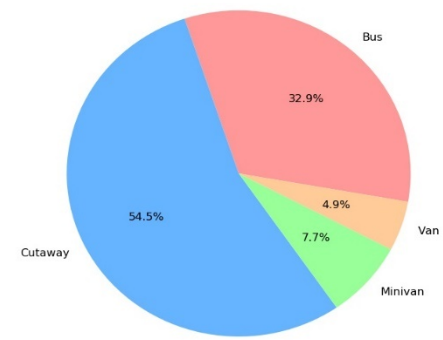


Funds Needed for Backlog by Vehicle Type

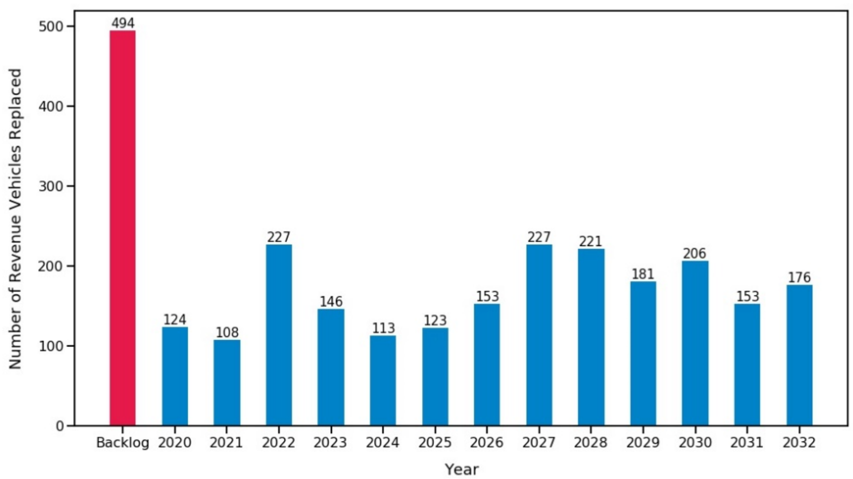
05 CA – Revenue Vehicles Information for California's Small Urban and Rural Transit Systems (NTD 2017)



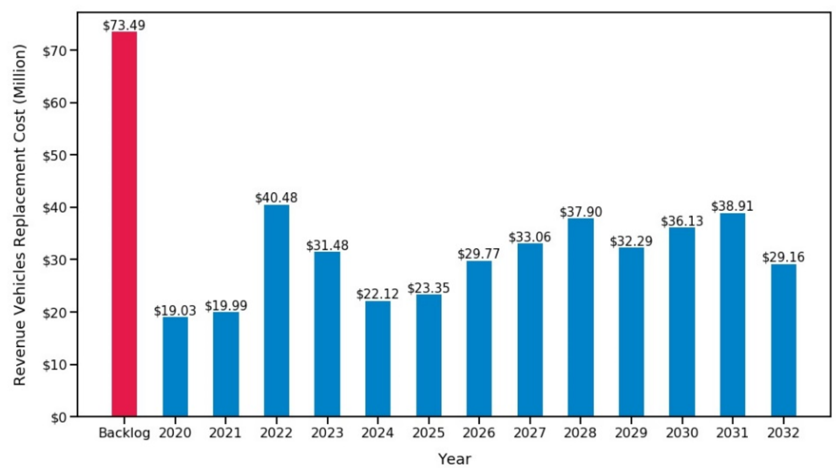
Number of Revenue Vehicles by Vehicle Type



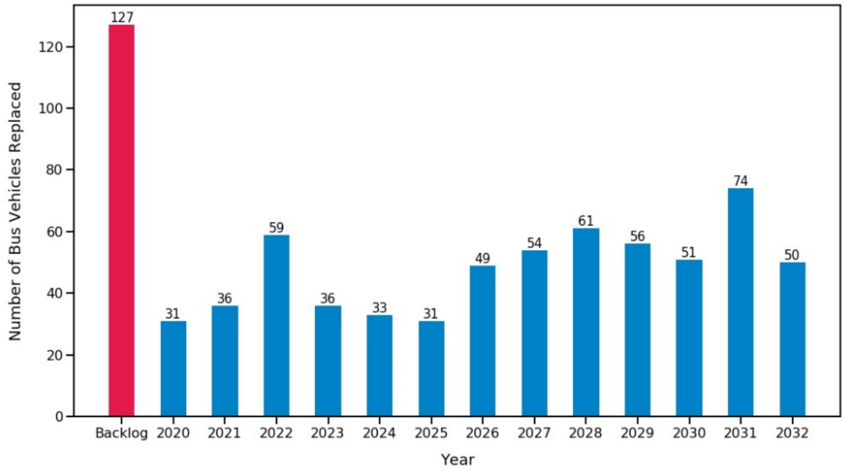
Percentage of Revenue Vehicles



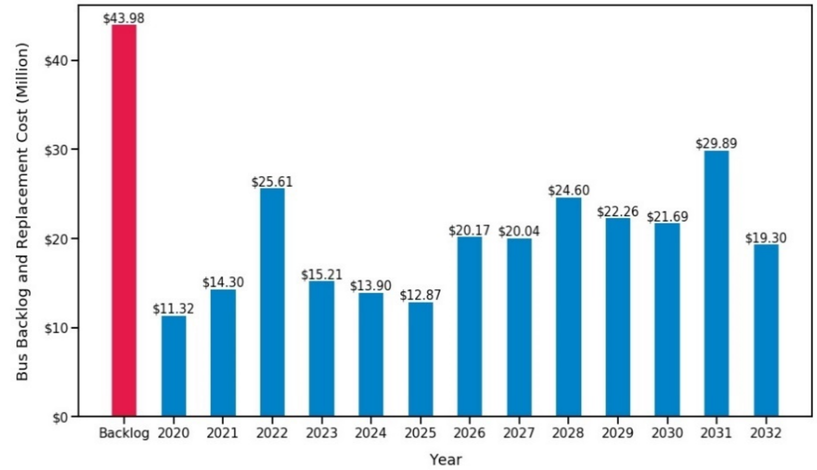
Backlog and Projected Replacement of Revenue Vehicles



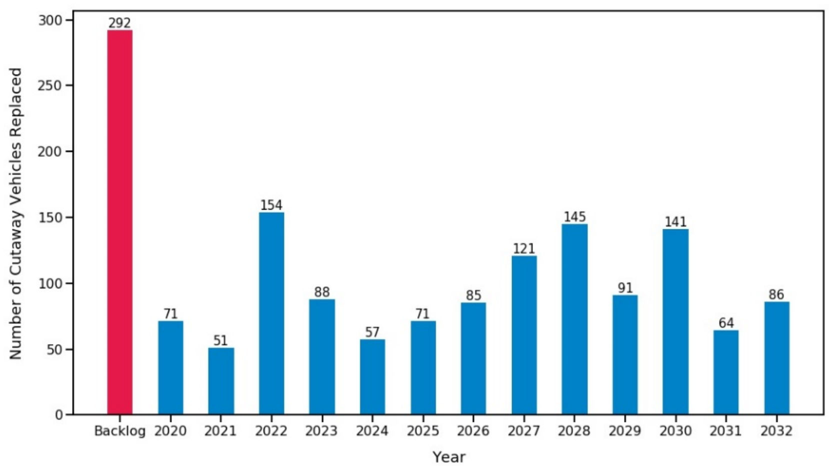
Backlog and Projected Replacement Costs for Revenue Vehicles



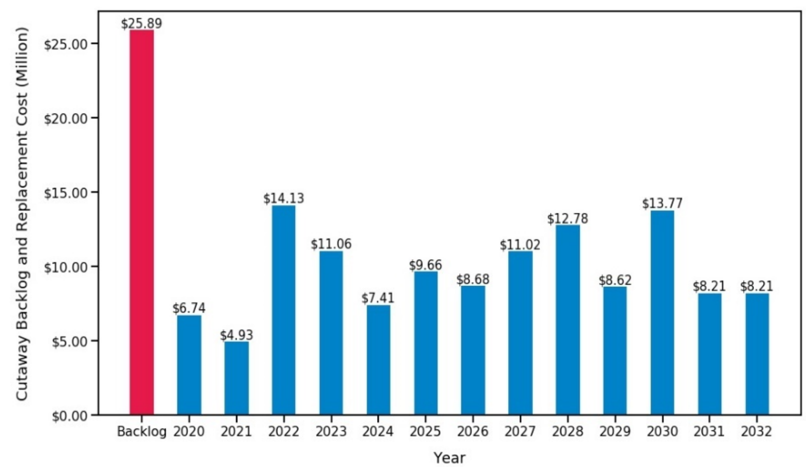
Backlog and Projected Replacement of Buses



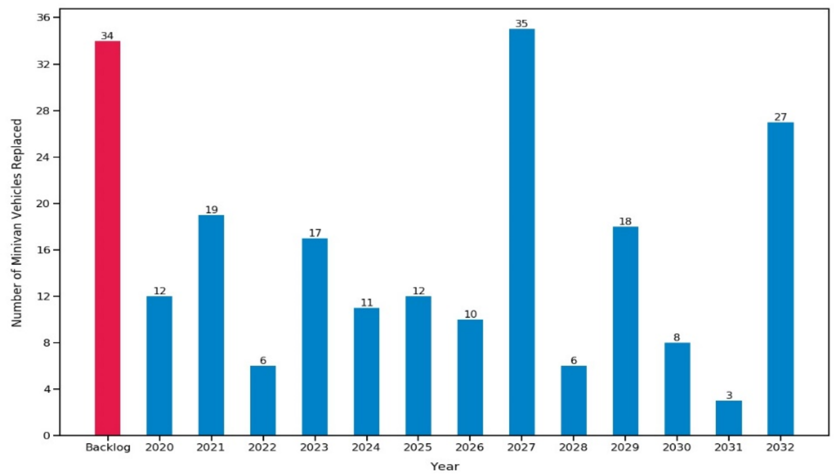
Backlog and Projected Replacement Cost for Buses



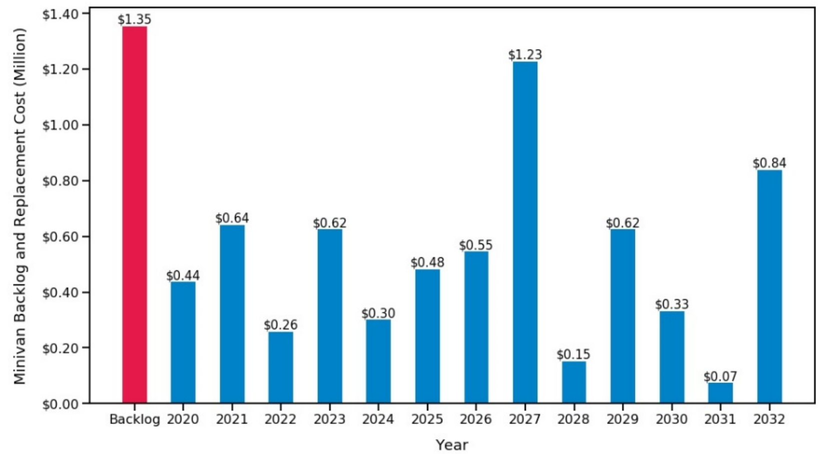
Backlog and Projected Replacement of Cutaways



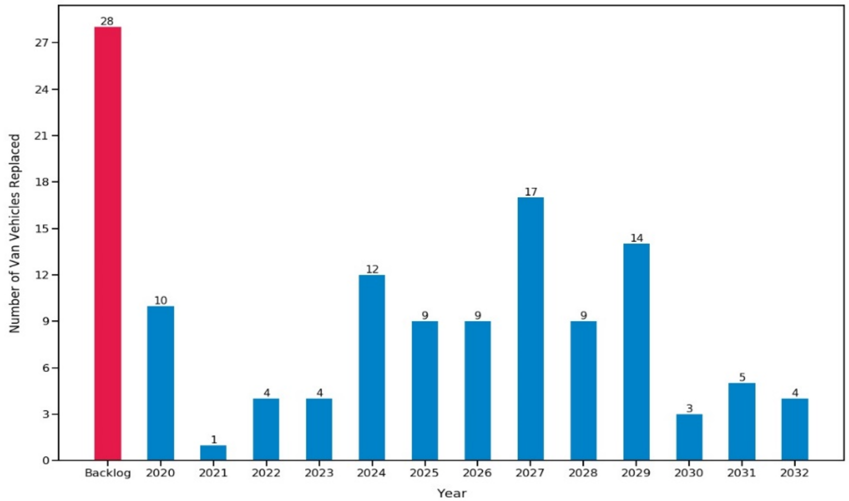
Backlog and Projected Replacement Cost for Cutaways



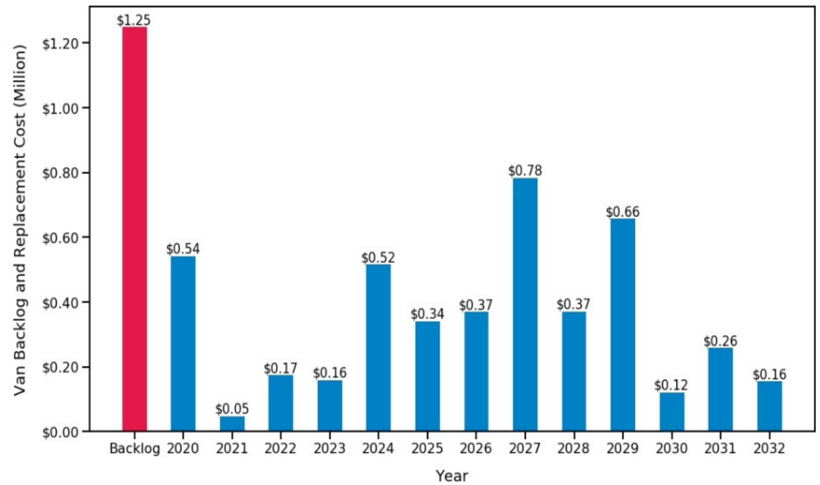
Backlog and Projected Replacement of Minivans



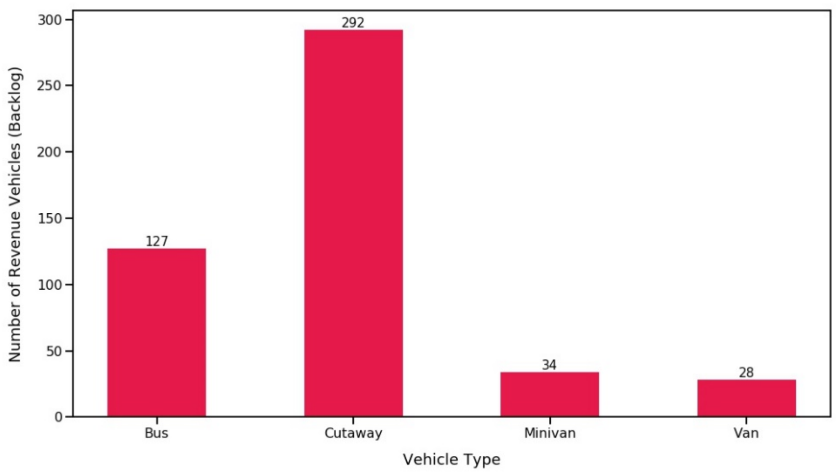
Backlog and Projected Replacement Cost for Minivans



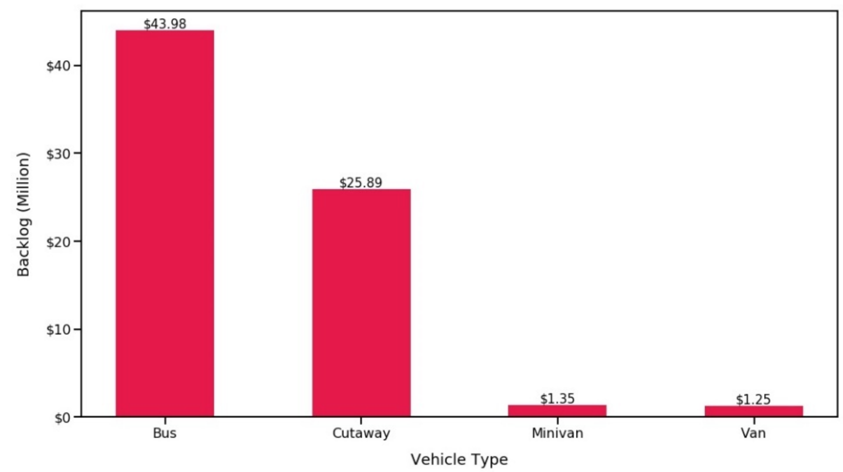
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

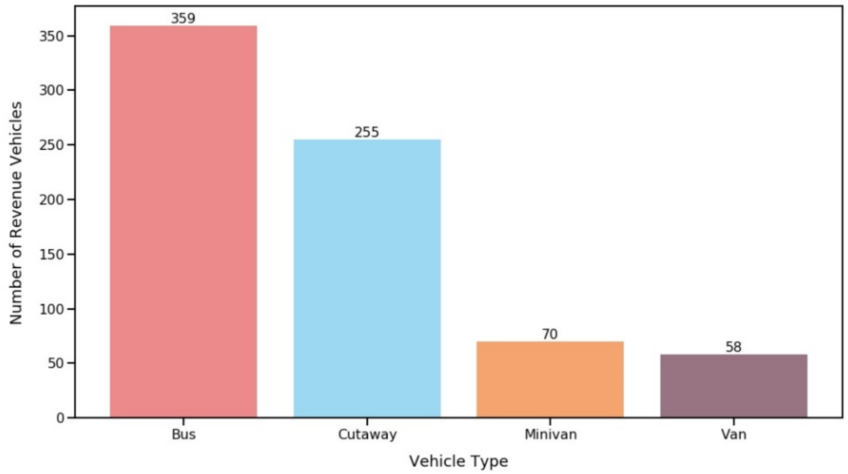


Backlog of the Revenue Vehicles by Vehicle Type

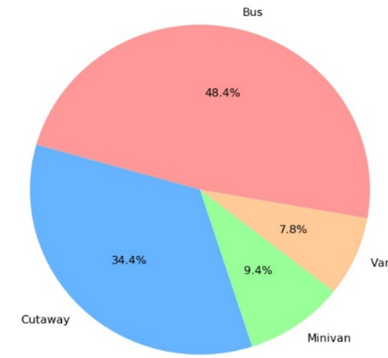


Funds Needed for Backlog by Vehicle Type

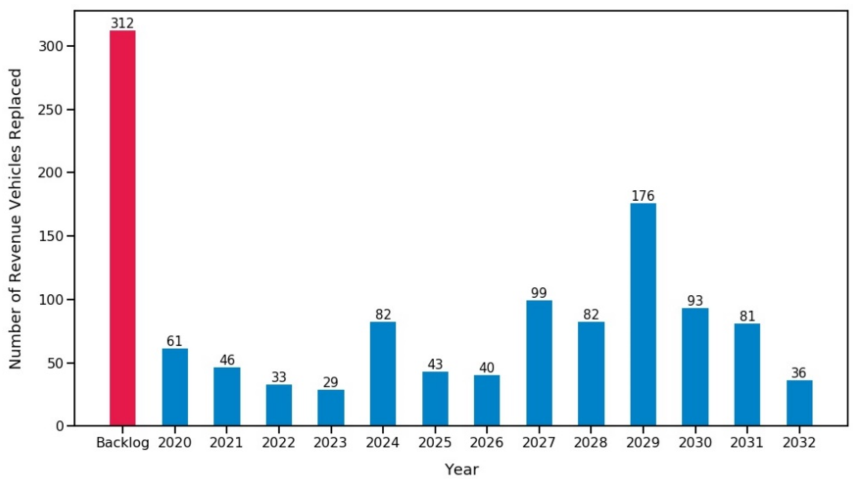
06 CO – Revenue Vehicles Information for Colorado's Small Urban and Rural Transit Systems (NTD 2017)



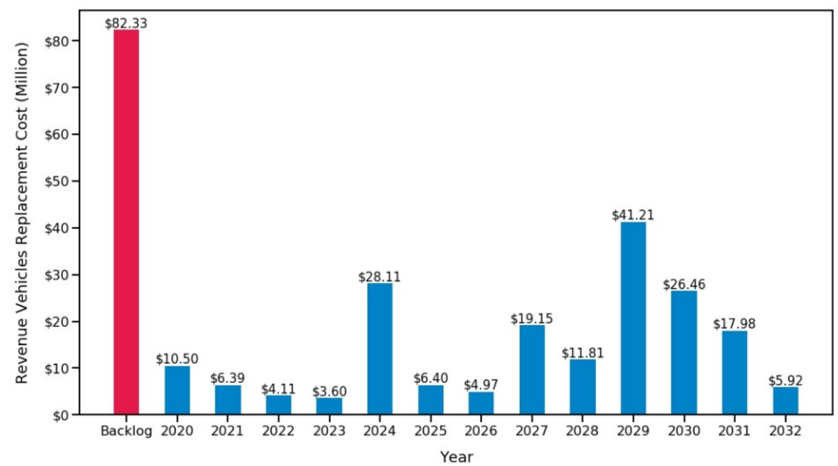
Number of Revenue Vehicles by Vehicle Type



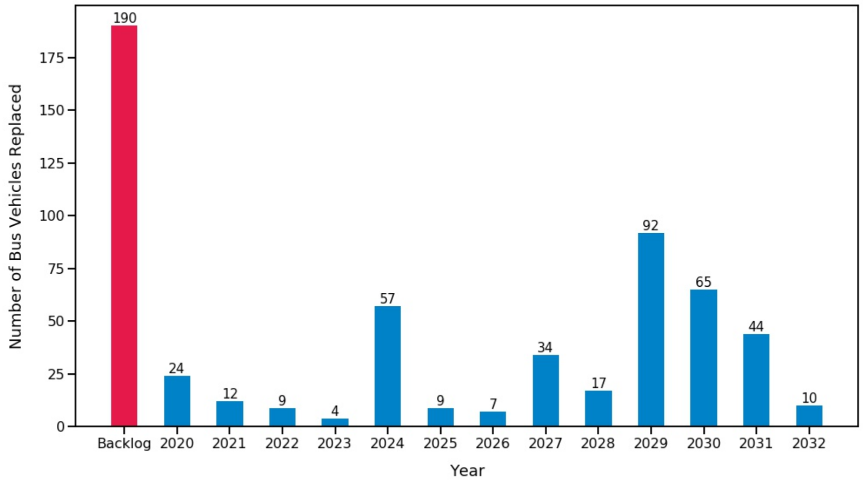
Percentage of Revenue Vehicles



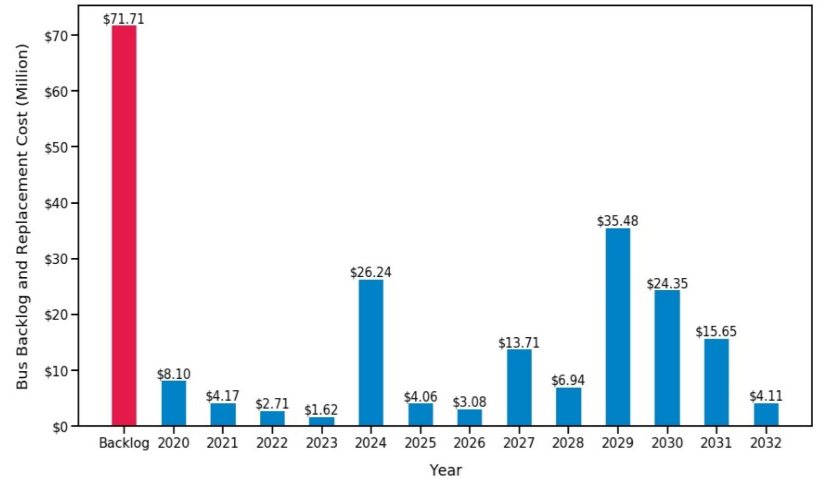
Backlog and Projected Replacement of Revenue Vehicles



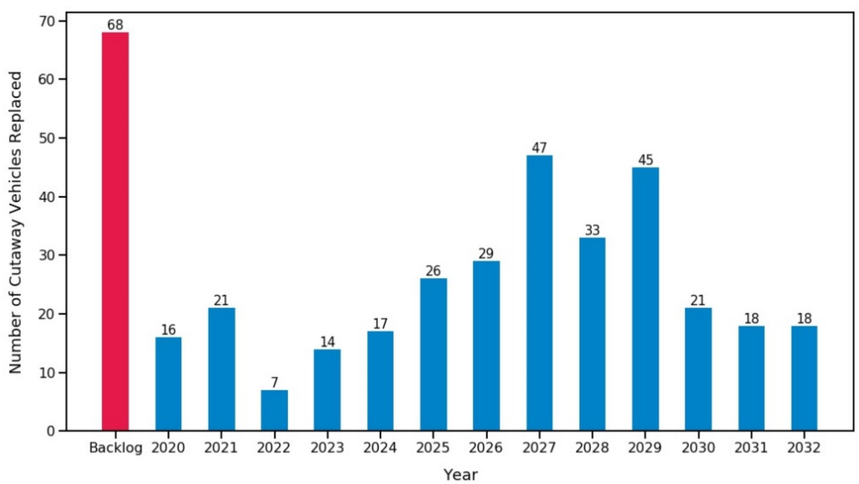
Backlog and Projected Replacement Costs for Revenue Vehicles



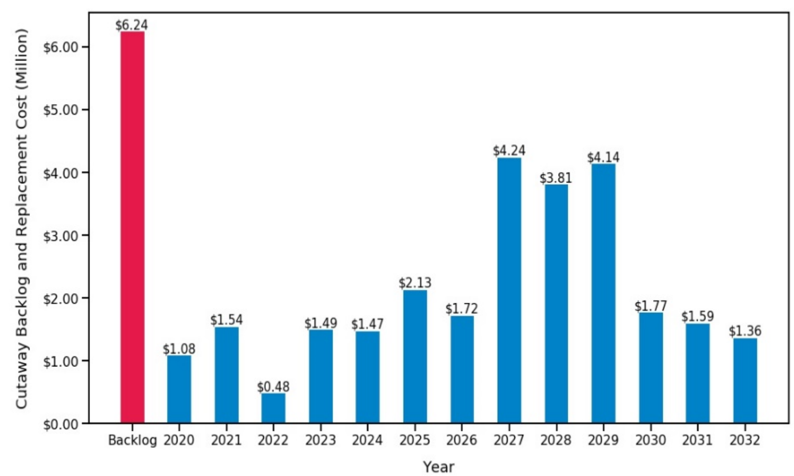
Backlog and Projected Replacement of Buses



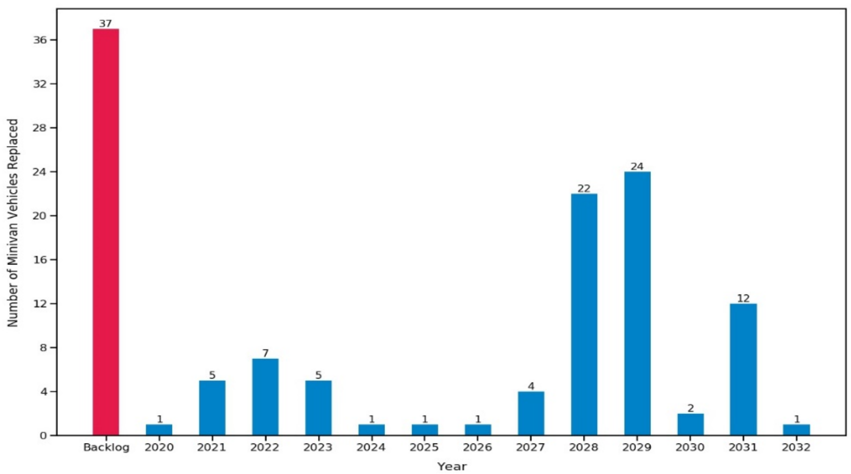
Backlog and Projected Replacement Cost for Buses



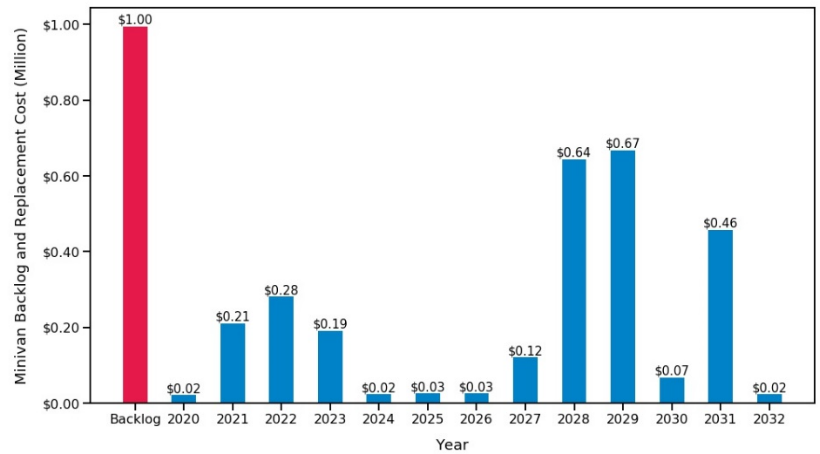
Backlog and Projected Replacement of Cutaways



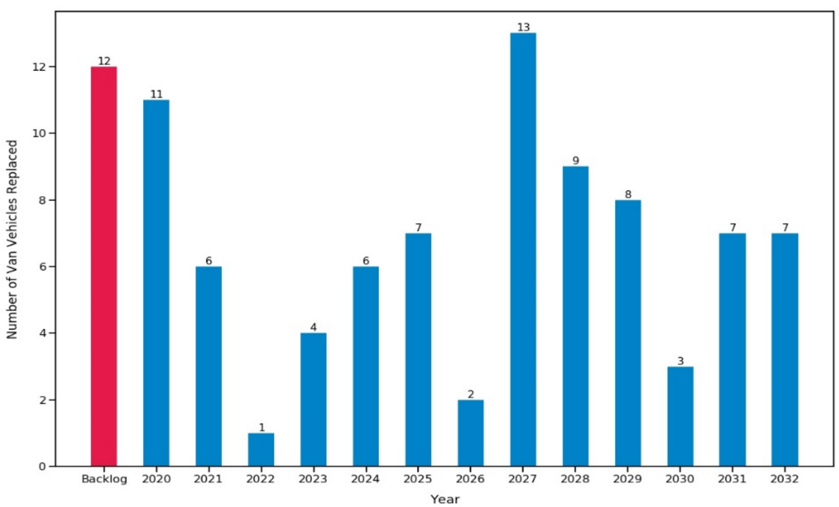
Backlog and Projected Replacement Cost for Cutaways



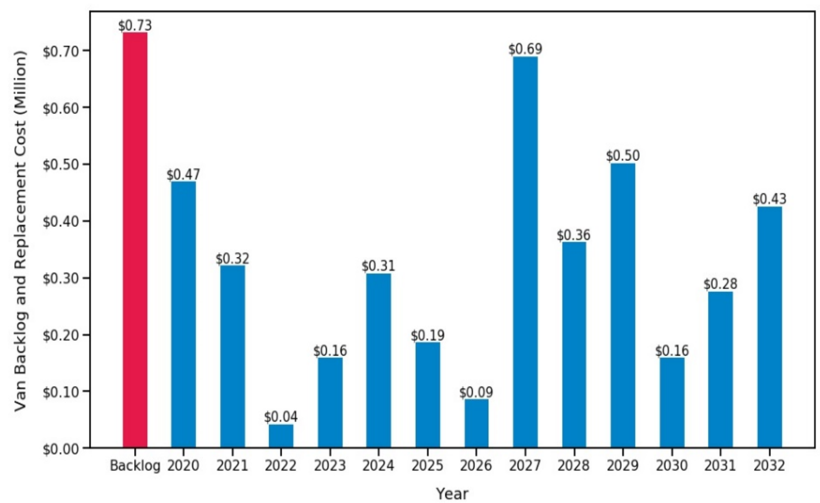
Backlog and Projected Replacement of Minivans



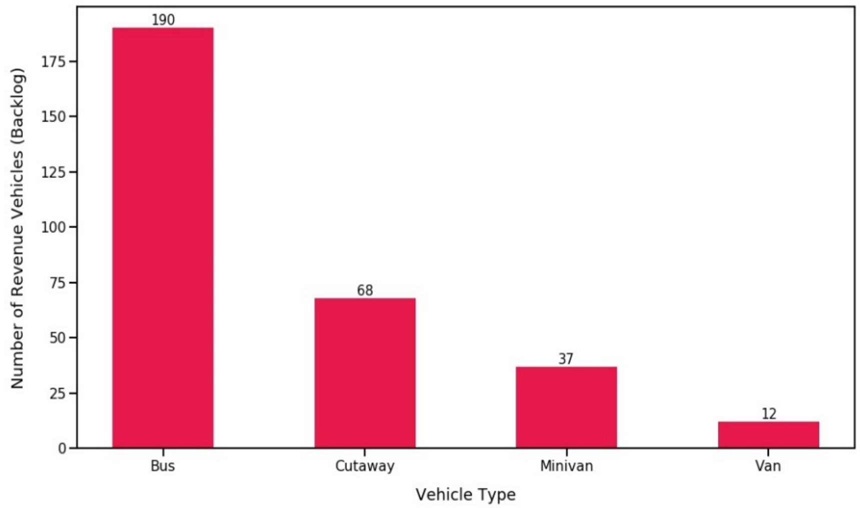
Backlog and Projected Replacement Cost for Minivans



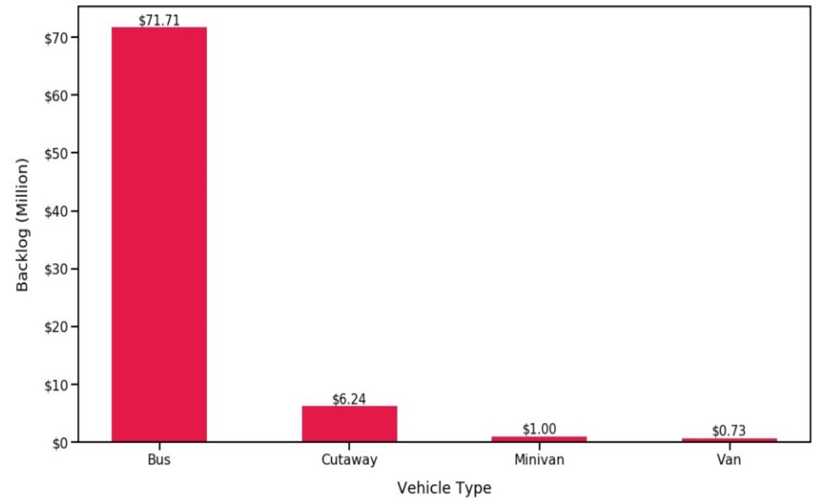
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

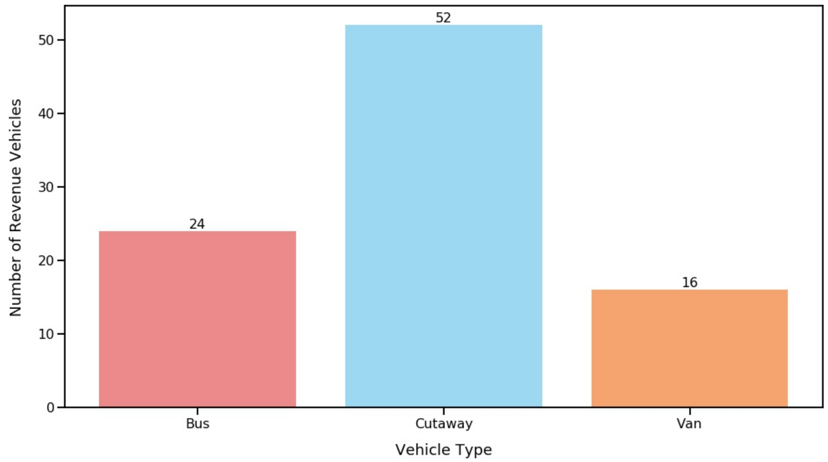


Backlog of the Revenue Vehicles by Vehicle Type

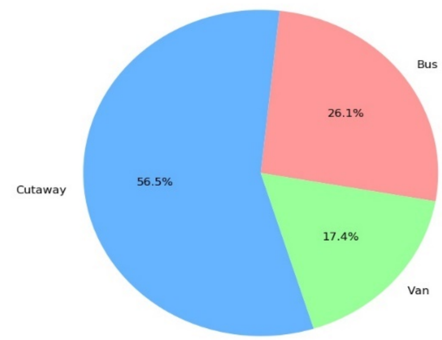


Funds Needed for Backlog by Vehicle Type

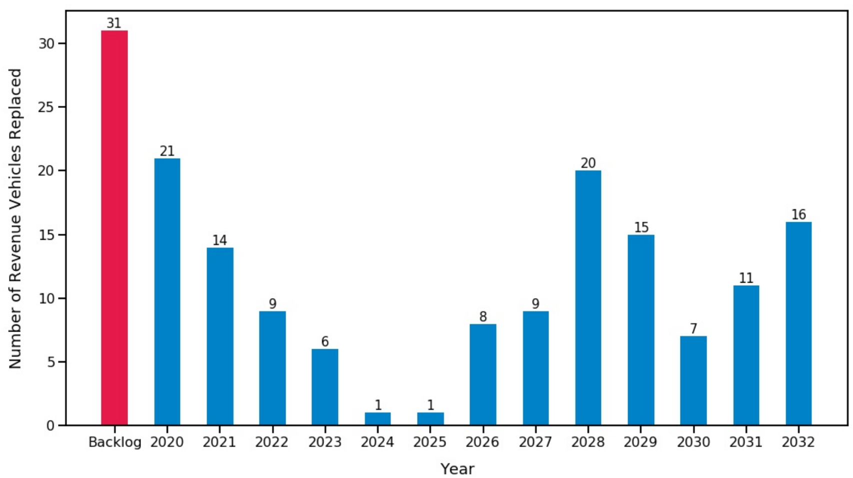
07 CT – Revenue Vehicles Information for Connecticut's Small Urban and Rural Transit Systems (NTD 2017)



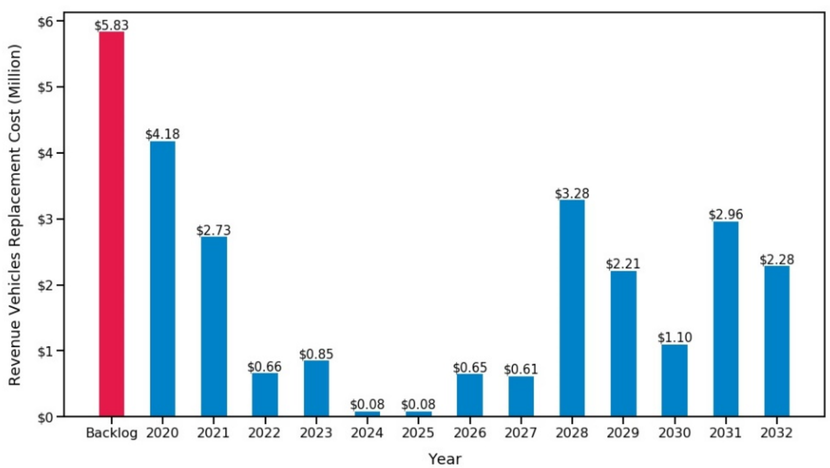
Number of Revenue Vehicles by Vehicle Type



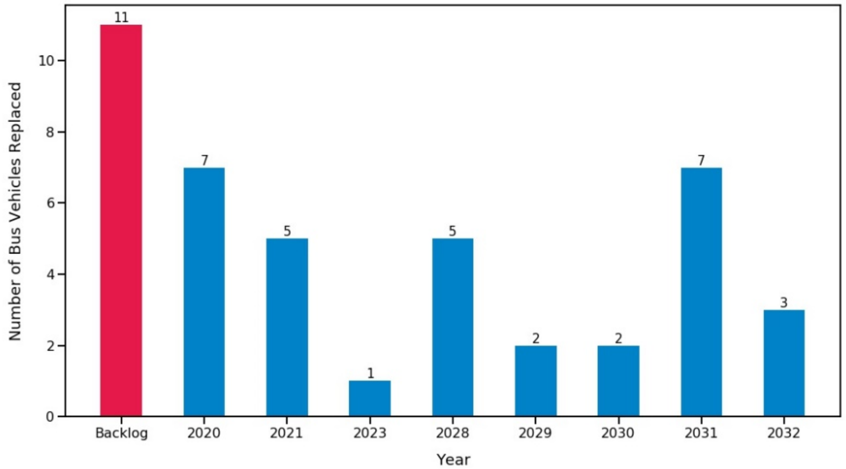
Percentage of Revenue Vehicles



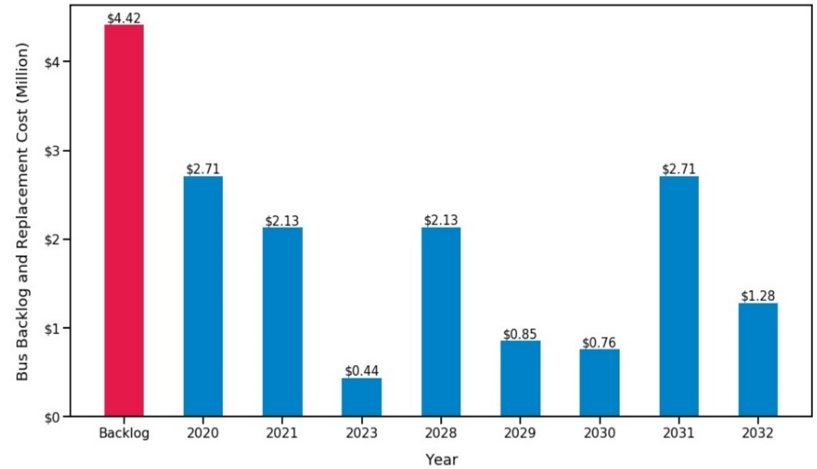
Backlog and Projected Replacement of Revenue Vehicles



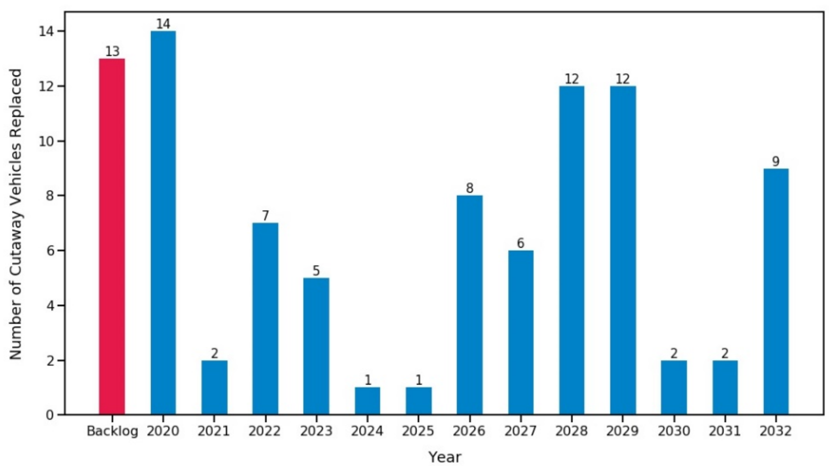
Backlog and Projected Replacement Costs for Revenue Vehicles



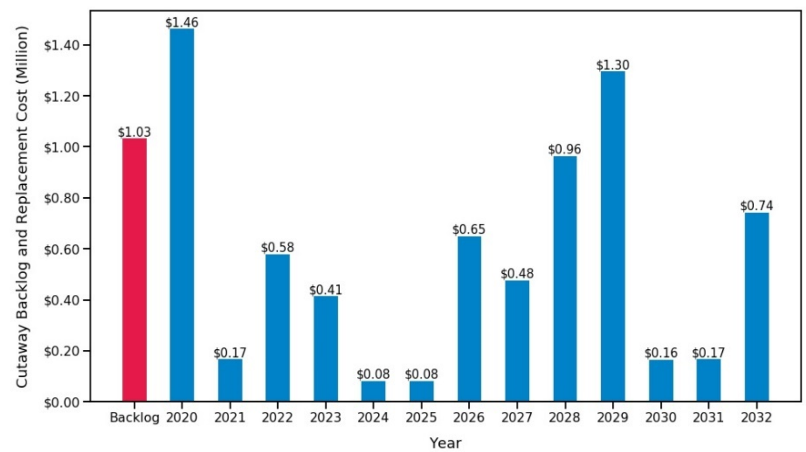
Backlog and Projected Replacement of Buses



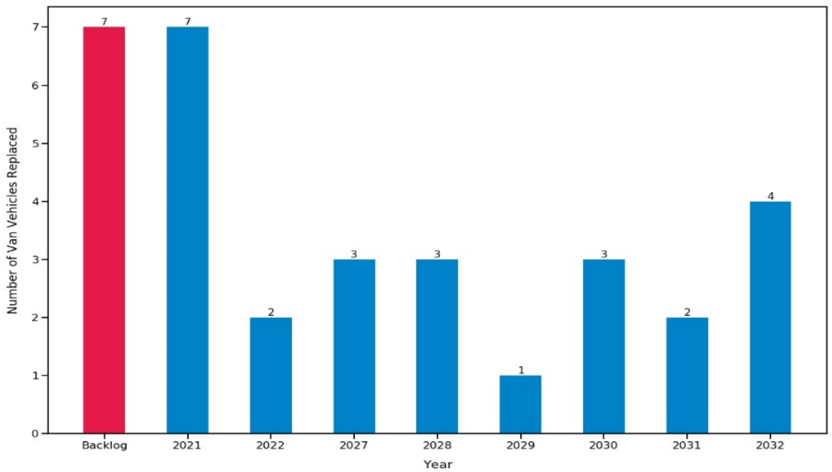
Backlog and Projected Replacement Cost for Buses



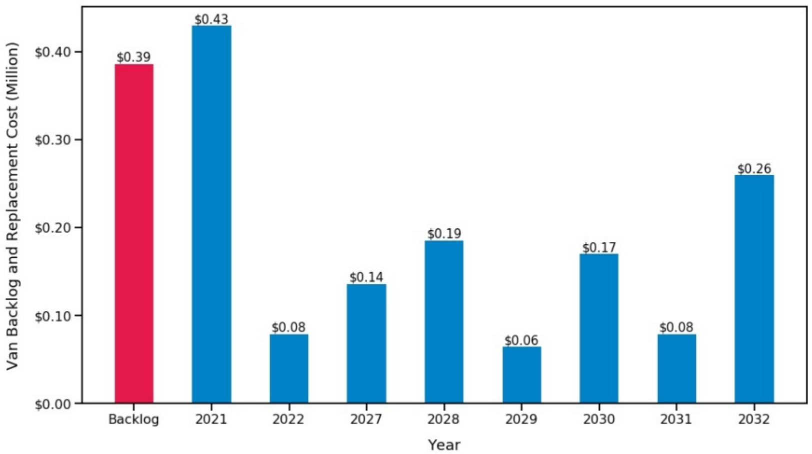
Backlog and Projected Replacement of Cutaways



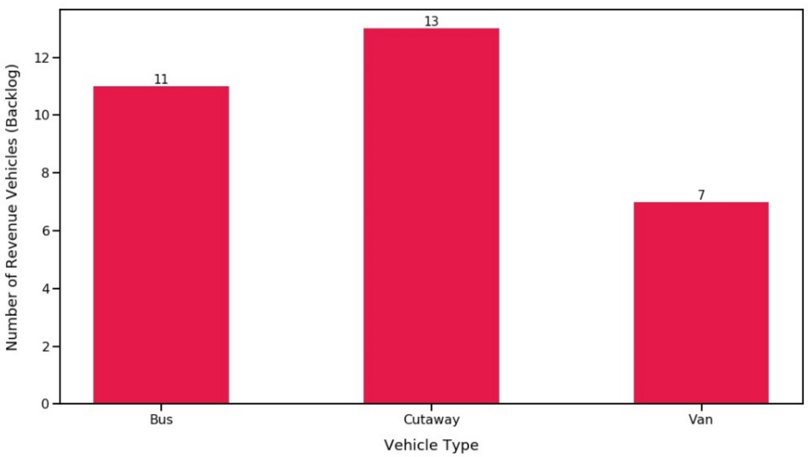
Backlog and Projected Replacement Cost for Cutaways



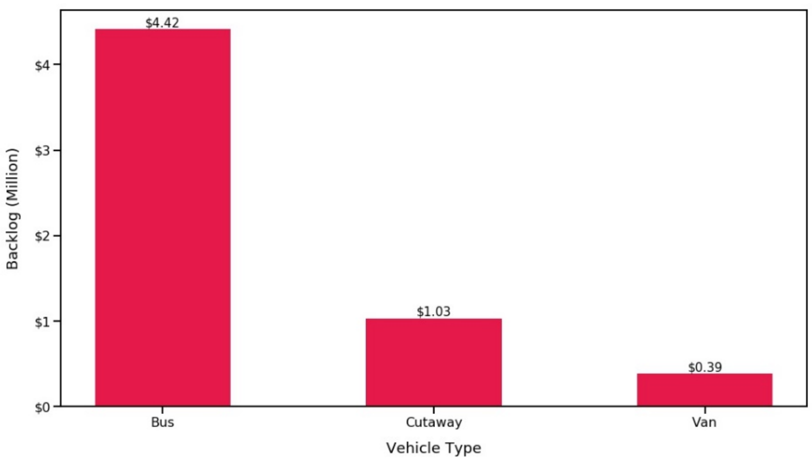
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

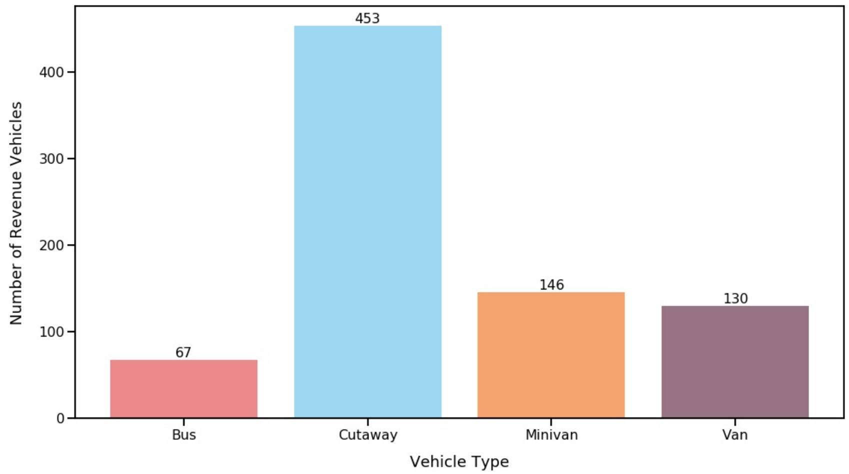


Backlog of the Revenue Vehicles by Vehicle Type

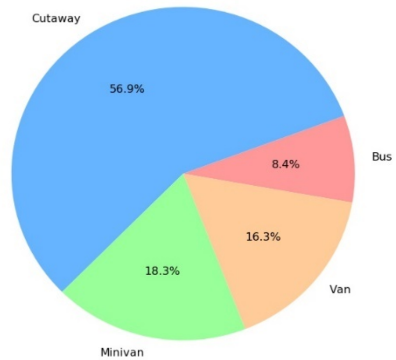


Funds Needed for Backlog by Vehicle Type

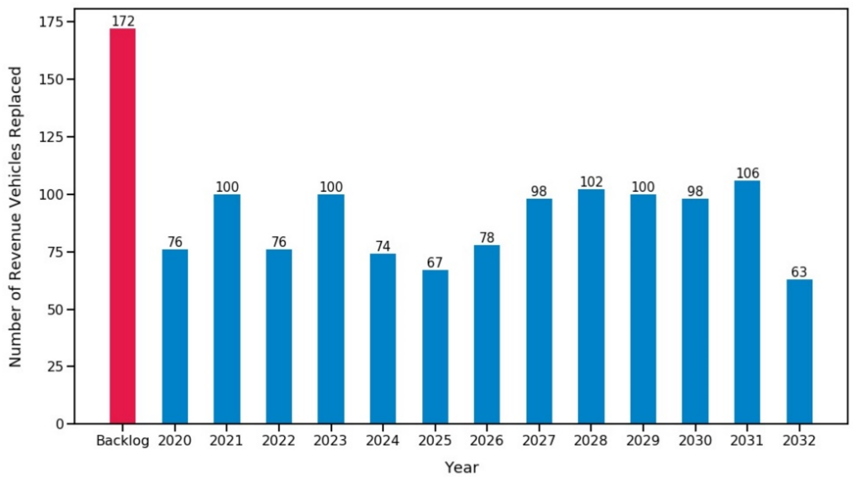
08 FL – Revenue Vehicles Information for Florida's Small Urban and Rural Transit Systems (NTD 2017)



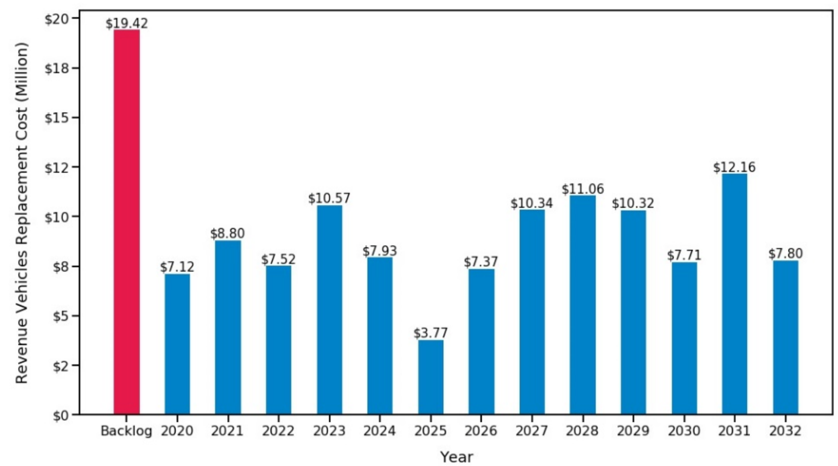
Number of Revenue Vehicles by Vehicle Type



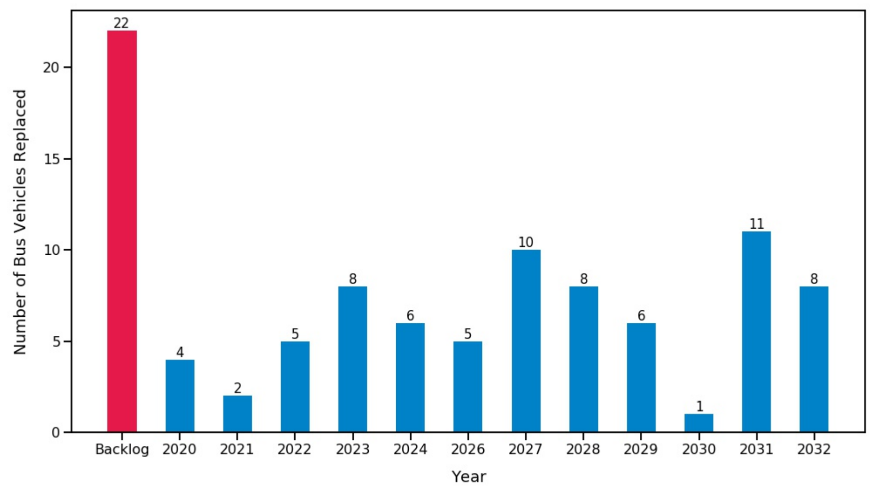
Percentage of Revenue Vehicles



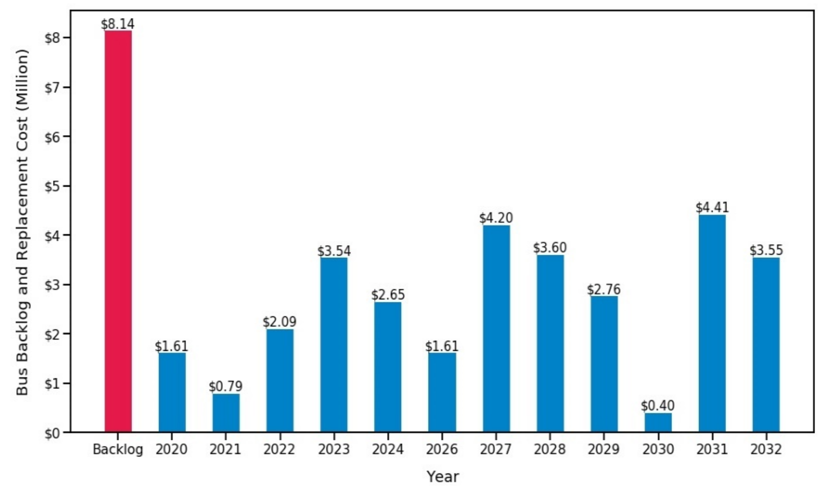
Backlog and Projected Replacement of Revenue Vehicles



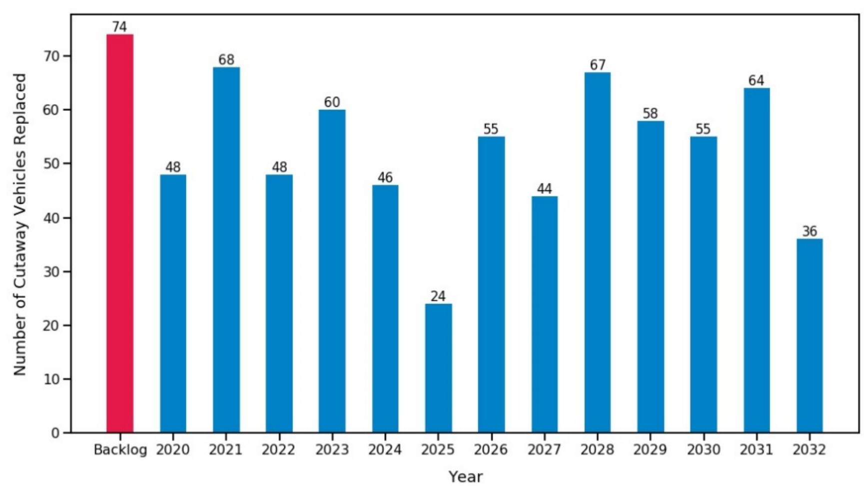
Backlog and Projected Replacement Costs for Revenue Vehicles



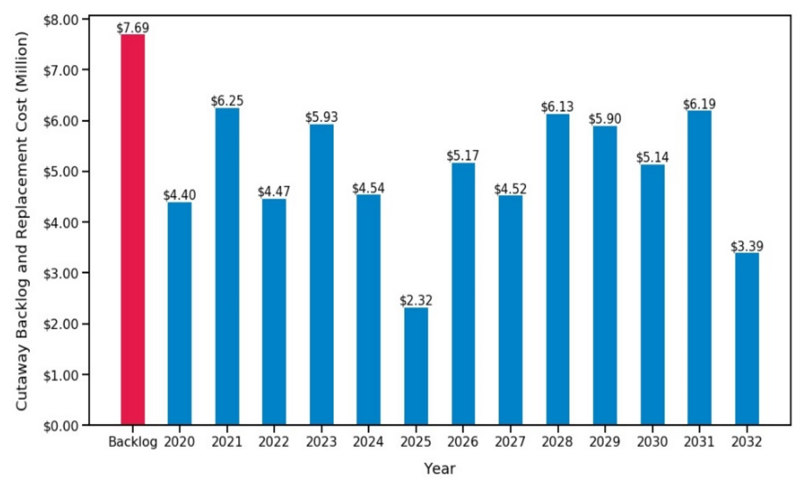
Backlog and Projected Replacement of Buses



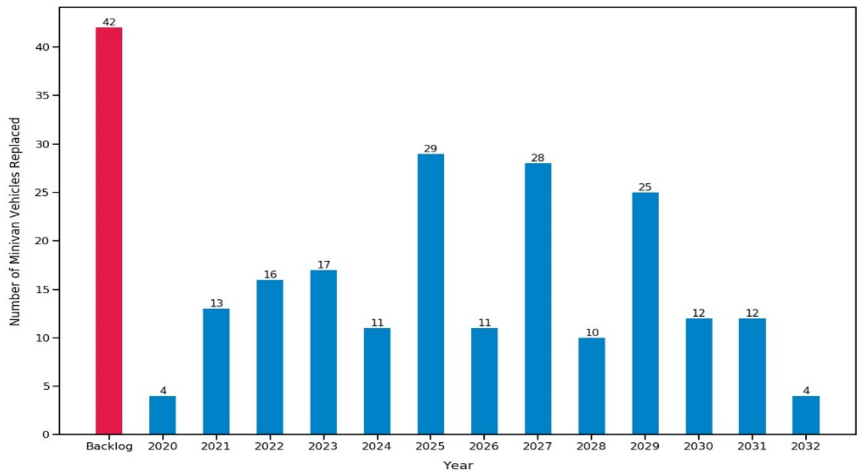
Backlog and Projected Replacement Cost for Buses



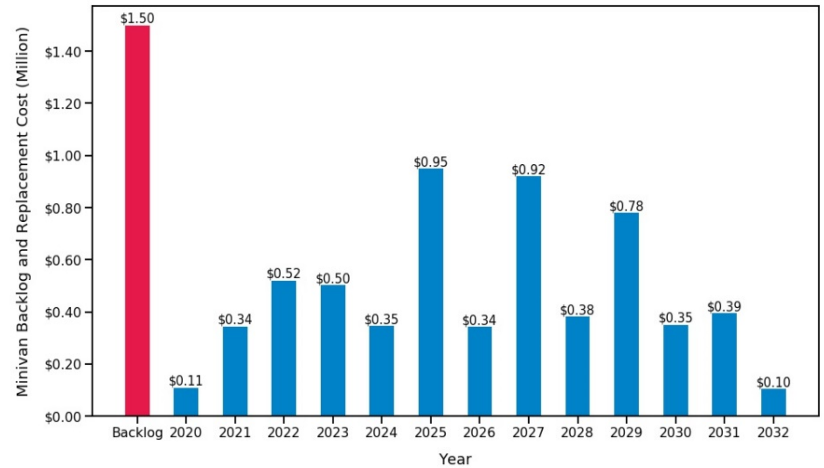
Backlog and Projected Replacement of Cutaways



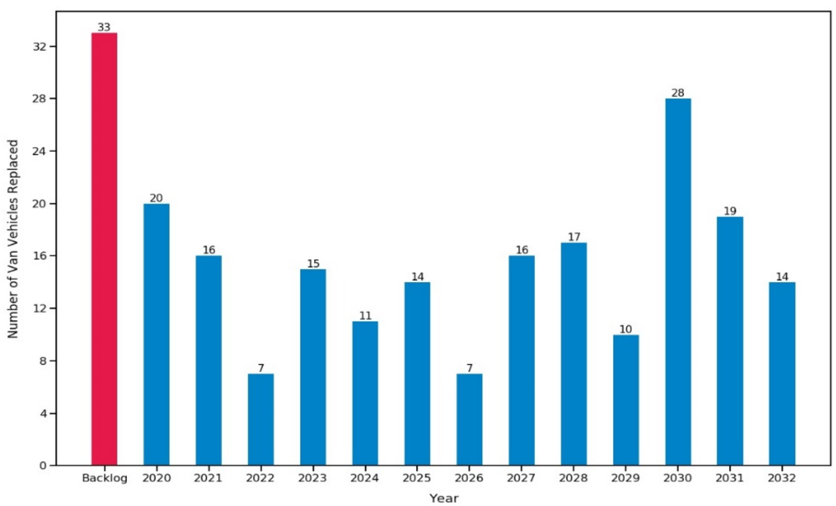
Backlog and Projected Replacement Cost for Cutaways



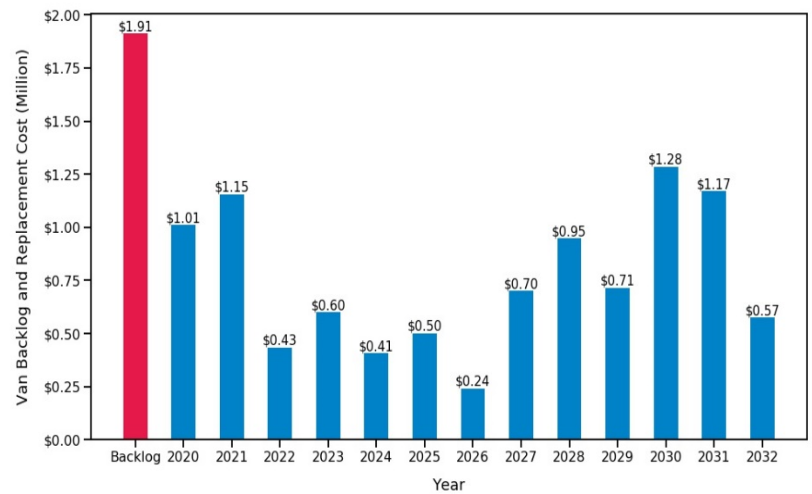
Backlog and Projected Replacement of Minivans



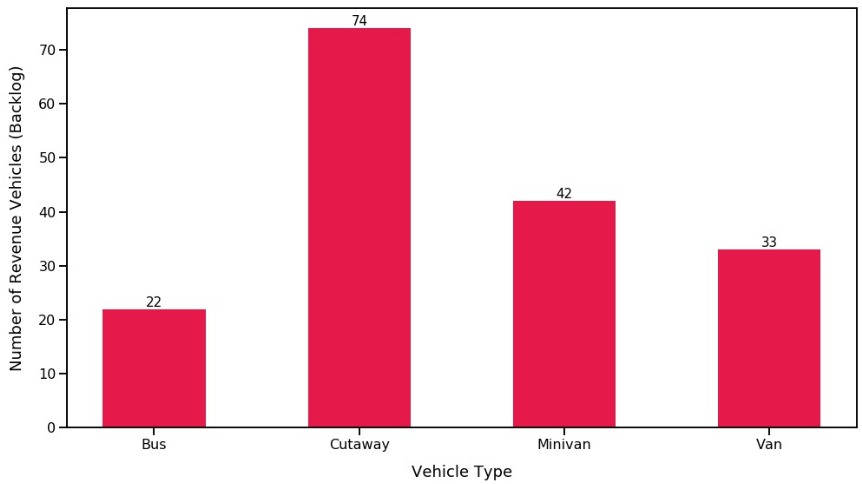
Backlog and Projected Replacement Cost for Minivans



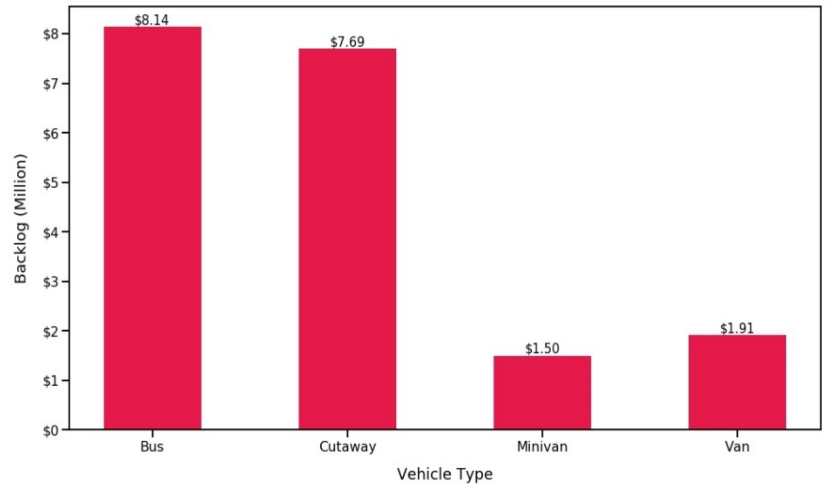
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

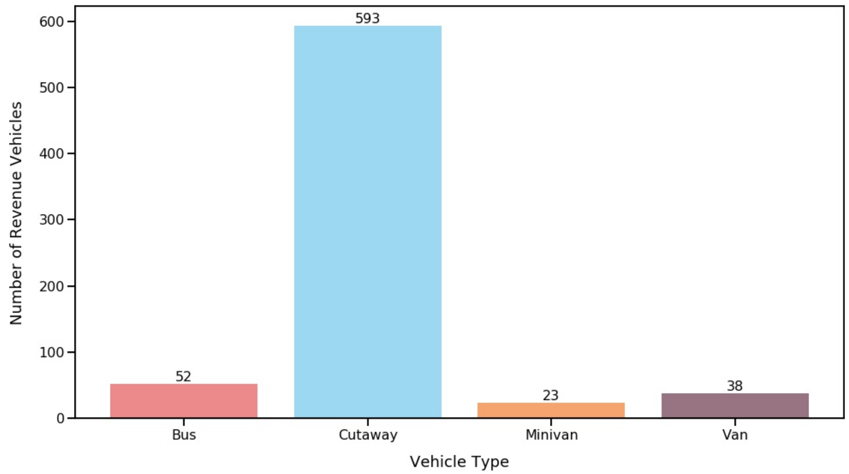


Backlog of the Revenue Vehicles by Vehicle Type

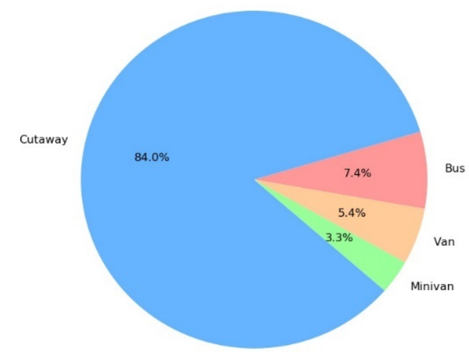


Funds Needed for Backlog by Vehicle Type

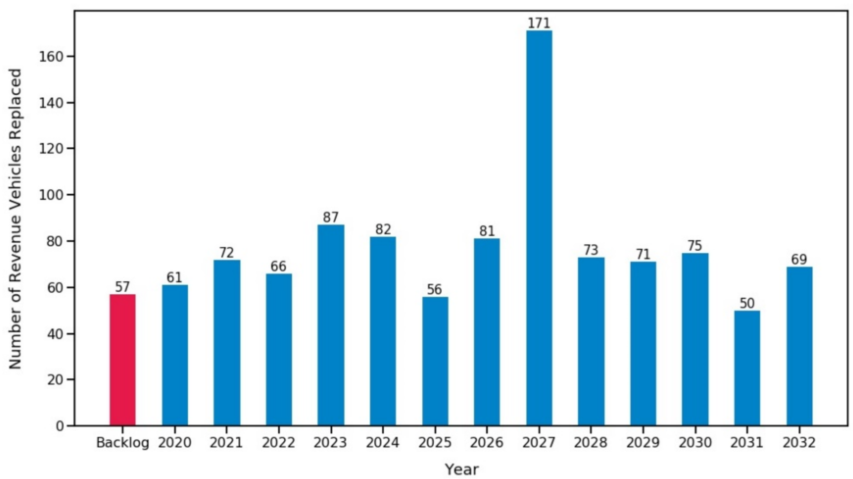
09 GA – Revenue Vehicles Information for Georgia's Small Urban and Rural Transit Systems (NTD 2017)



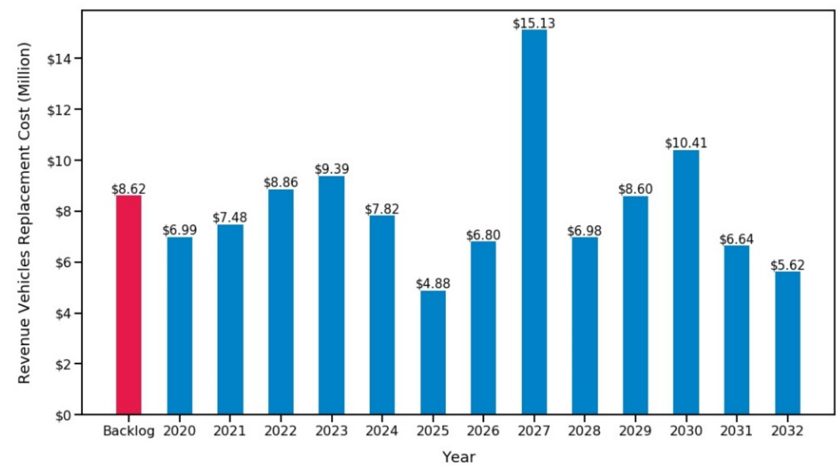
Number of Revenue Vehicles by Vehicle Type



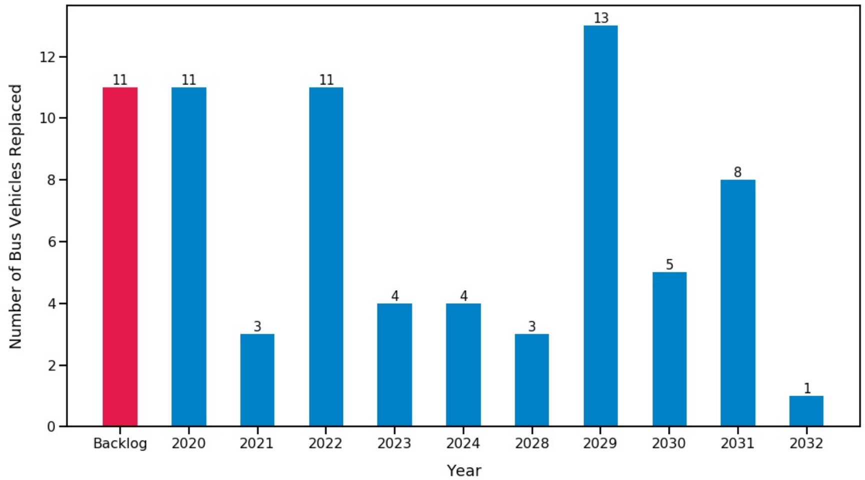
Percentage of Revenue Vehicles



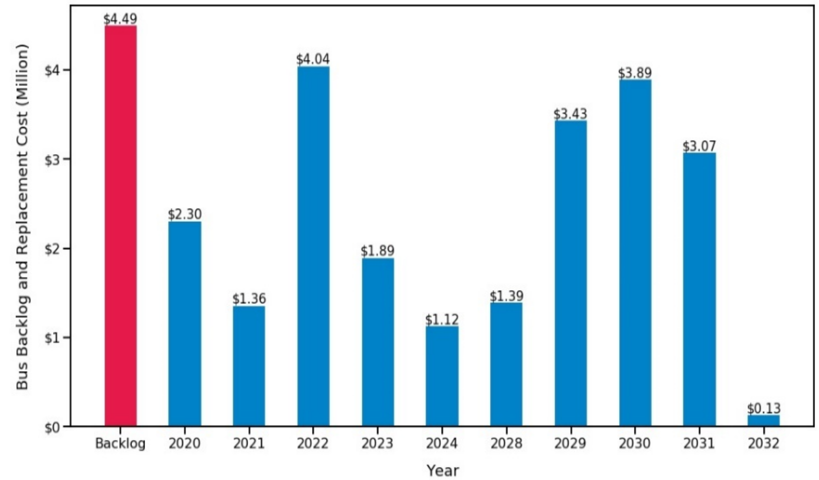
Backlog and Projected Replacement of Revenue Vehicles



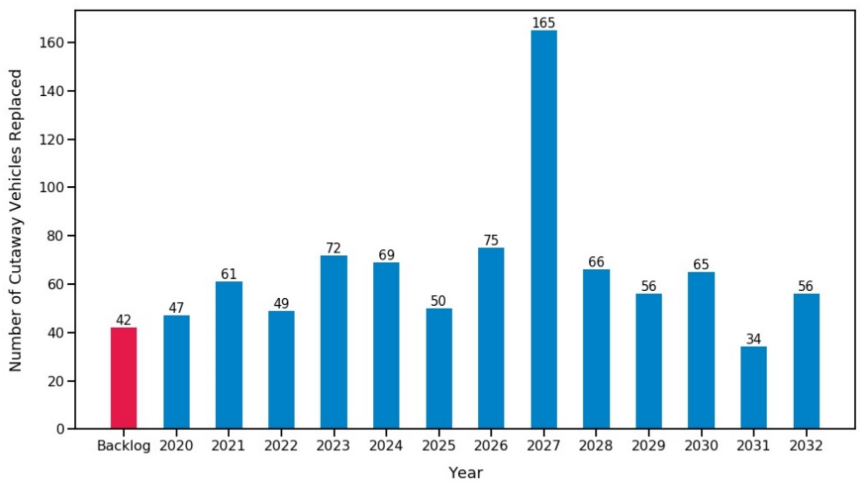
Backlog and Projected Replacement Costs for Revenue Vehicles



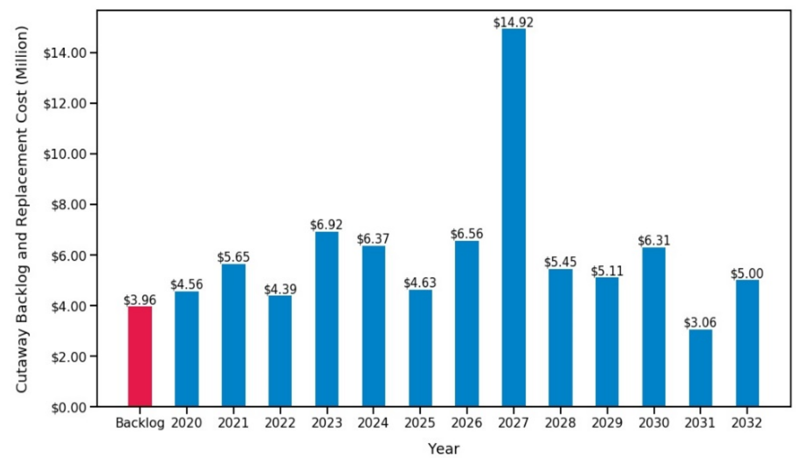
Backlog and Projected Replacement of Buses



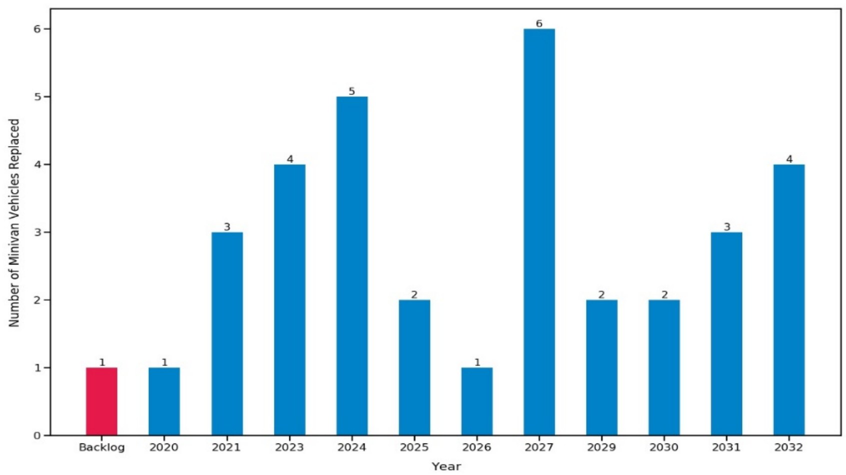
Backlog and Projected Replacement Cost for Buses



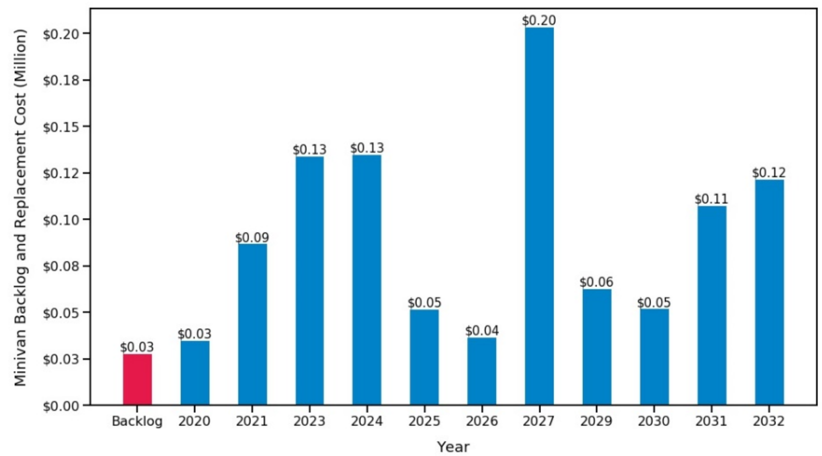
Backlog and Projected Replacement of Cutaways



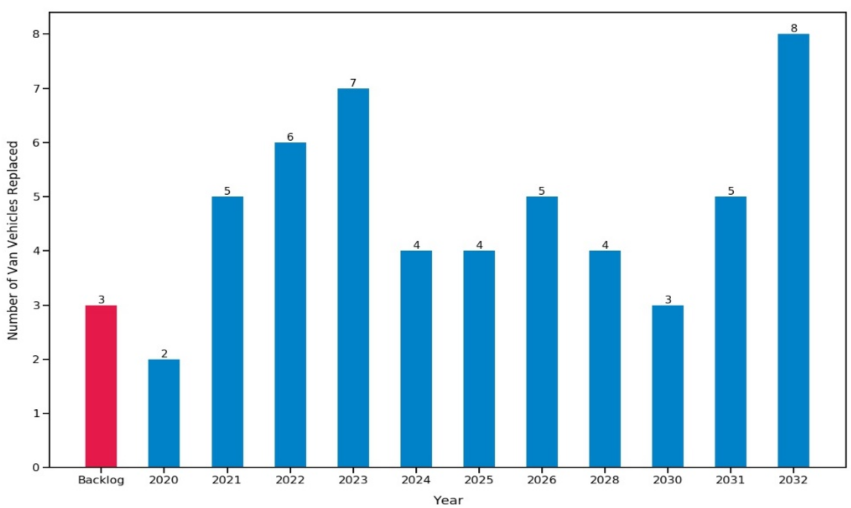
Backlog and Projected Replacement Cost for Cutaways



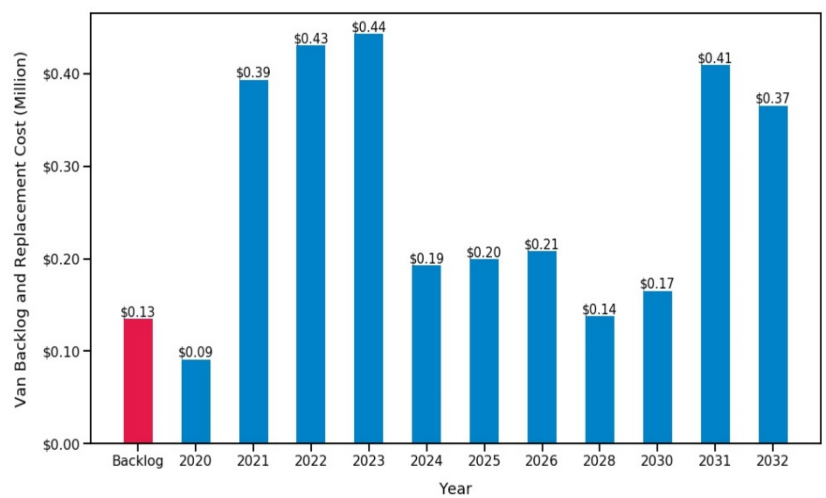
Backlog and Projected Replacement of Minivans



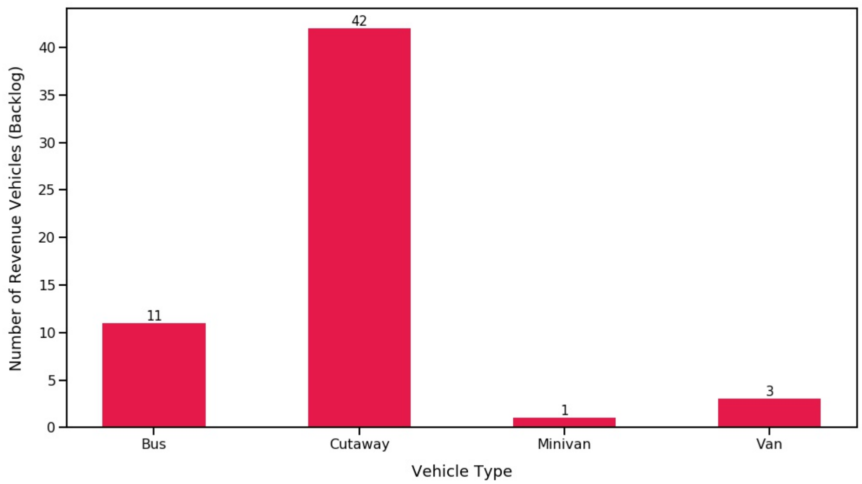
Backlog and Projected Replacement Cost for Minivans



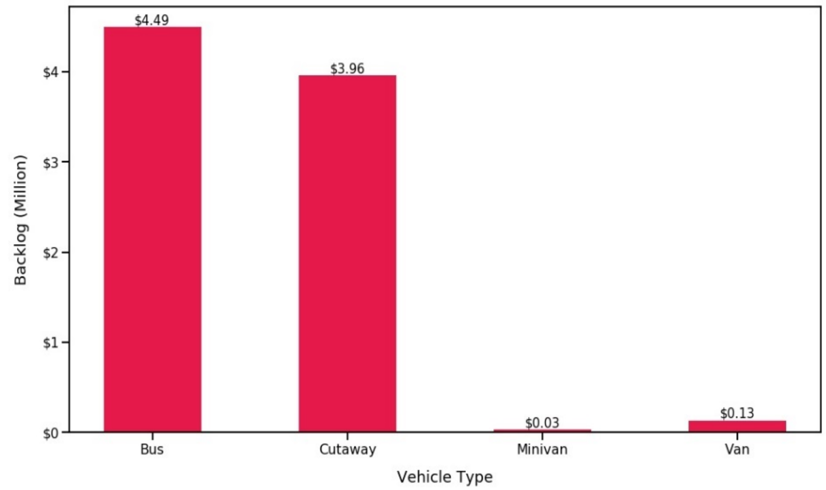
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

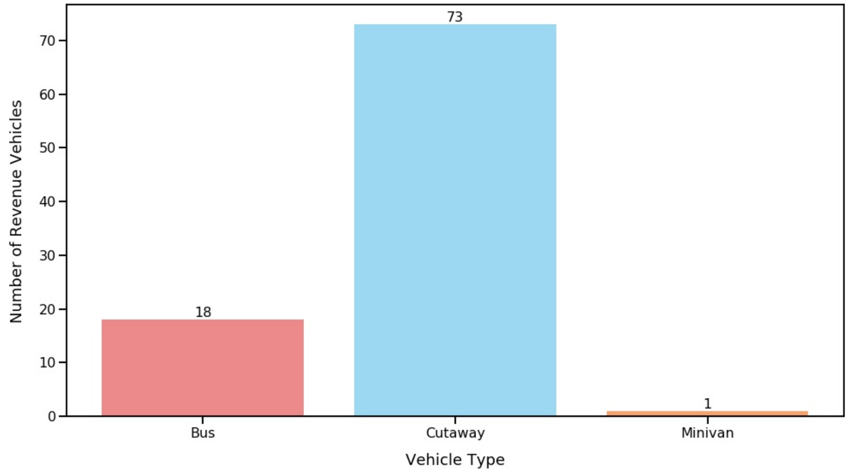


Backlog of the Revenue Vehicles by Vehicle Type

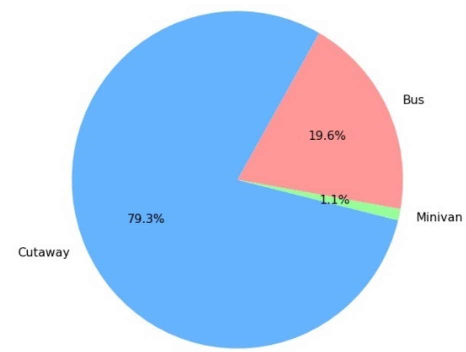


Funds Needed for Backlog by Vehicle Type

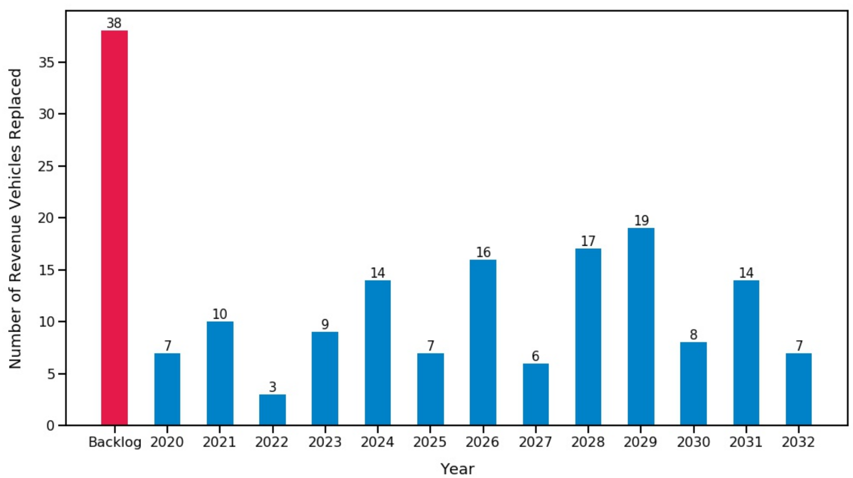
10 HI – Revenue Vehicles Information for Hawaii's Small Urban and Rural Transit Systems (NTD 2017)



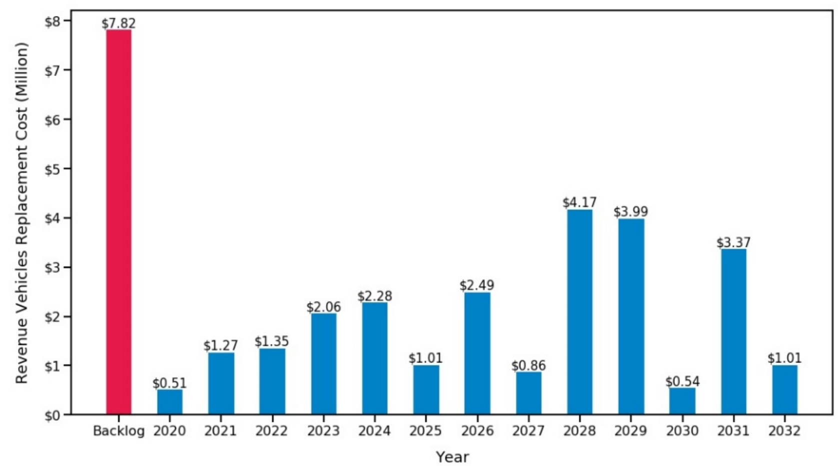
Number of Revenue Vehicles by Vehicle Type



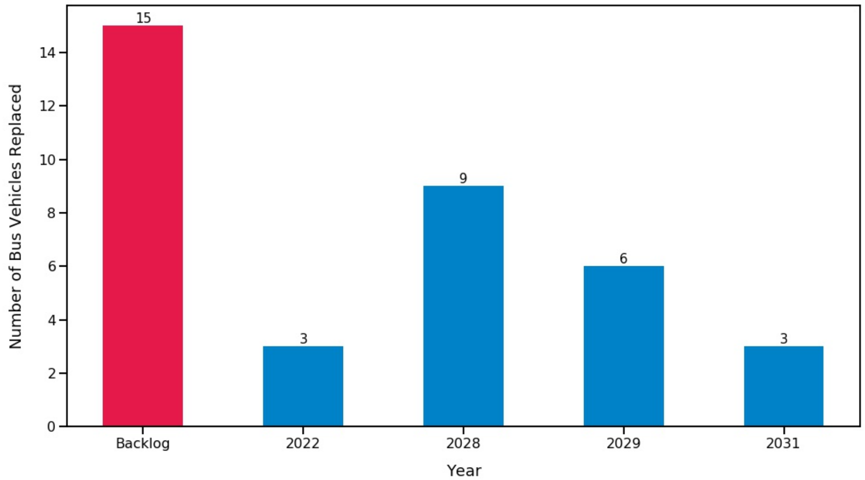
Percentage of Revenue Vehicles



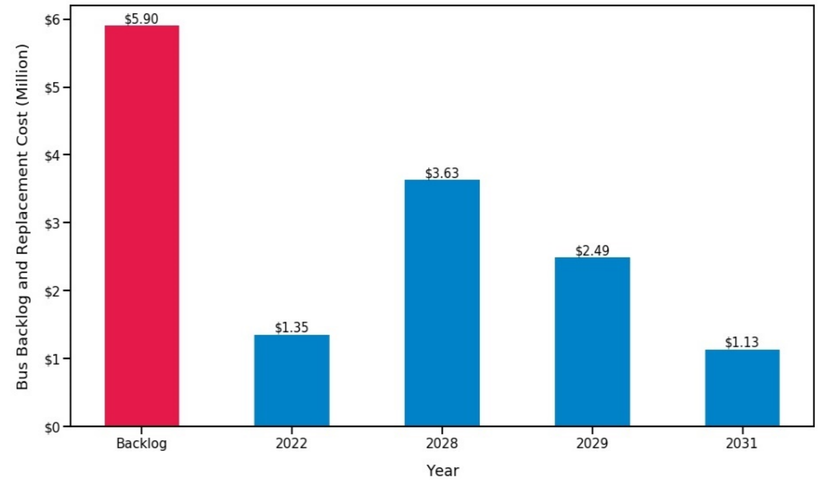
Backlog and Projected Replacement of Revenue Vehicles



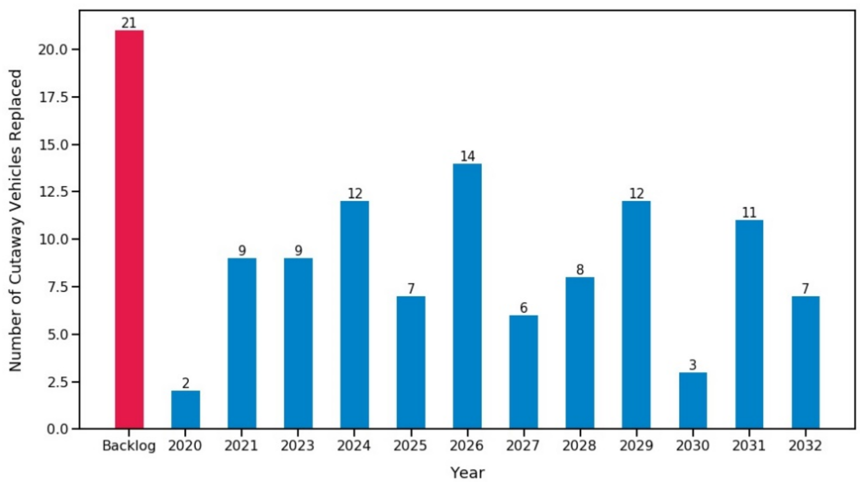
Backlog and Projected Replacement Costs for Revenue Vehicles



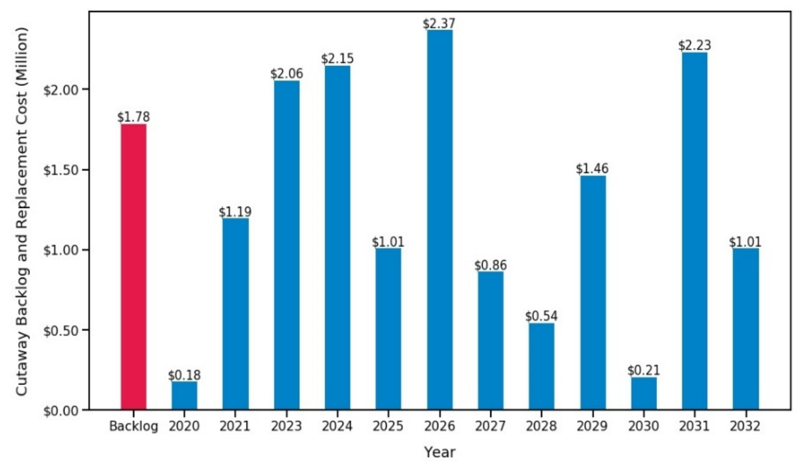
Backlog and Projected Replacement of Buses



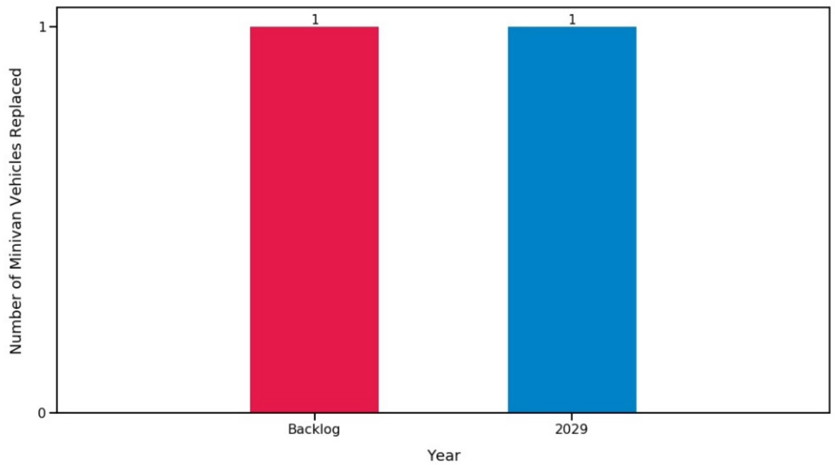
Backlog and Projected Replacement Cost for Buses



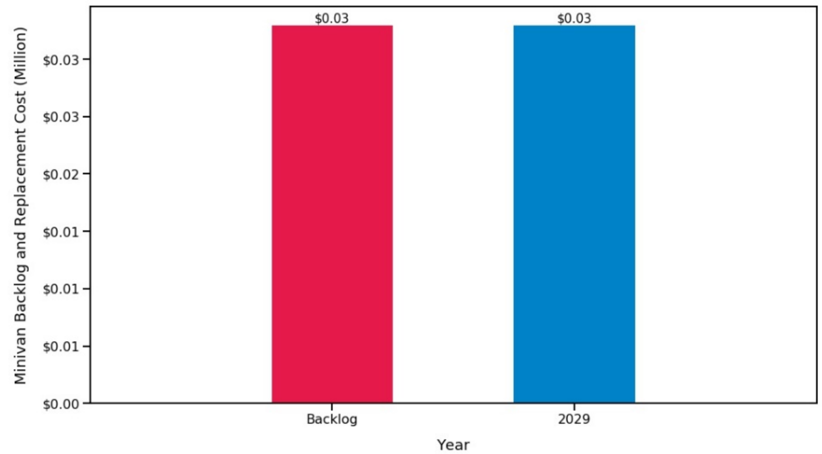
Backlog and Projected Replacement of Cutaways



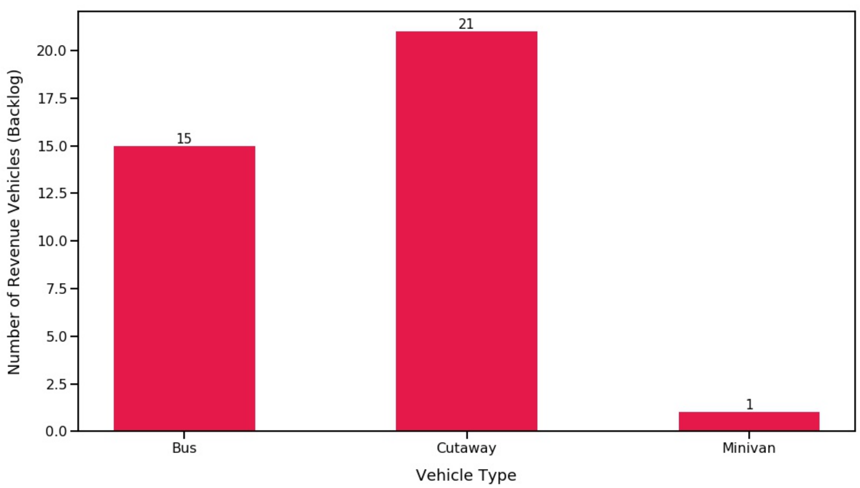
Backlog and Projected Replacement Cost for Cutaways



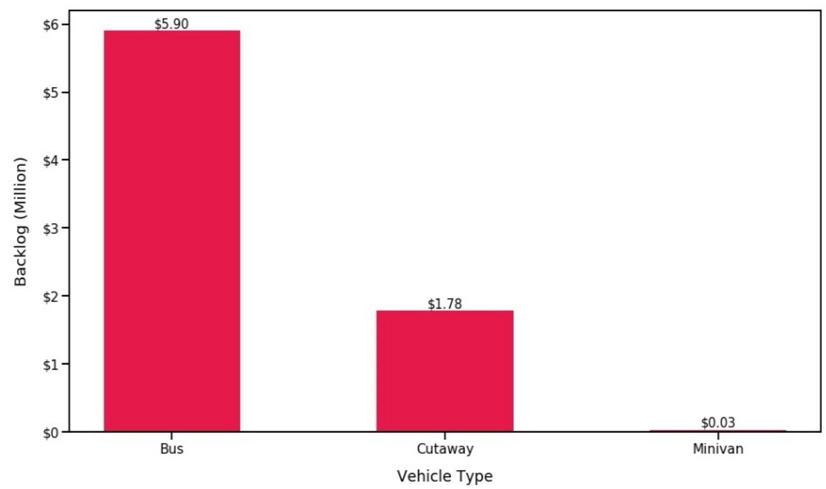
Backlog and Projected Replacement of Minivans



Backlog and Projected Replacement Cost for Minivans

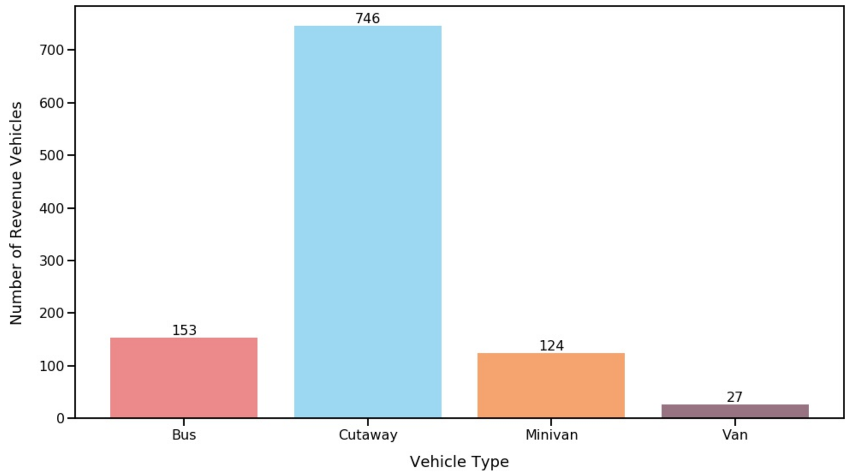


Backlog of the Revenue Vehicles by Vehicle Type

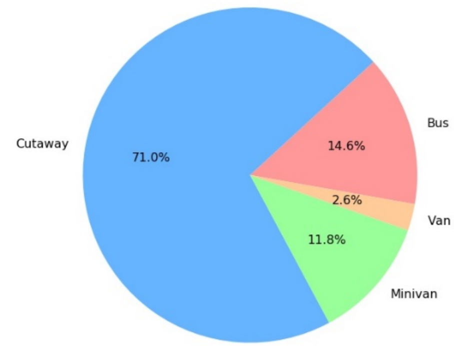


Funds Needed for Backlog by Vehicle Type

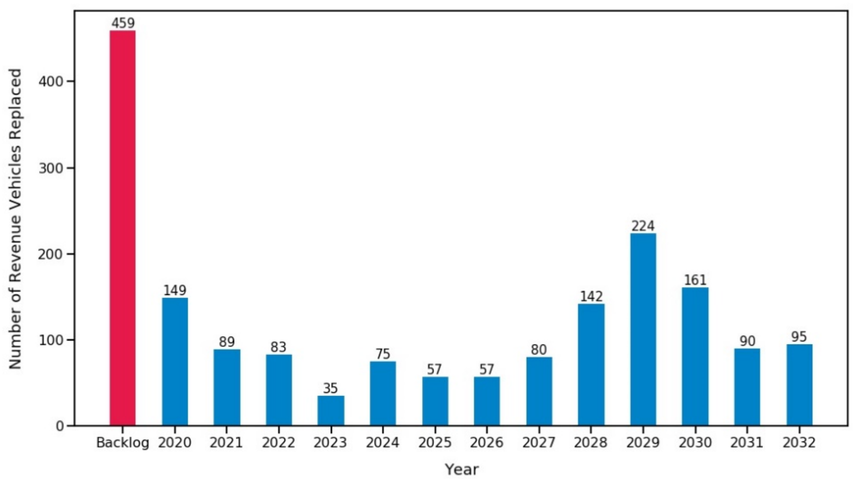
11 IA – Revenue Vehicles Information for Iowa's Small Urban and Rural Transit Systems (NTD 2017)



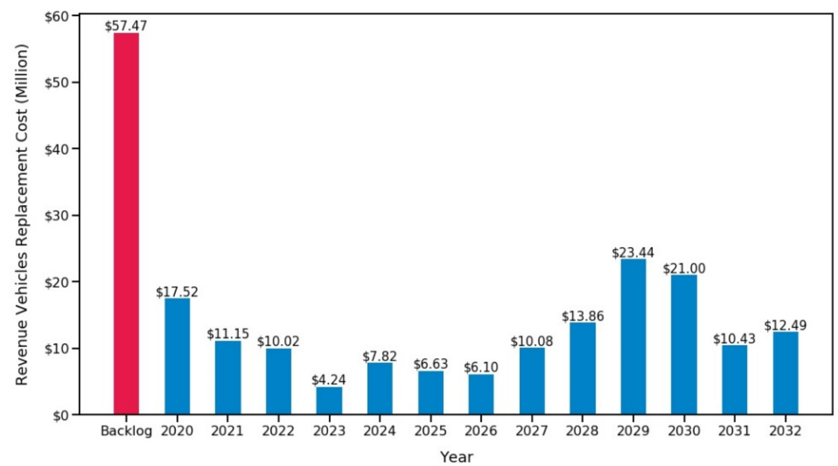
Number of Revenue Vehicles by Vehicle Type



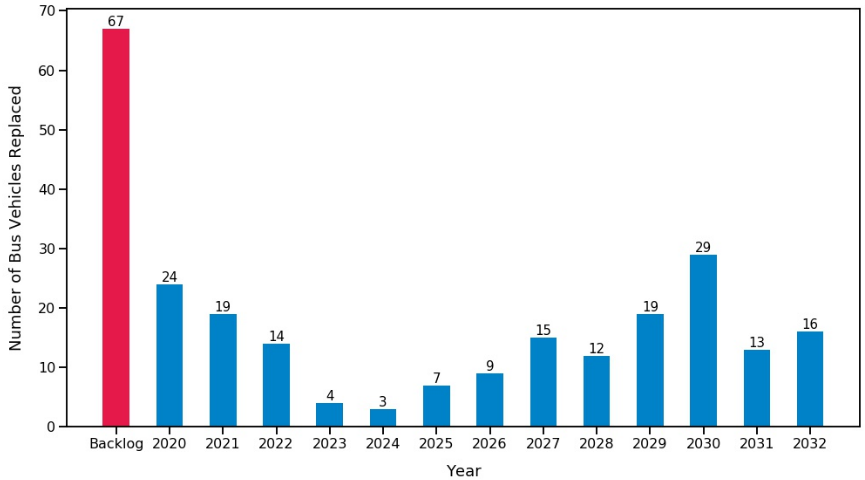
Percentage of Revenue Vehicles



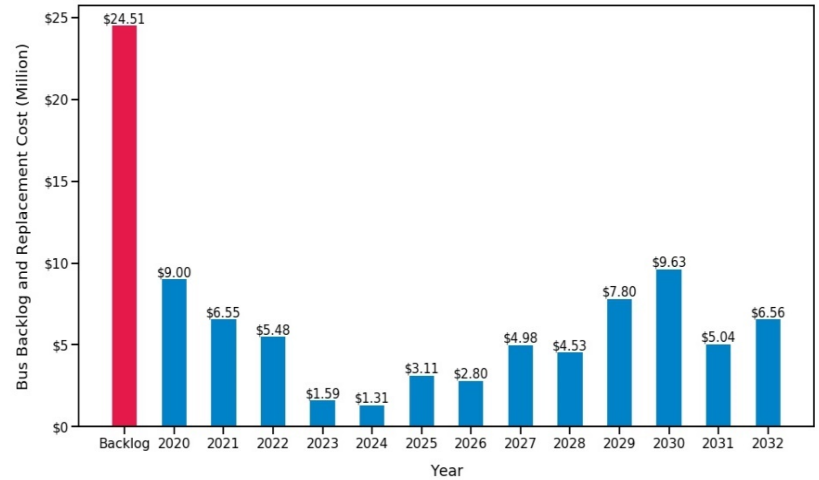
Backlog and Projected Replacement of Revenue Vehicles



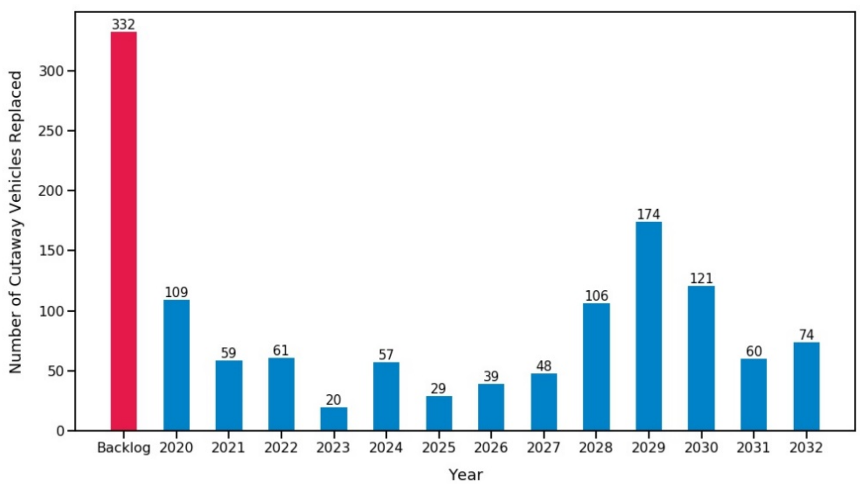
Backlog and Projected Replacement Costs for Revenue Vehicles



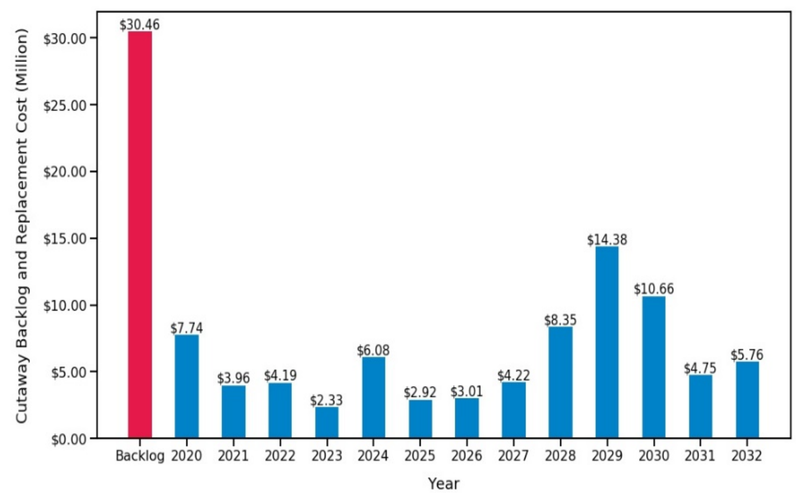
Backlog and Projected Replacement of Buses



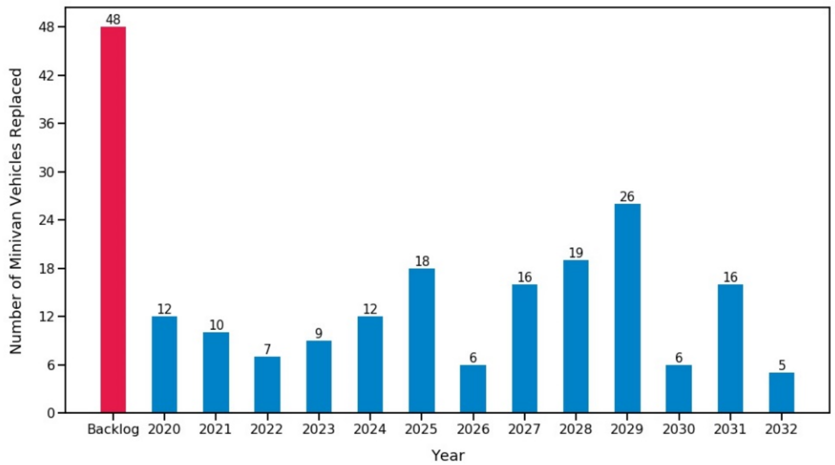
Backlog and Projected Replacement Cost for Buses



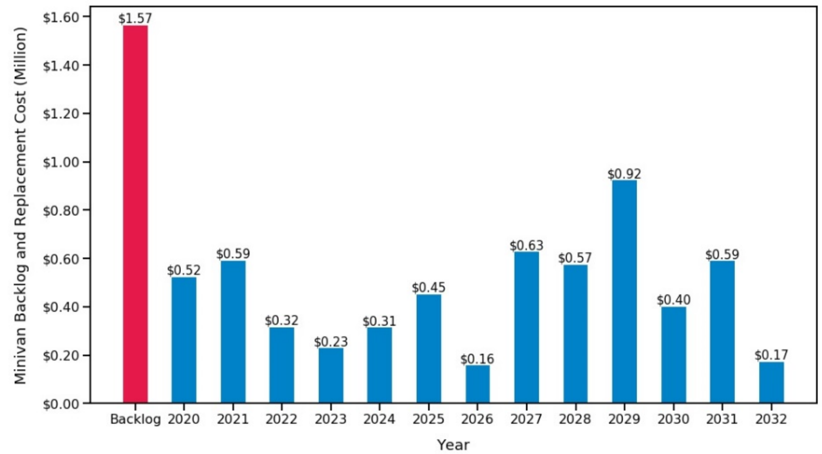
Backlog and Projected Replacement of Cutaways



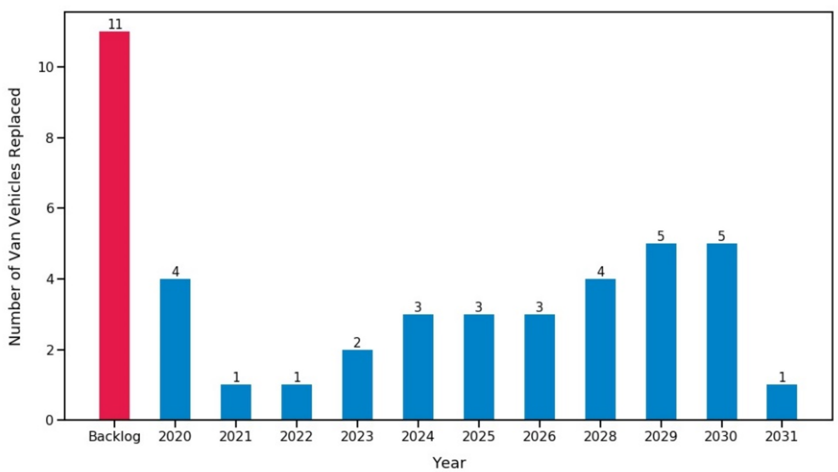
Backlog and Projected Replacement Cost for Cutaways



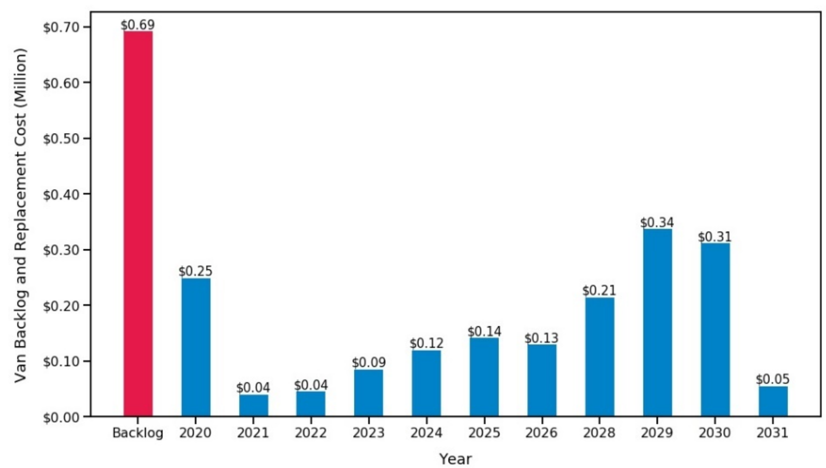
Backlog and Projected Replacement of Minivans



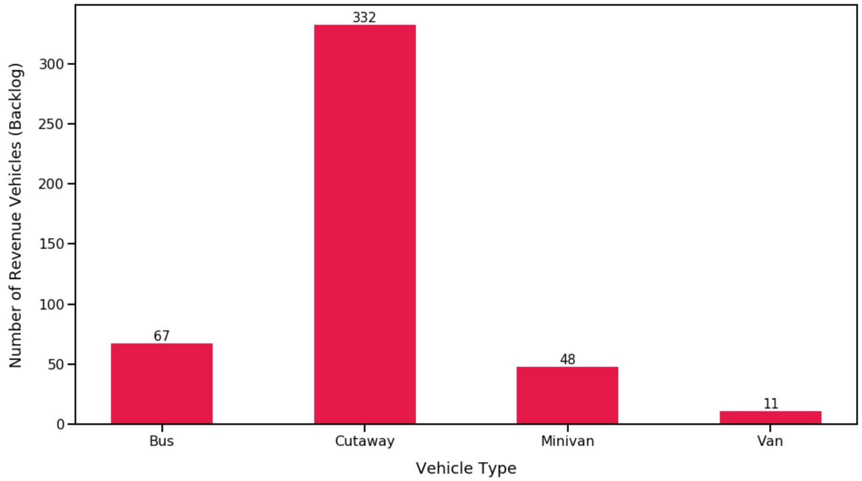
Backlog and Projected Replacement Cost for Minivans



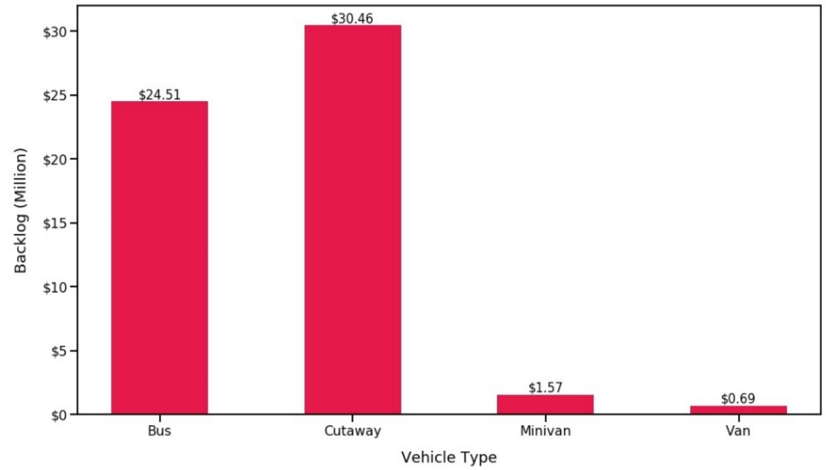
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

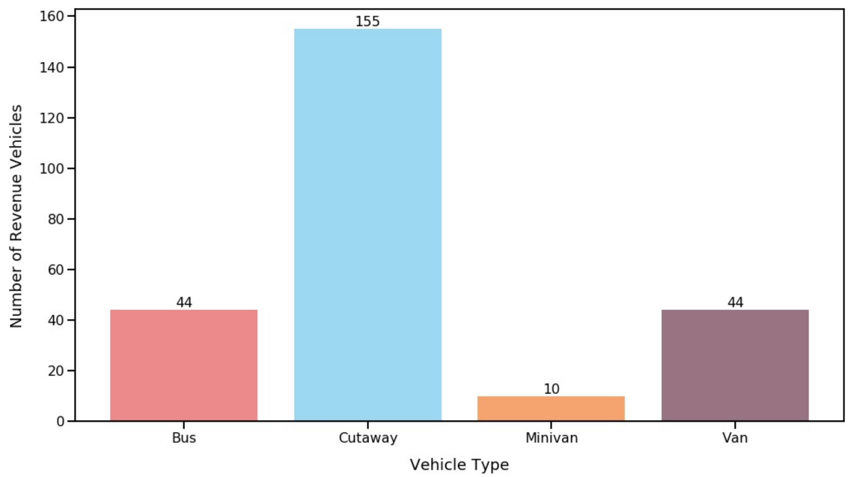


Backlog of the Revenue Vehicles by Vehicle Type

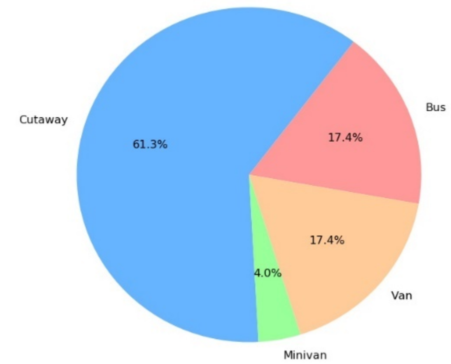


Funds Needed for Backlog by Vehicle Type

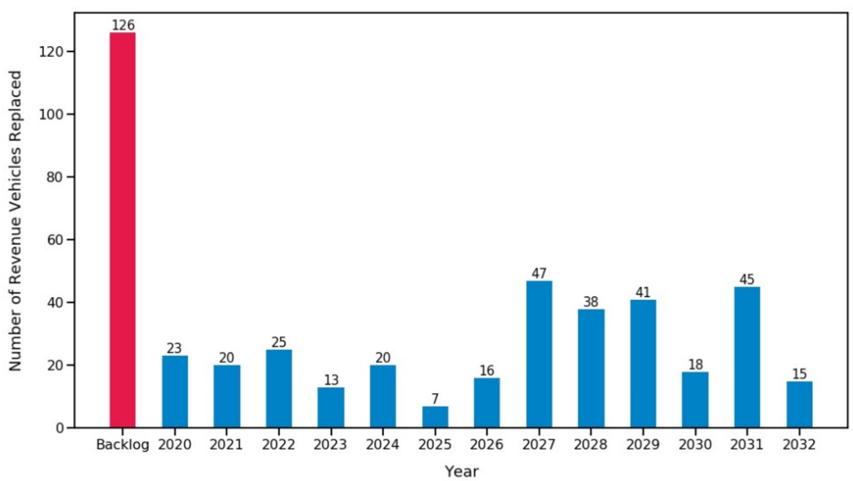
12 ID – Revenue Vehicles Information for Idaho's Small Urban and Rural Transit Systems (NTD 2017)



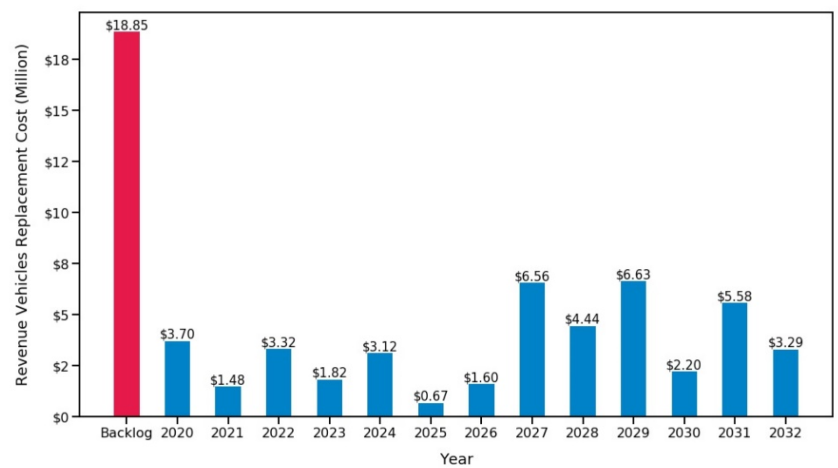
Number of Revenue Vehicles by Vehicle Type



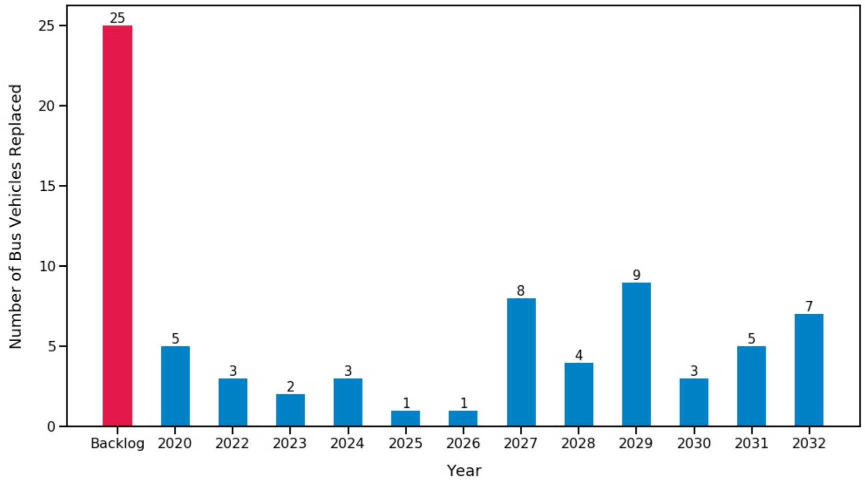
Percentage of Revenue Vehicles



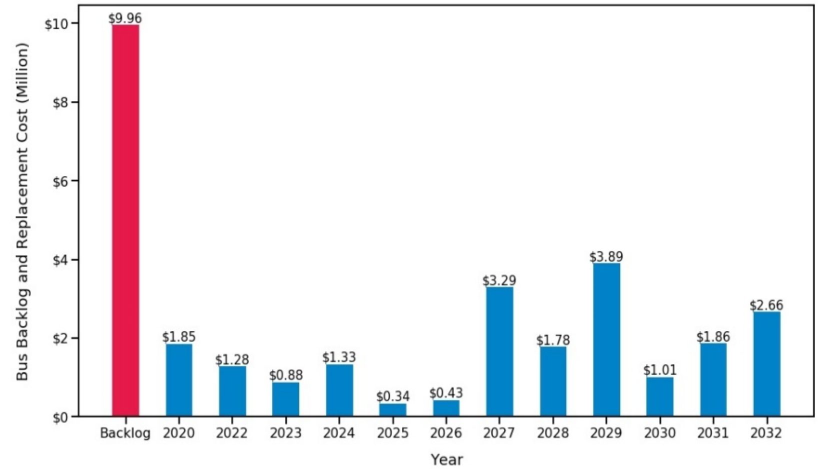
Backlog and Projected Replacement of Revenue Vehicles



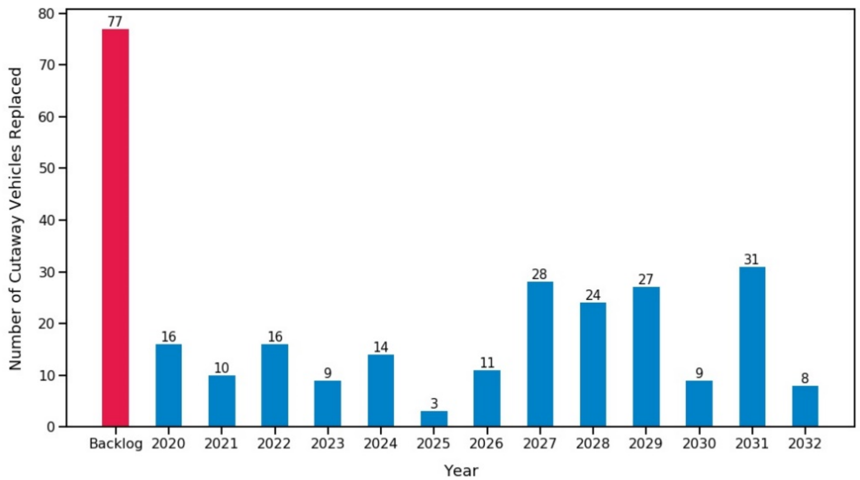
Backlog and Projected Replacement Costs for Revenue Vehicles



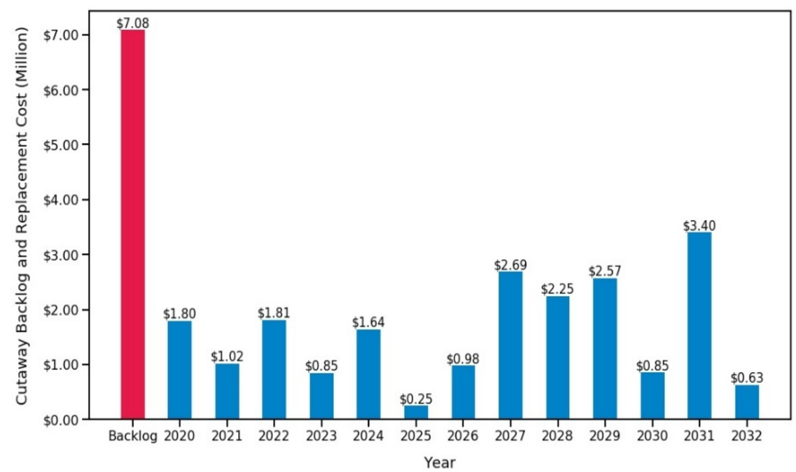
Backlog and Projected Replacement of Buses



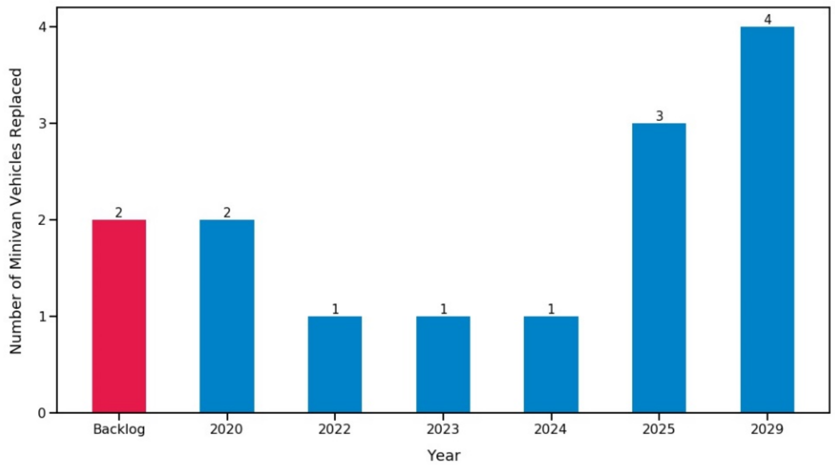
Backlog and Projected Replacement Cost for Buses



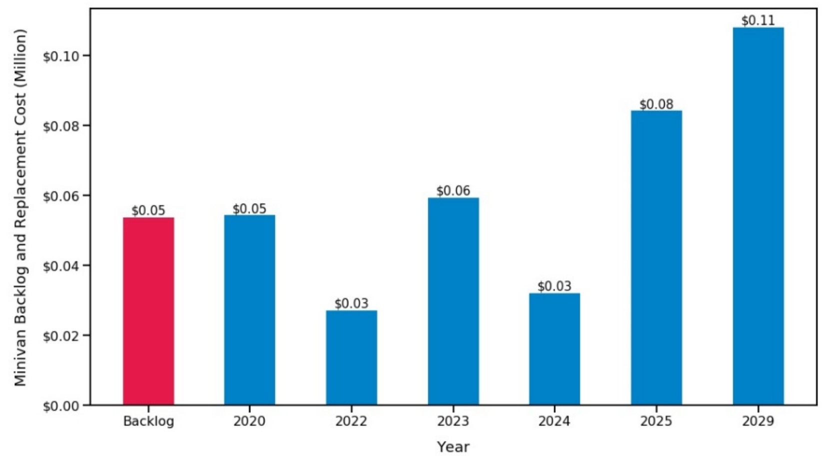
Backlog and Projected Replacement of Cutaways



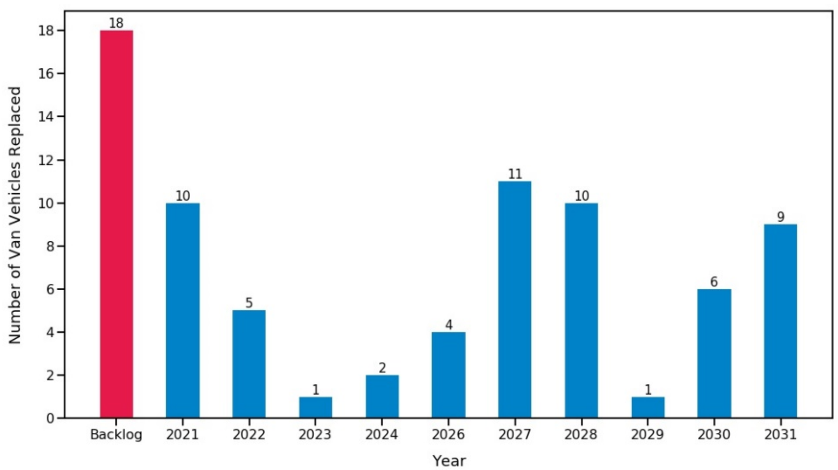
Backlog and Projected Replacement Cost for Cutaways



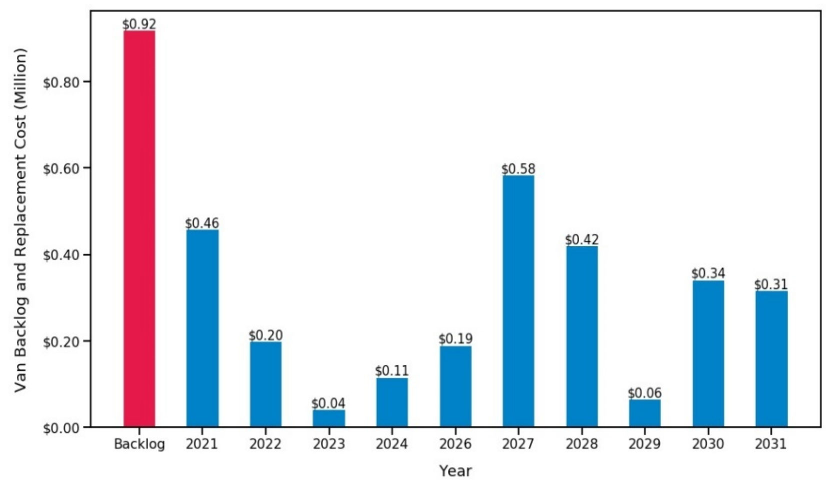
Backlog and Projected Replacement of Minivans



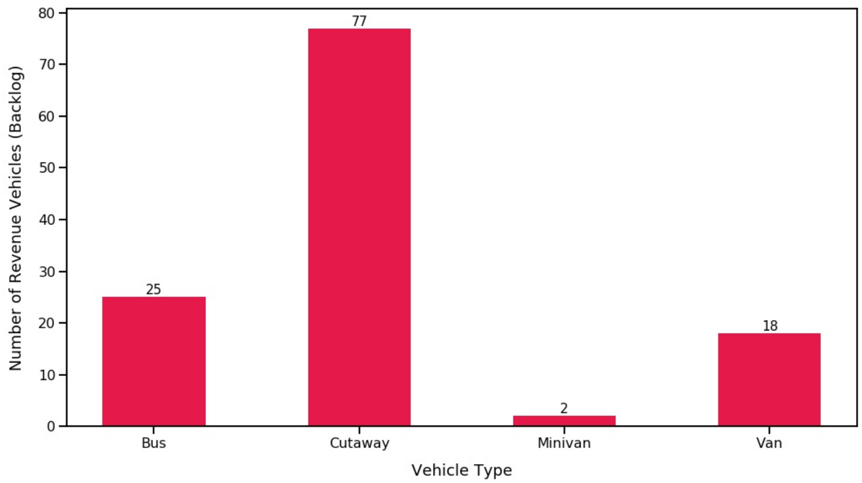
Backlog and Projected Replacement Cost for Minivans



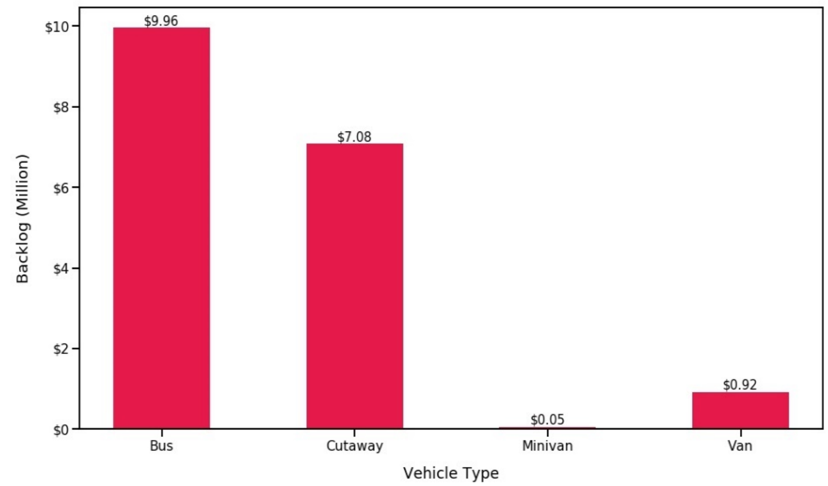
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

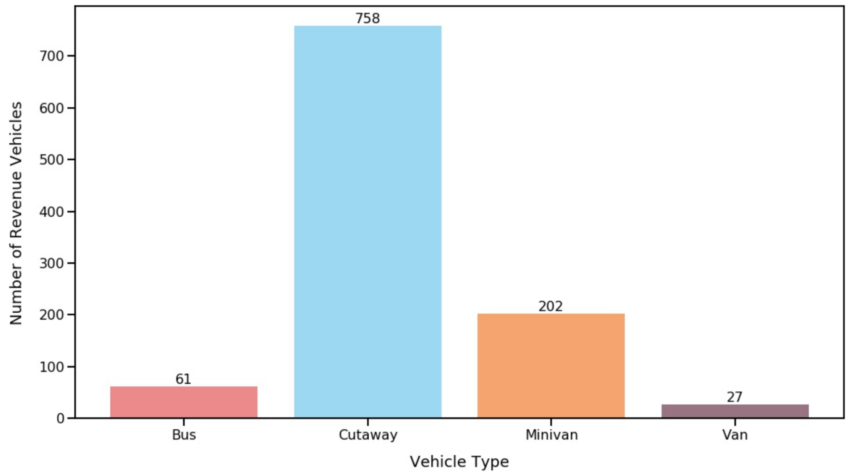


Backlog of the Revenue Vehicles by Vehicle Type

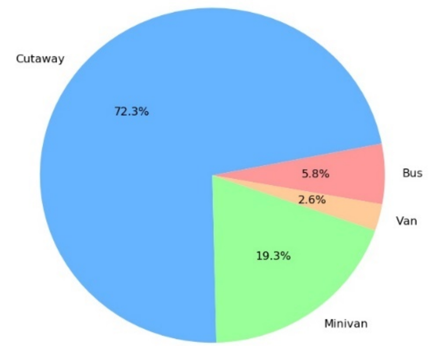


Funds Needed for Backlog by Vehicle Type

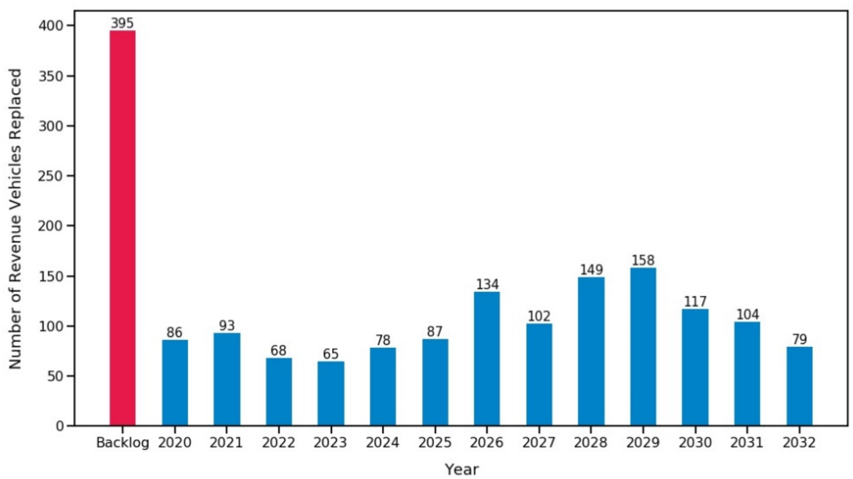
13 IL – Revenue Vehicles Information for Illinois's Small Urban and Rural Transit Systems (NTD 2017)



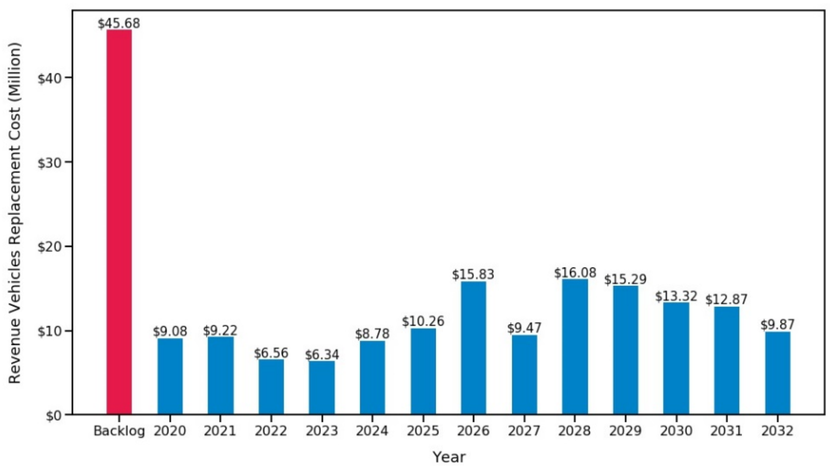
Number of Revenue Vehicles by Vehicle Type



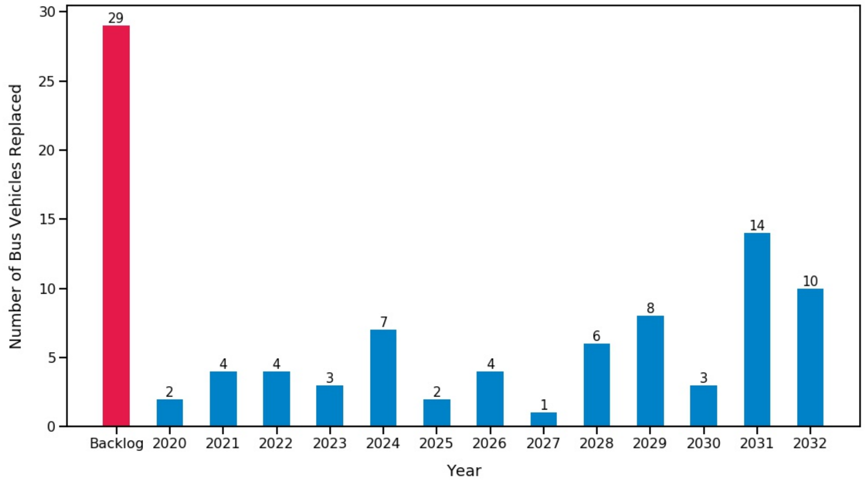
Percentage of Revenue Vehicles



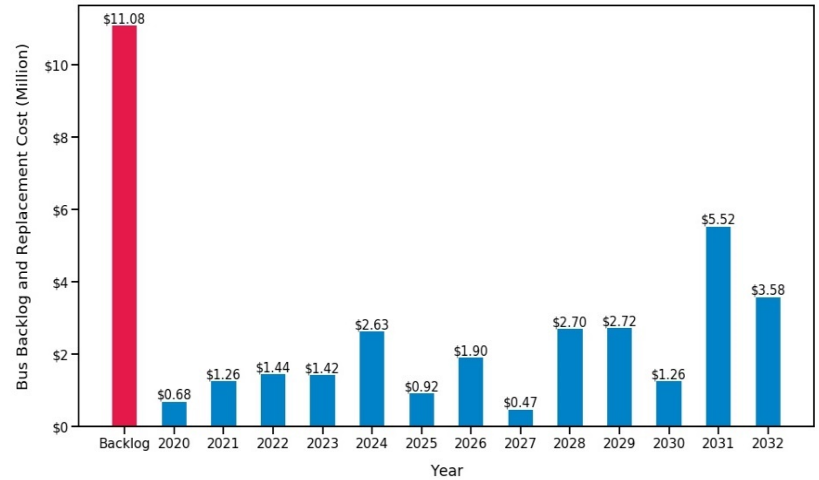
Backlog and Projected Replacement of Revenue Vehicles



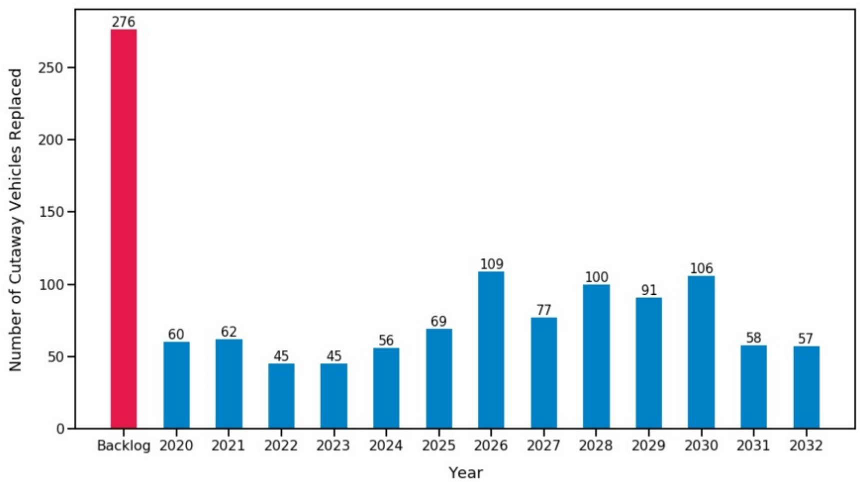
Backlog and Projected Replacement Costs for Revenue Vehicles



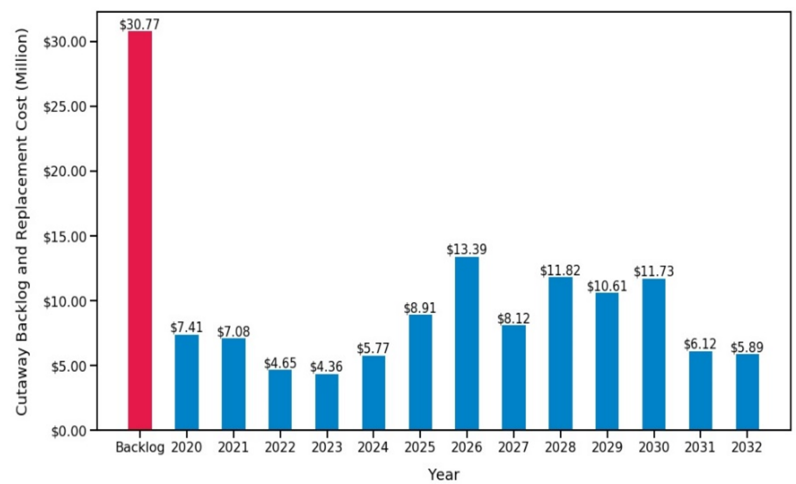
Backlog and Projected Replacement of Buses



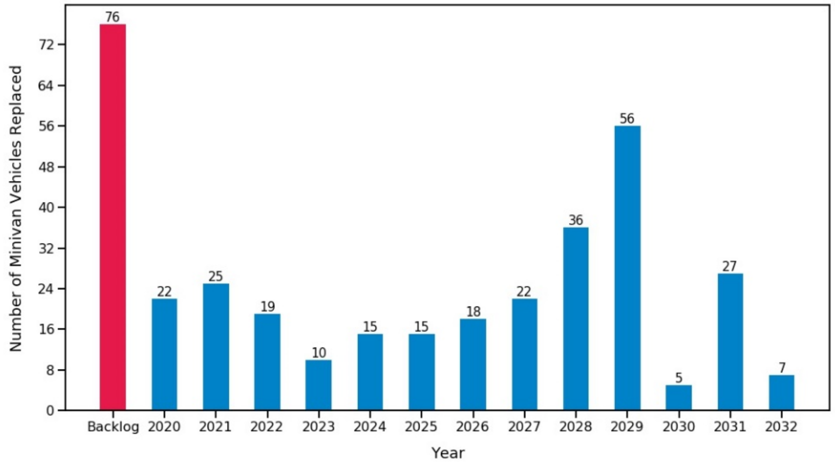
Backlog and Projected Replacement Cost for Buses



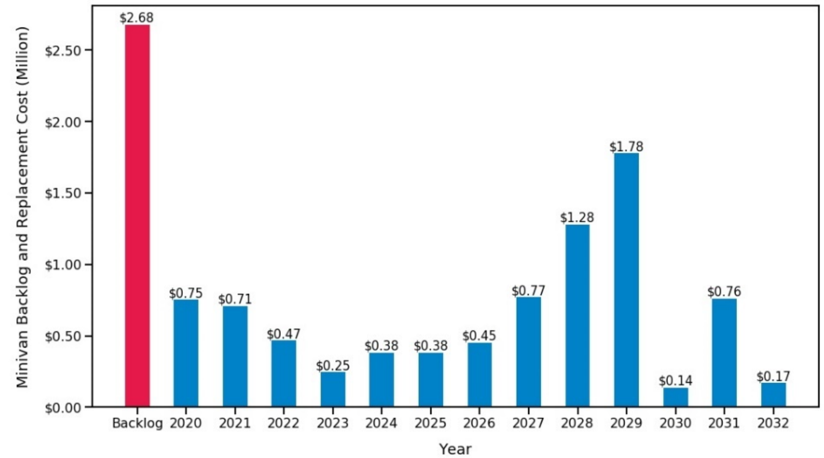
Backlog and Projected Replacement of Cutaways



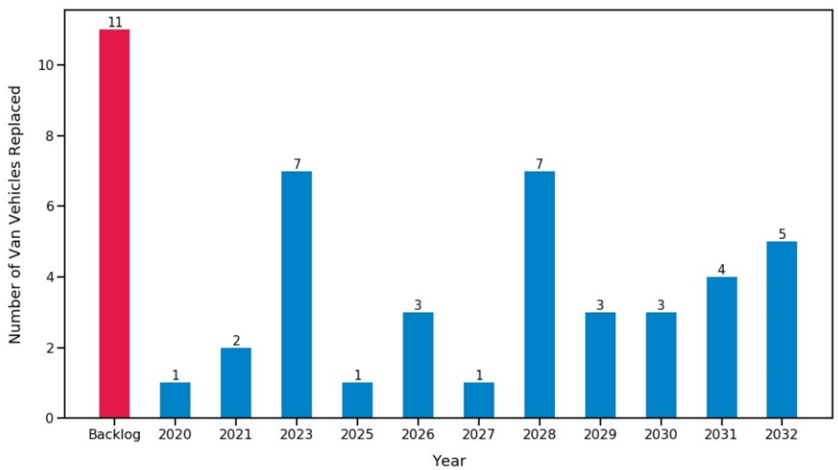
Backlog and Projected Replacement Cost for Cutaways



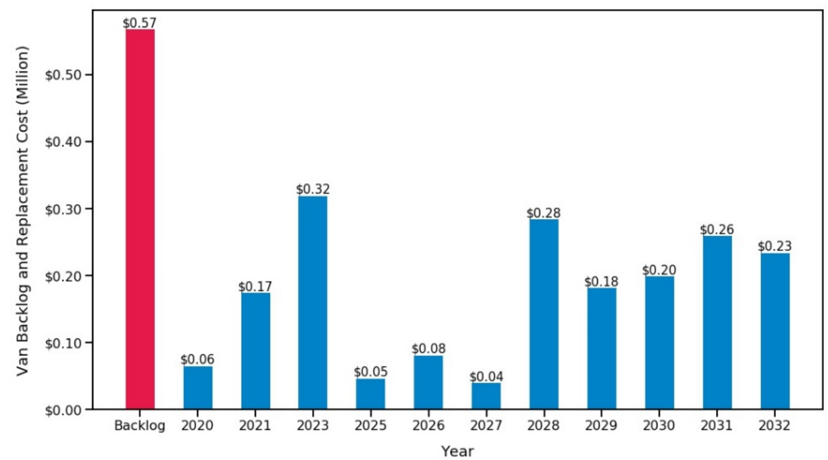
Backlog and Projected Replacement of Minivans



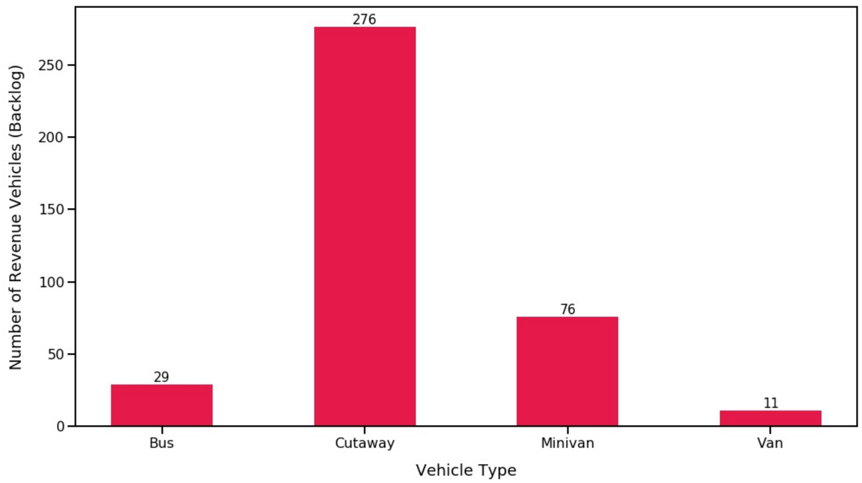
Backlog and Projected Replacement Cost for Minivans



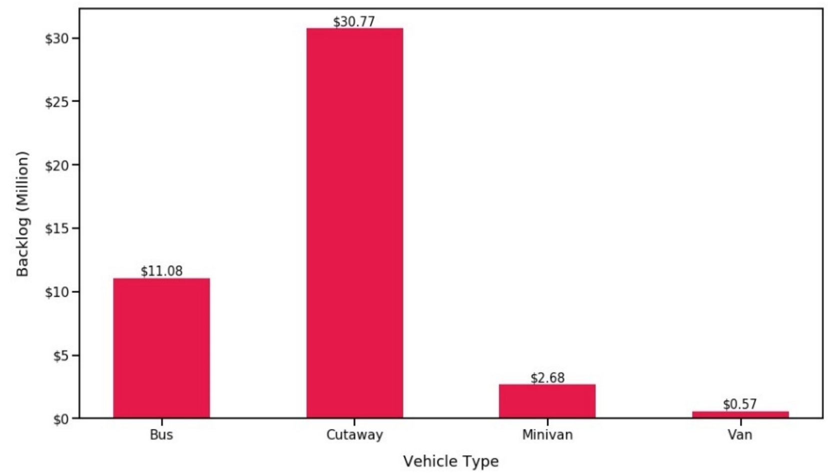
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

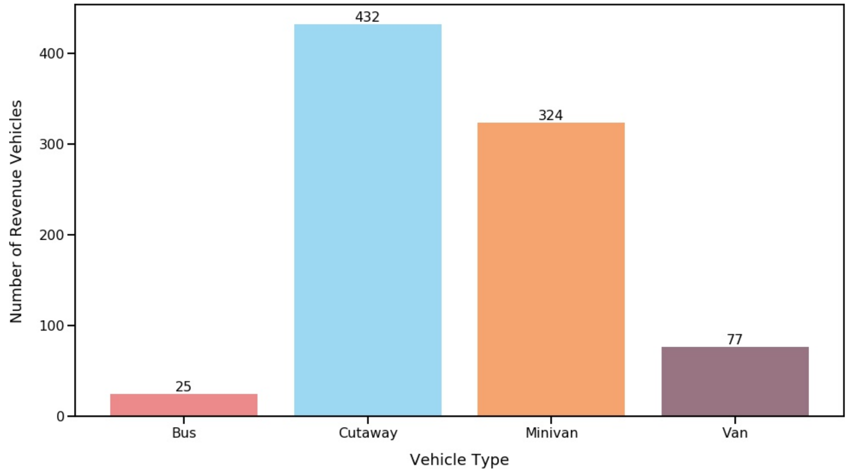


Backlog of the Revenue Vehicles by Vehicle Type

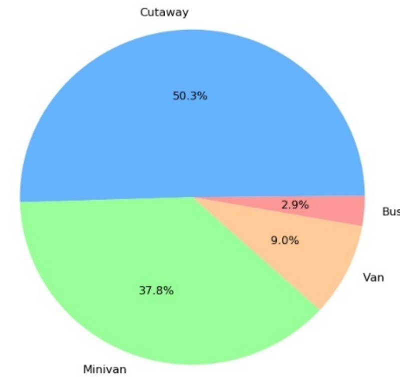


Funds Needed for Backlog by Vehicle Type

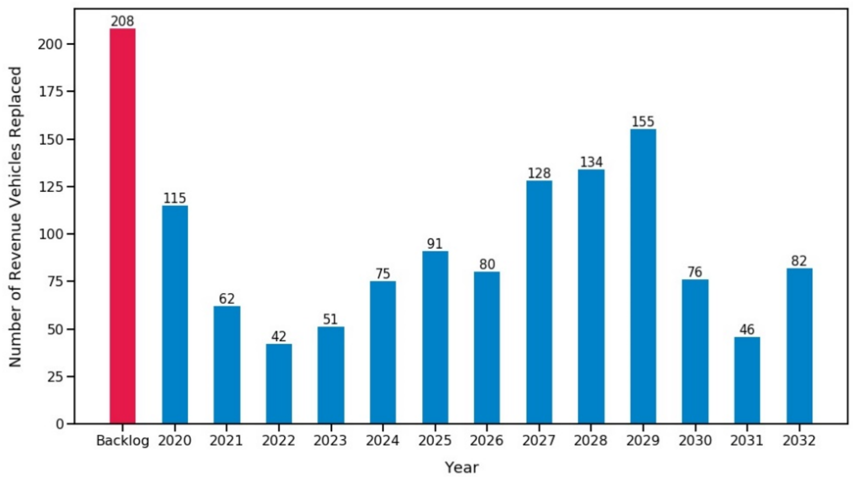
14 IN – Revenue Vehicles Information for Indiana's Small Urban and Rural Transit Systems (NTD 2017)



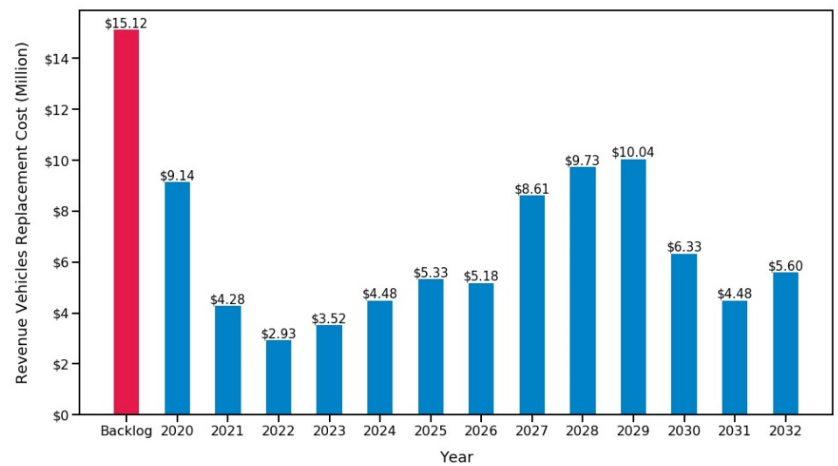
Number of Revenue Vehicles by Vehicle Type



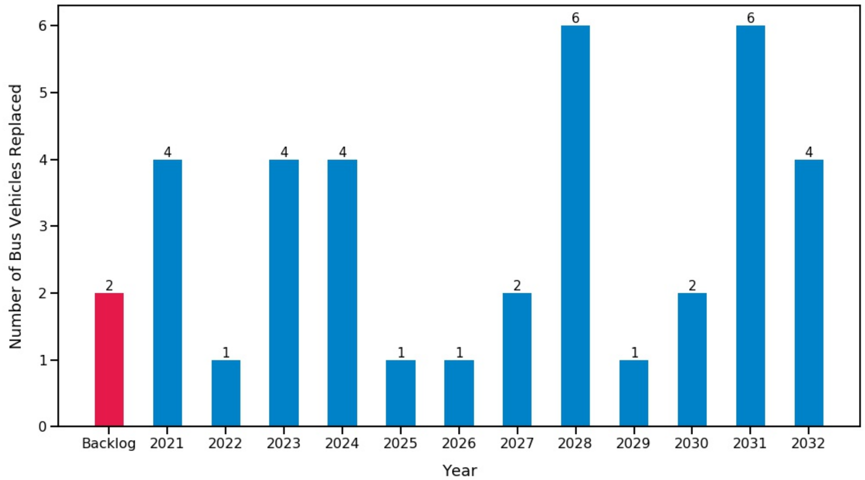
Percentage of Revenue Vehicles



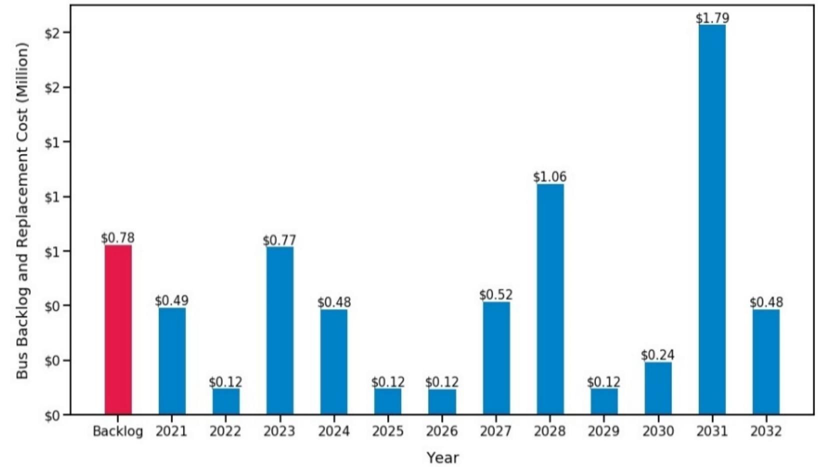
Backlog and Projected Replacement of Revenue Vehicles



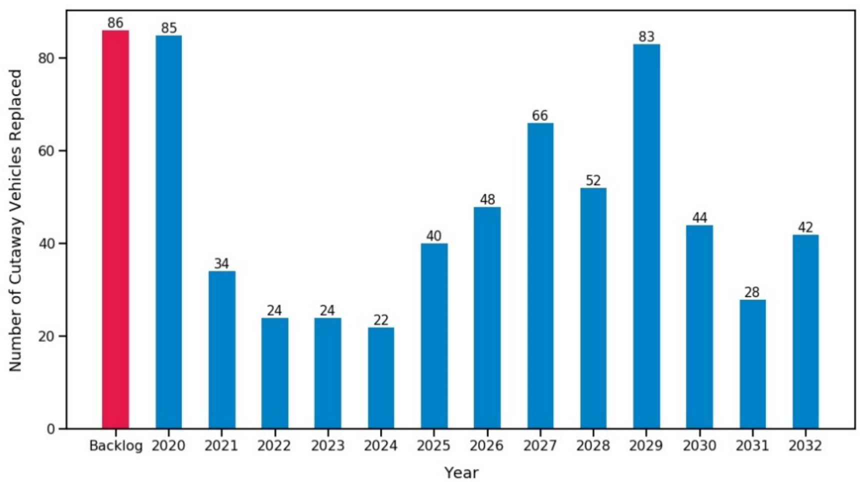
Backlog and Projected Replacement Costs for Revenue Vehicles



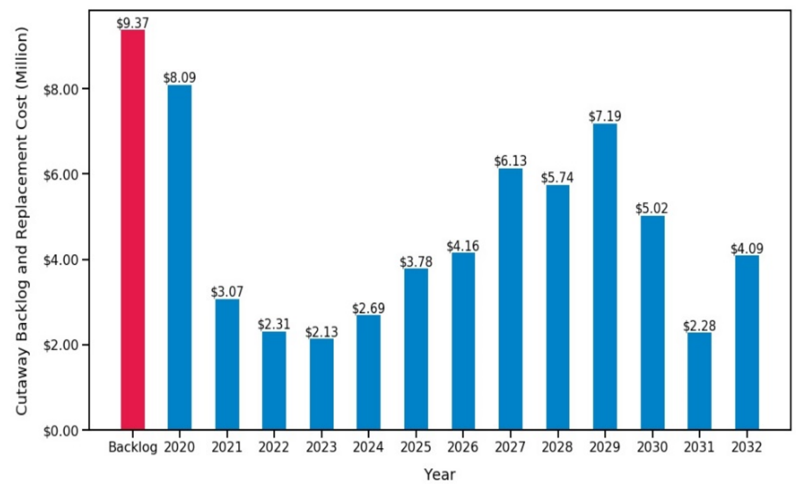
Backlog and Projected Replacement of Buses



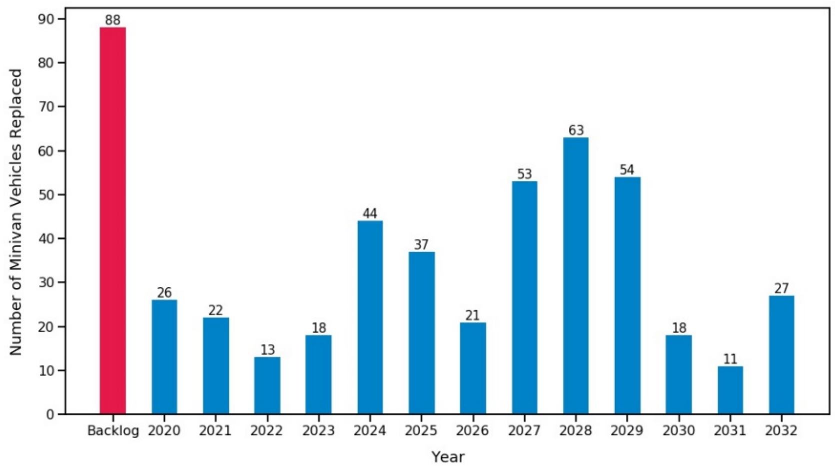
Backlog and Projected Replacement Cost for Buses



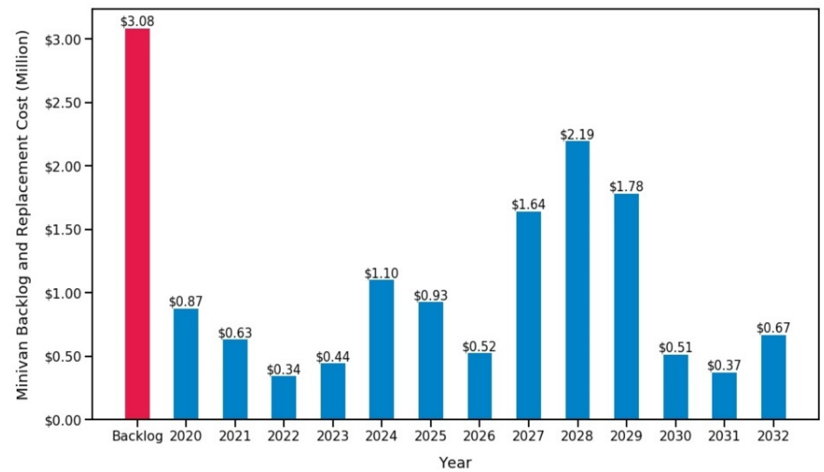
Backlog and Projected Replacement of Cutaways



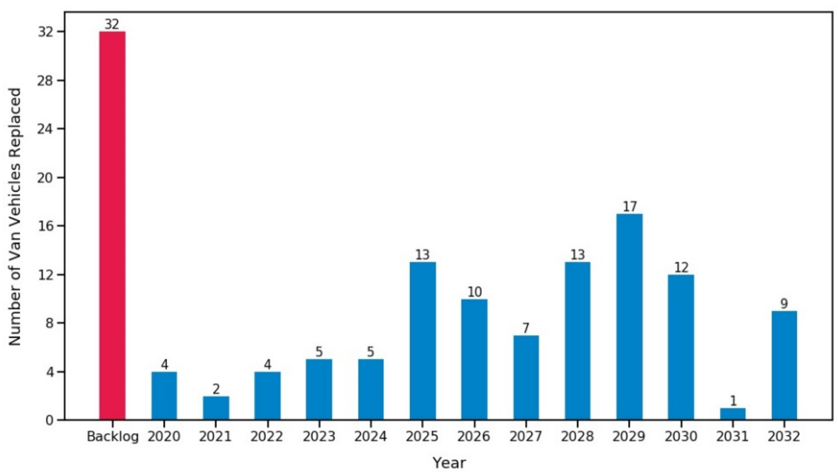
Backlog and Projected Replacement Cost for Cutaways



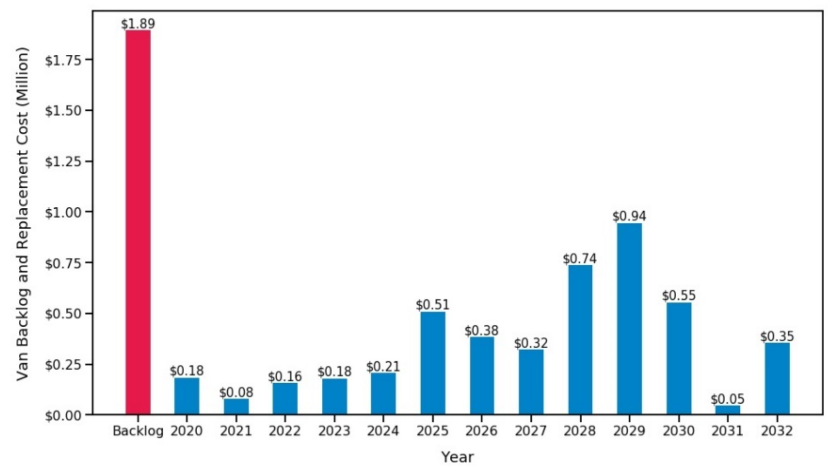
Backlog and Projected Replacement of Minivans



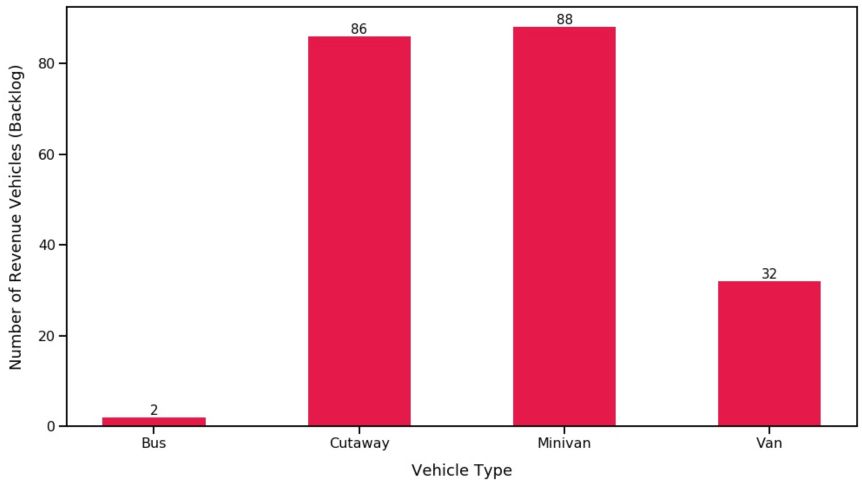
Backlog and Projected Replacement Cost for Minivans



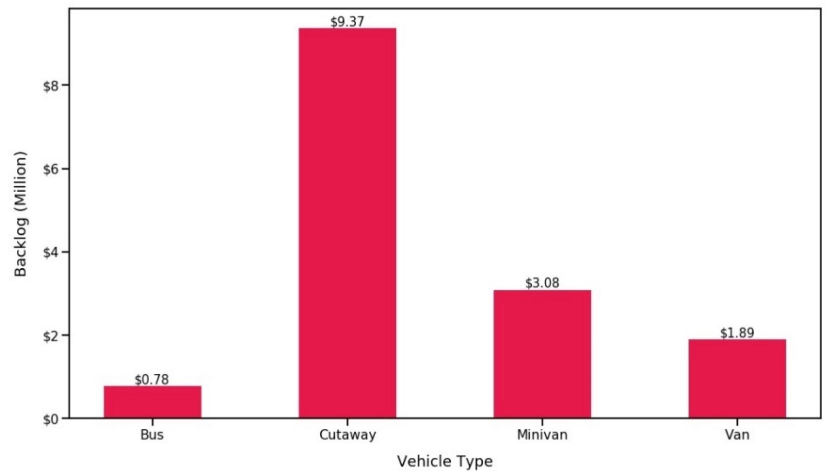
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

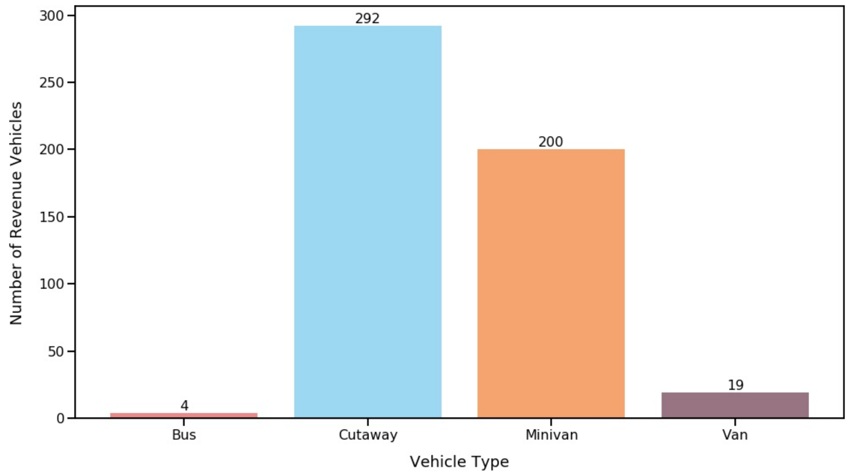


Backlog of the Revenue Vehicles by Vehicle Type

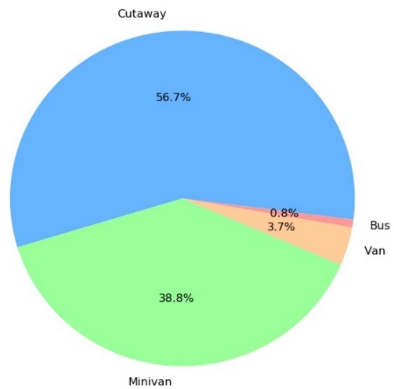


Funds Needed for Backlog by Vehicle Type

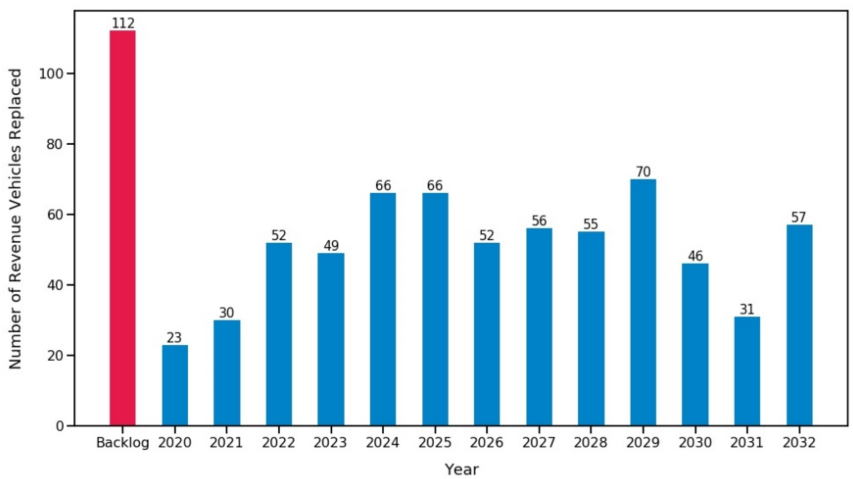
15 KS – Revenue Vehicles Information for Kansas's Small Urban and Rural Transit Systems (NTD 2017)



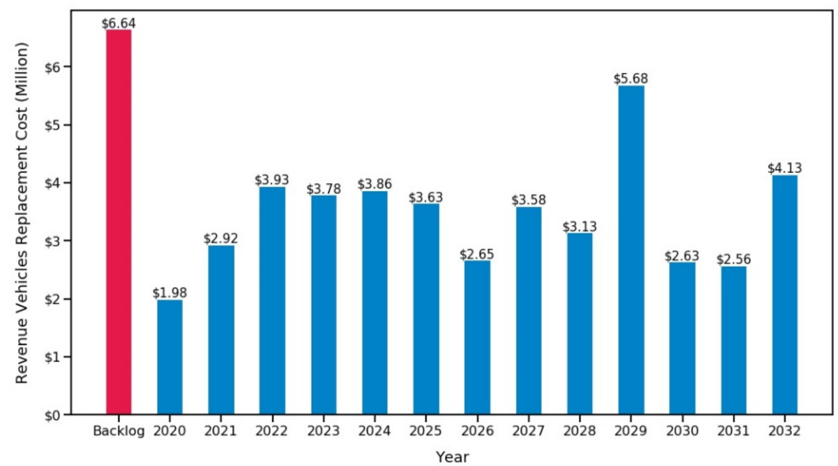
Number of Revenue Vehicles by Vehicle Type



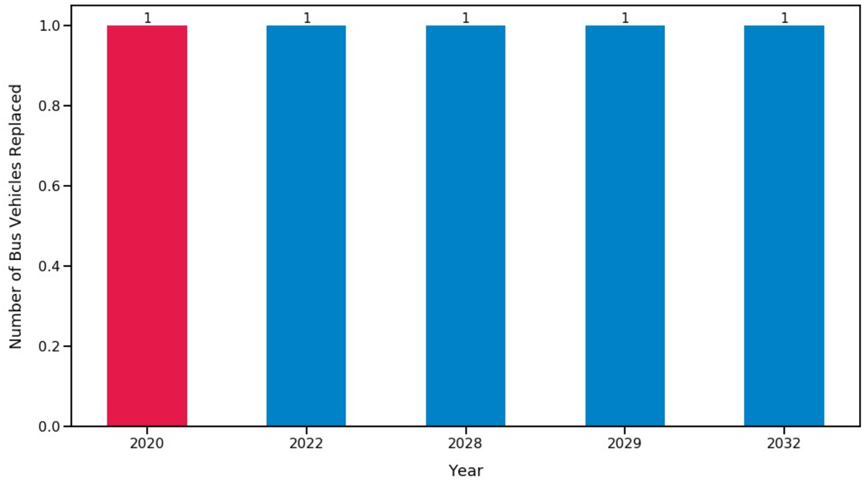
Percentage of Revenue Vehicles



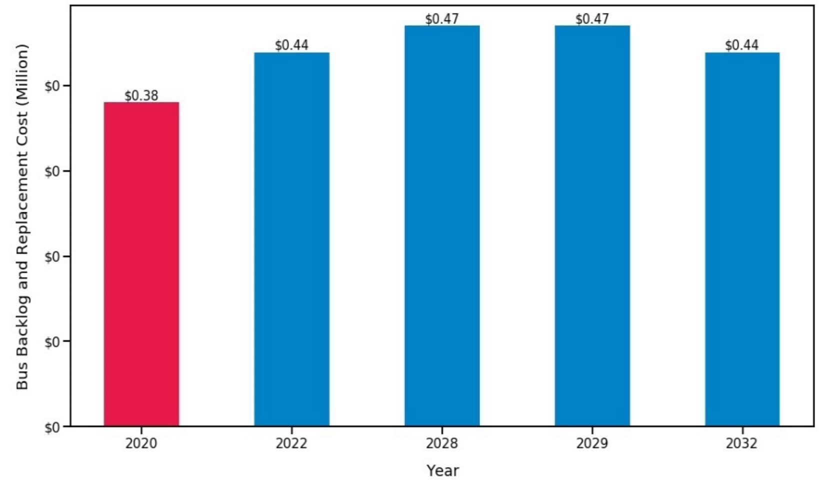
Backlog and Projected Replacement of Revenue Vehicles



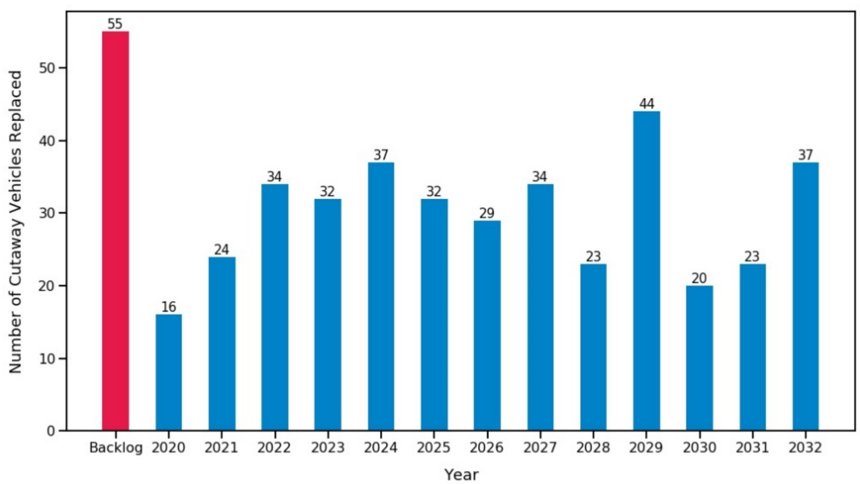
Backlog and Projected Replacement Costs for Revenue Vehicles



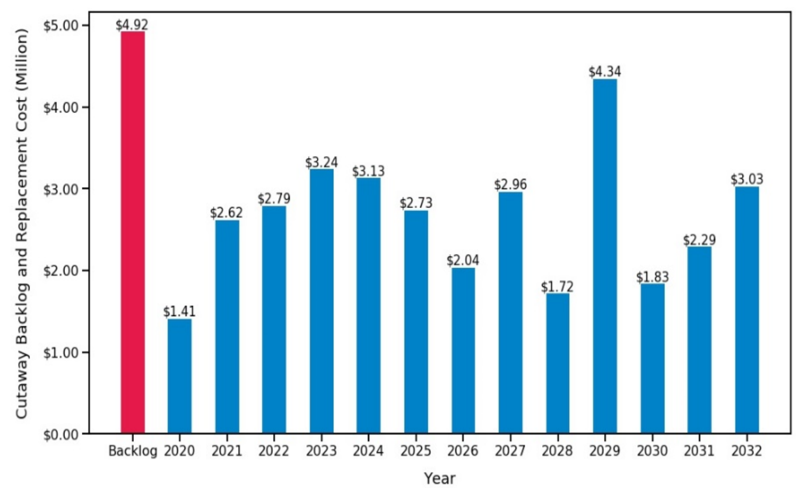
Backlog and Projected Replacement of Buses



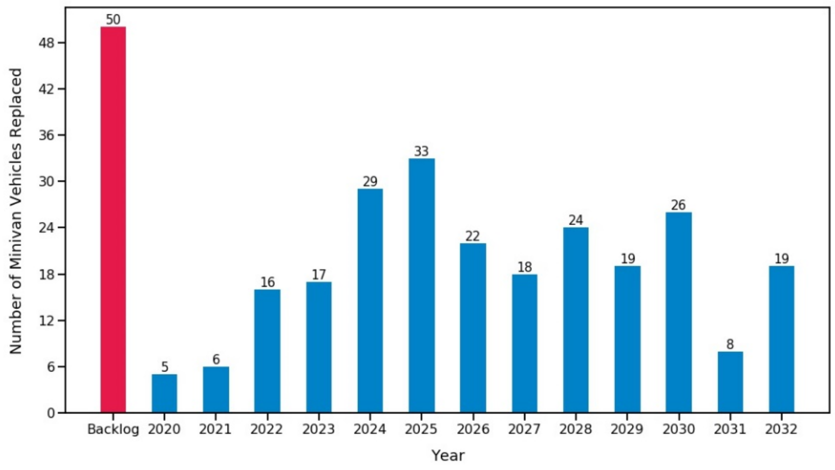
Backlog and Projected Replacement Cost for Buses



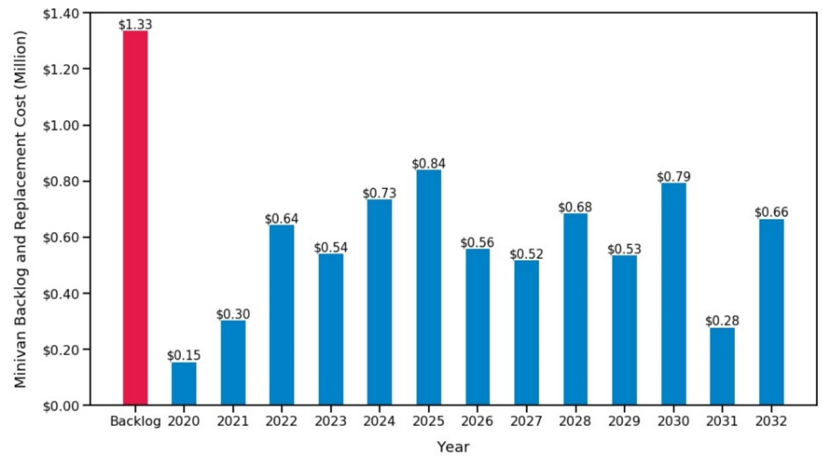
Backlog and Projected Replacement of Cutaways



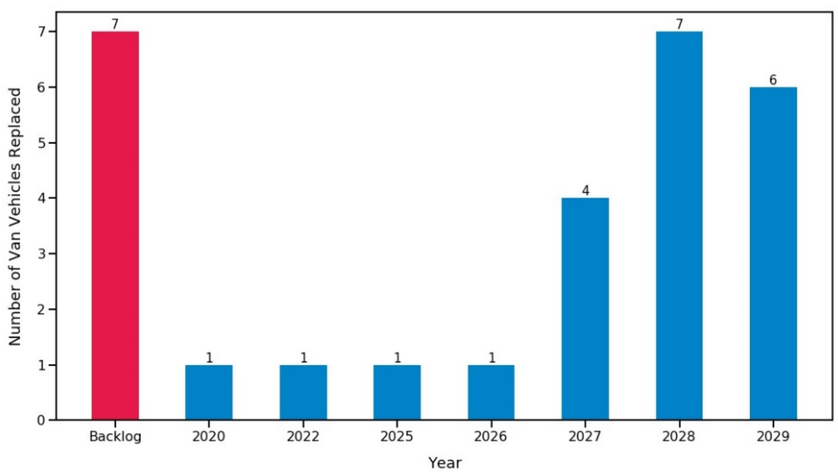
Backlog and Projected Replacement Cost for Cutaways



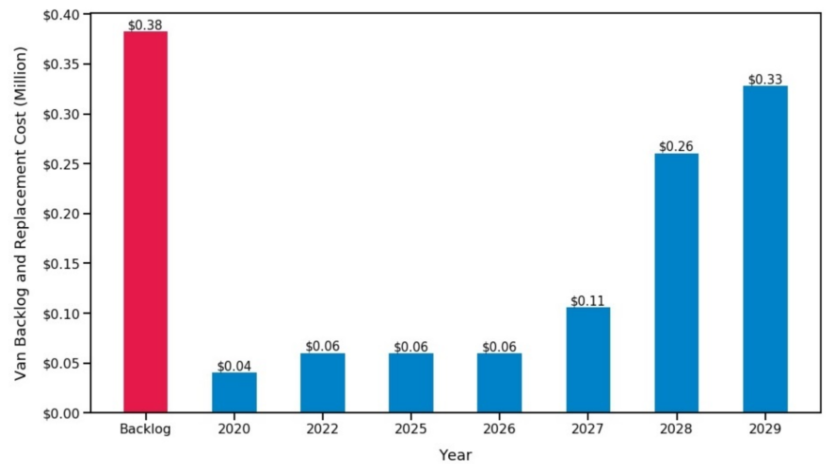
Backlog and Projected Replacement of Minivans



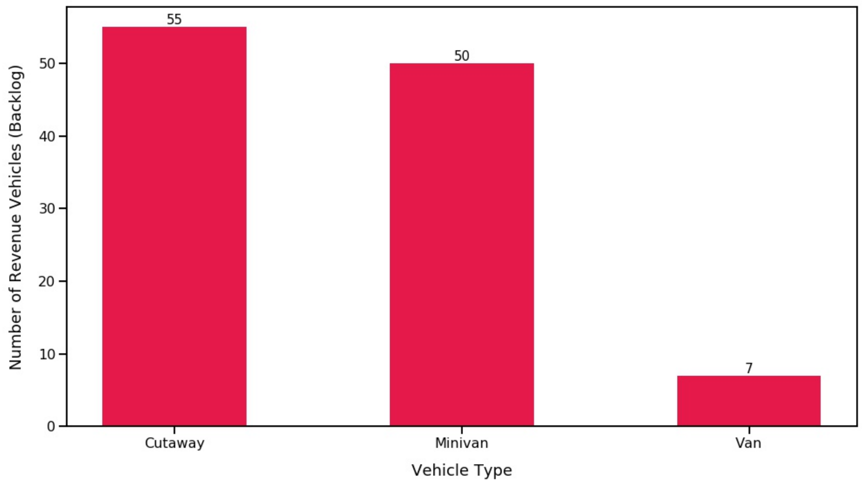
Backlog and Projected Replacement Cost for Minivans



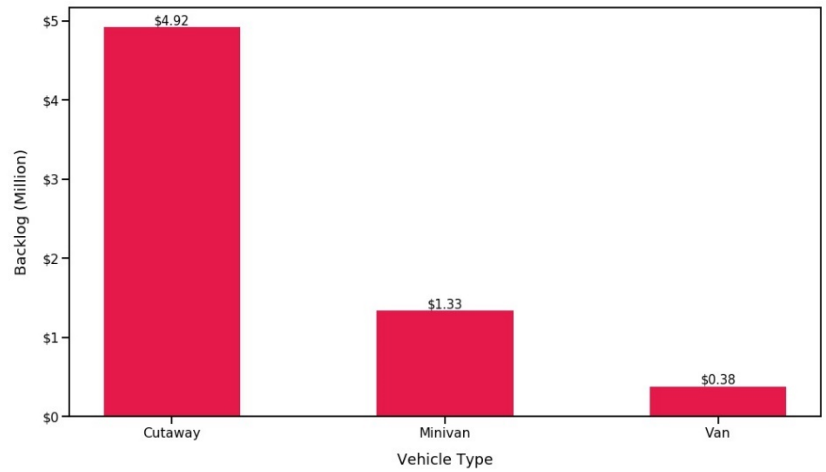
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

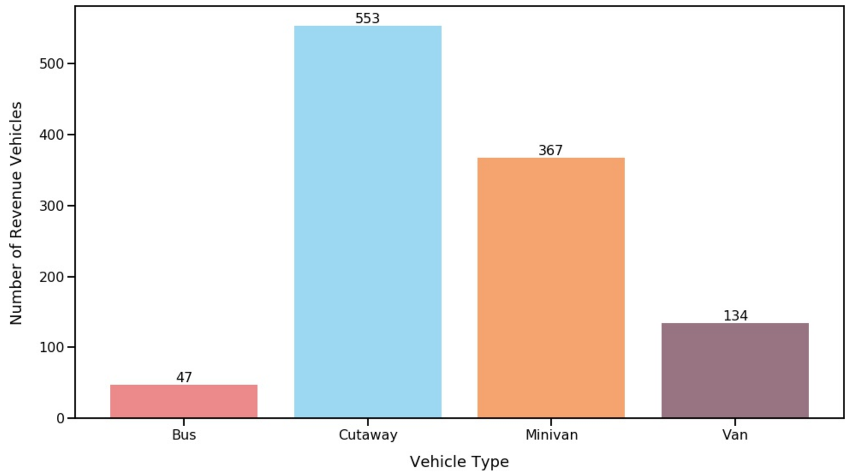


Backlog of the Revenue Vehicles by Vehicle Type

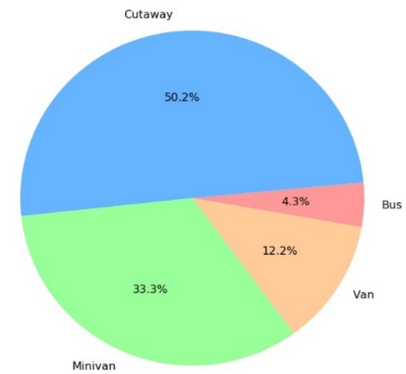


Funds Needed for Backlog by Vehicle Type

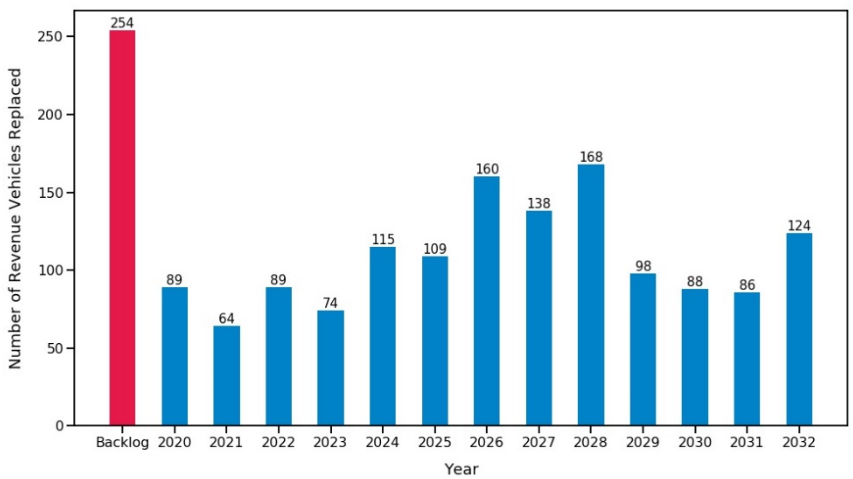
16 KY – Revenue Vehicles Information for Kentucky's Small Urban and Rural Transit Systems (NTD 2017)



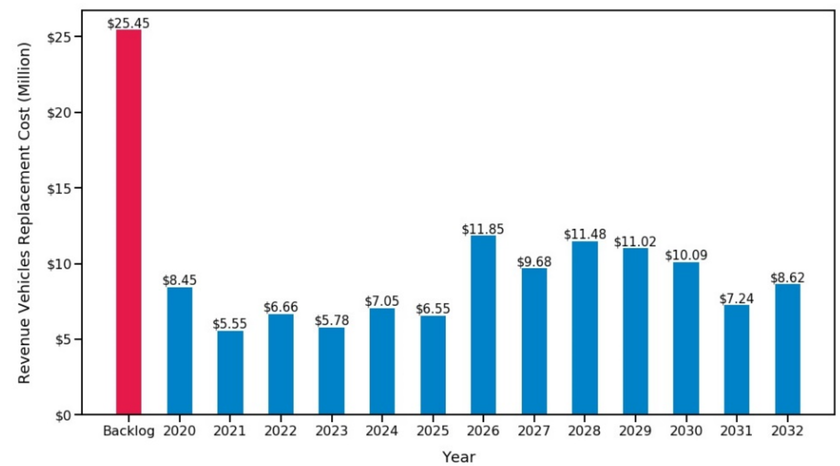
Number of Revenue Vehicles by Vehicle Type



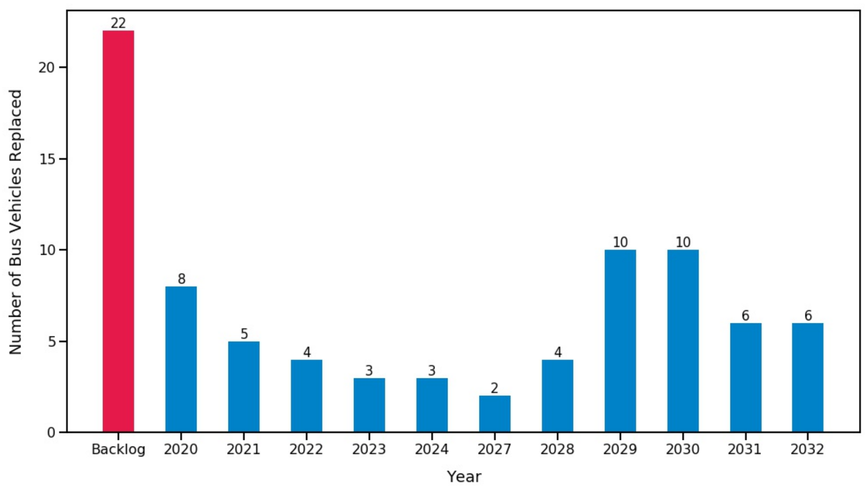
Percentage of Revenue Vehicles



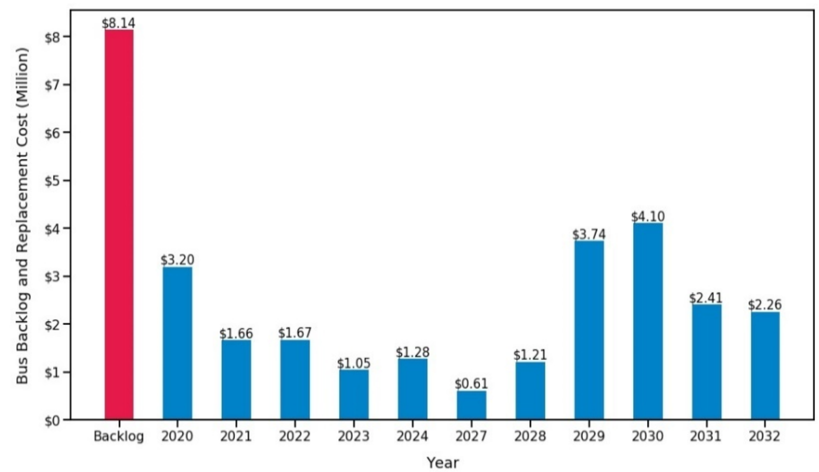
Backlog and Projected Replacement of Revenue Vehicles



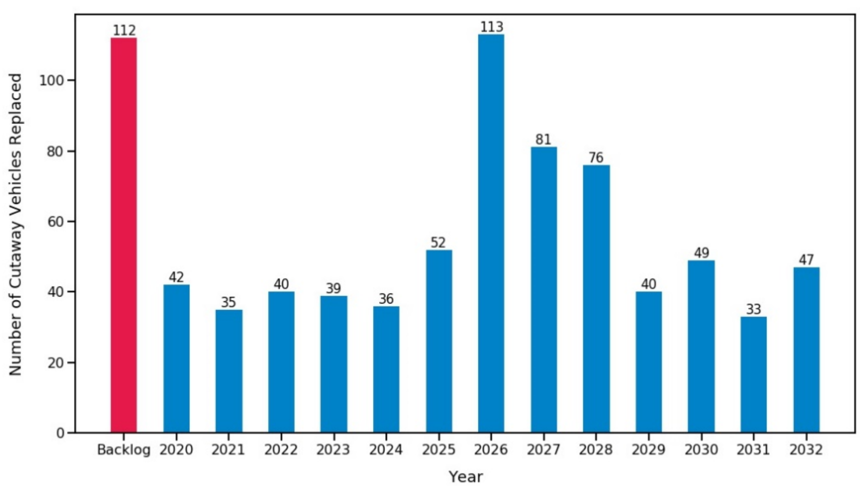
Backlog and Projected Replacement Costs for Revenue Vehicles



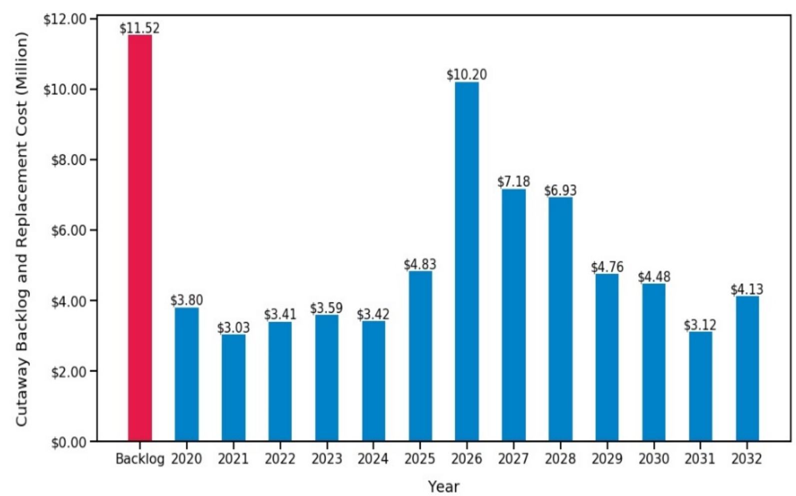
Backlog and Projected Replacement of Buses



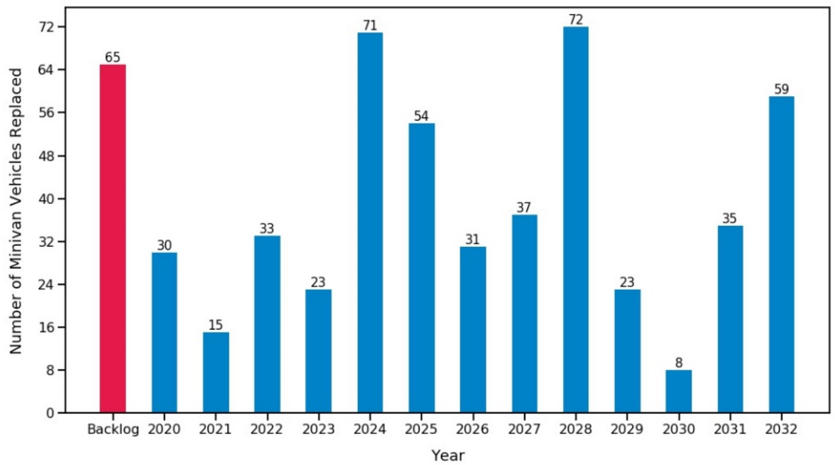
Backlog and Projected Replacement Cost for Buses



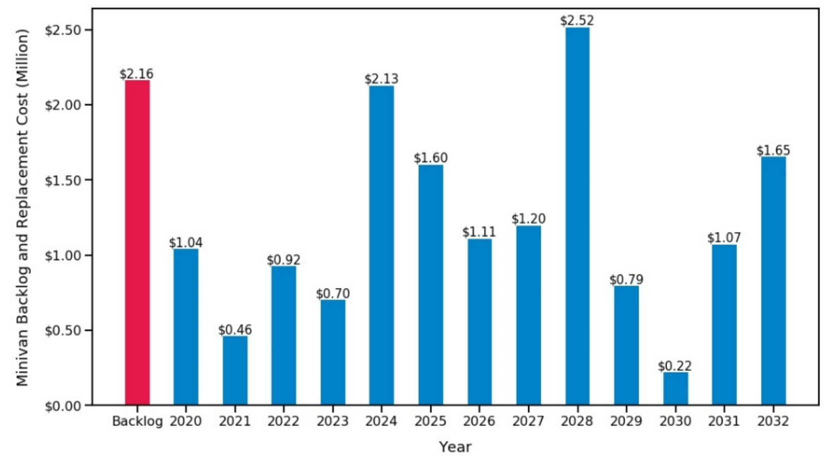
Backlog and Projected Replacement of Cutaways



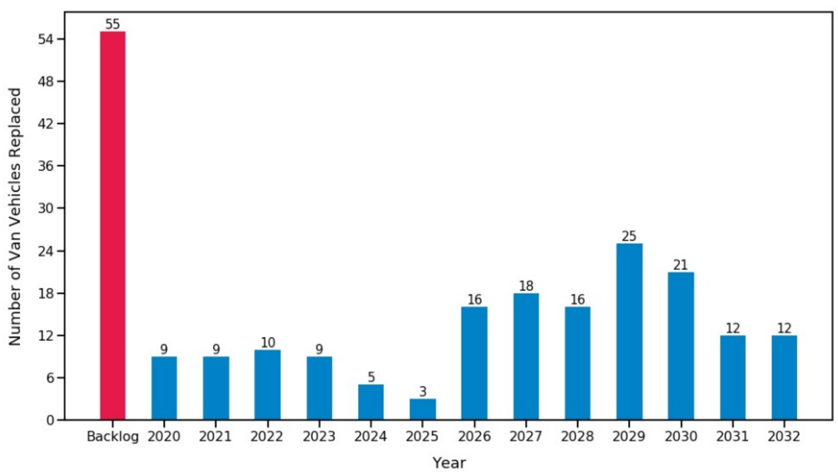
Backlog and Projected Replacement Cost for Cutaways



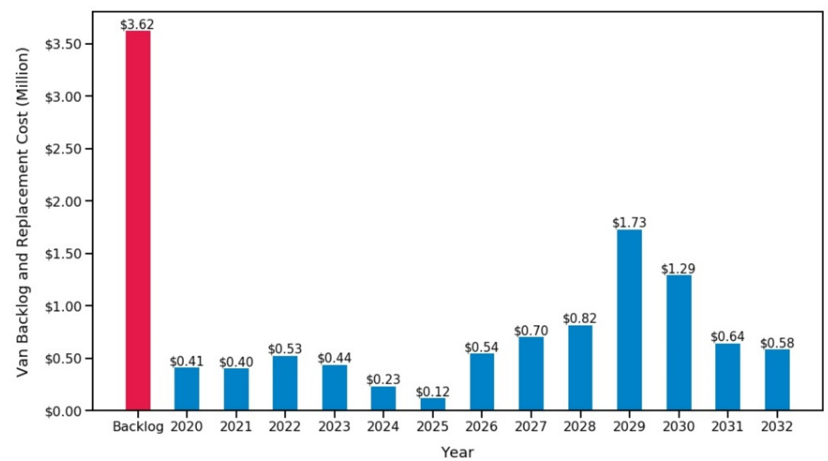
Backlog and Projected Replacement of Minivans



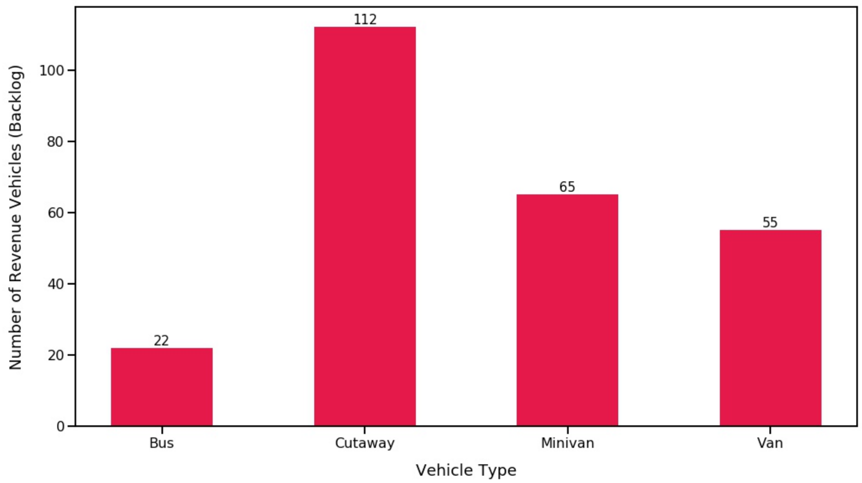
Backlog and Projected Replacement Cost for Minivans



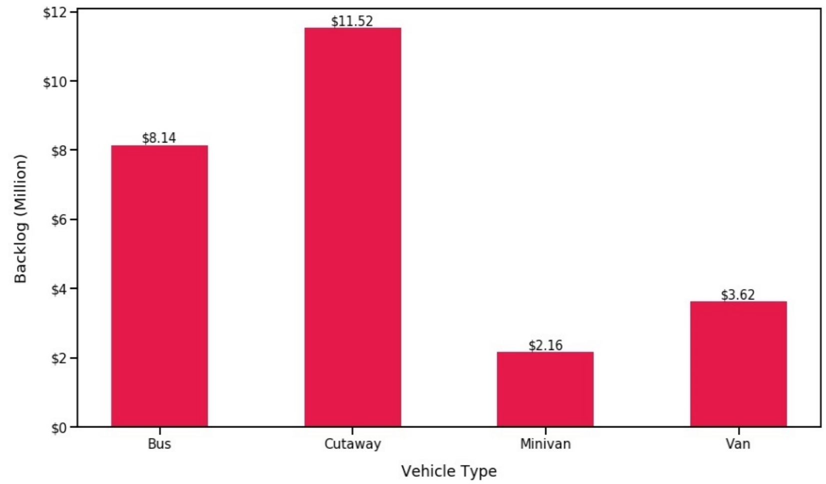
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

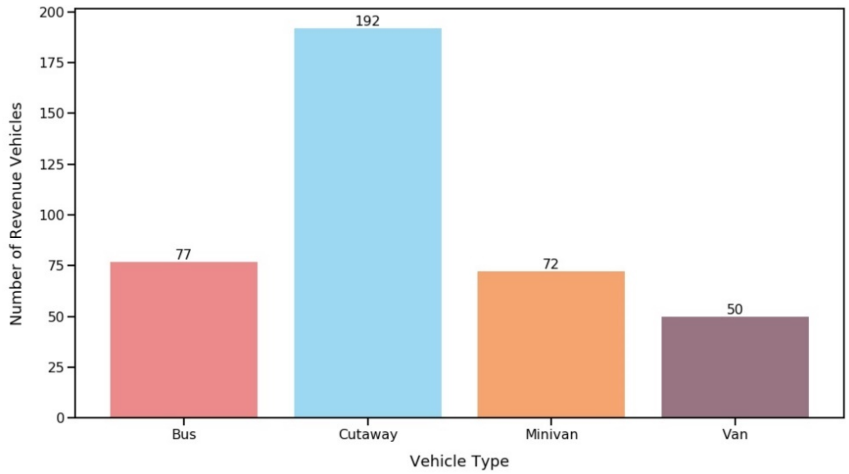


Backlog of the Revenue Vehicles by Vehicle Type

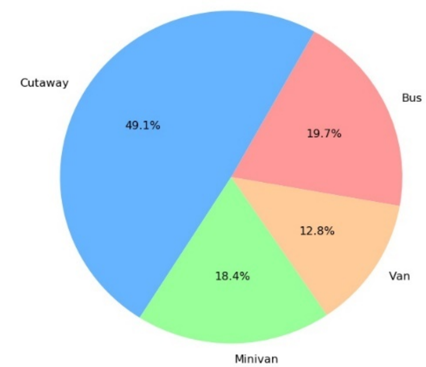


Funds Needed for Backlog by Vehicle Type

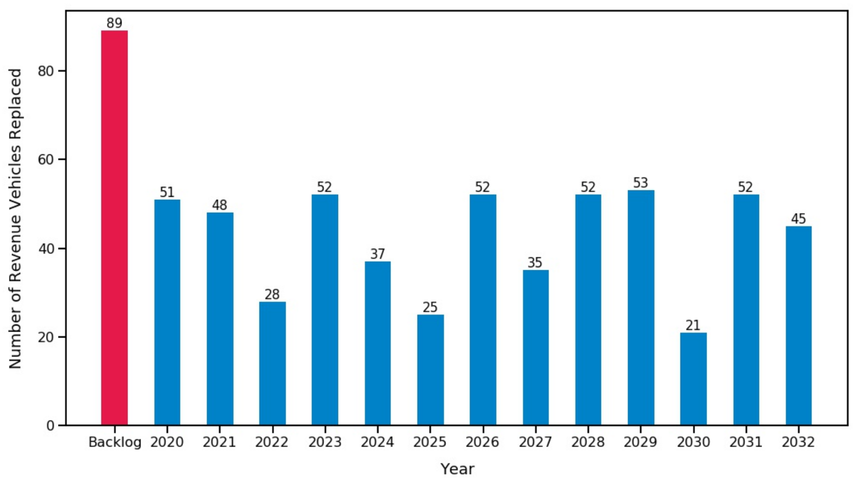
17 LA – Revenue Vehicles Information for Louisiana's Small Urban and Rural Transit Systems (NTD 2017)



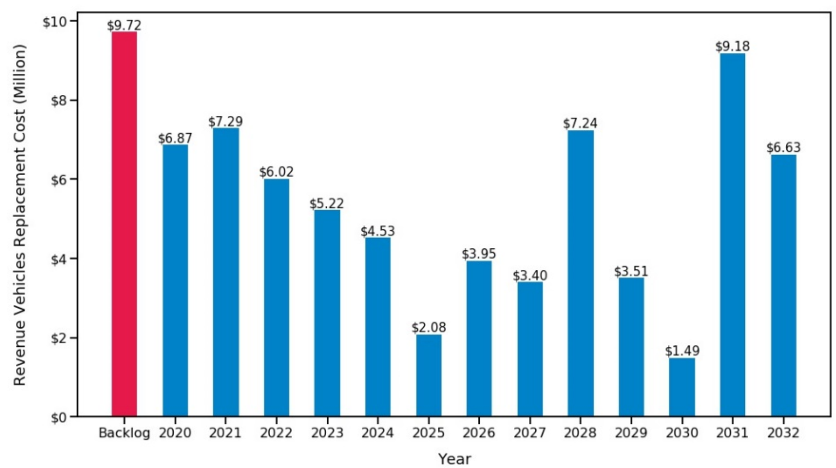
Number of Revenue Vehicles by Vehicle Type



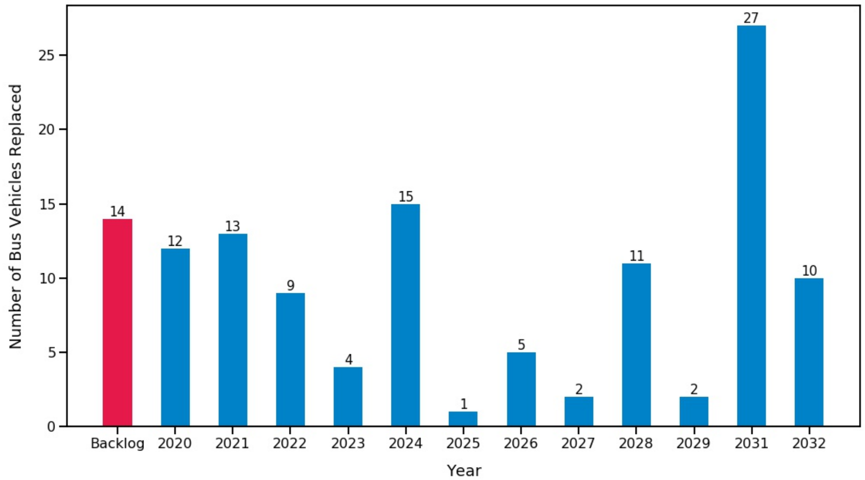
Percentage of Revenue Vehicles



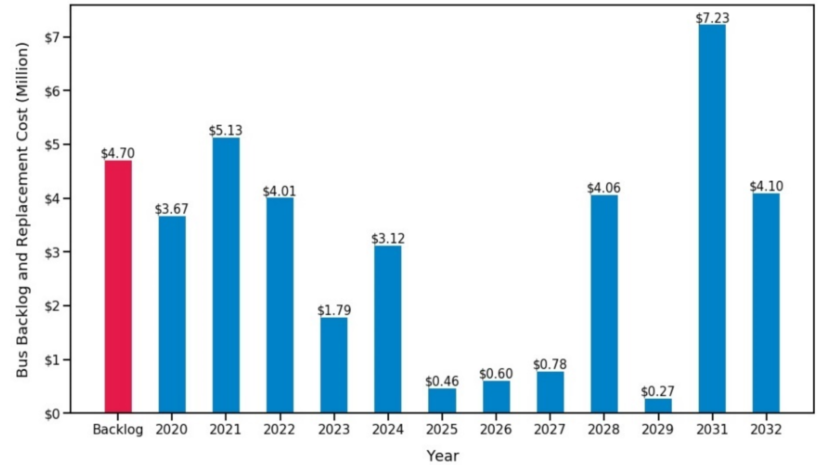
Backlog and Projected Replacement of Revenue Vehicles



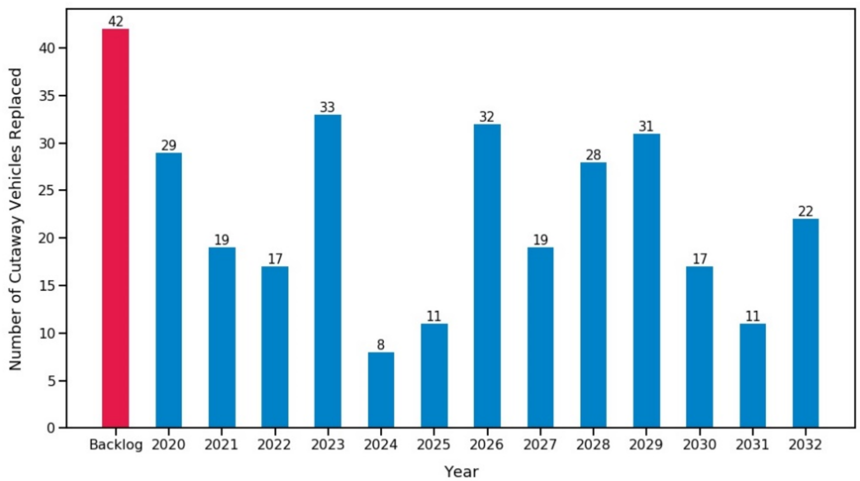
Backlog and Projected Replacement Costs for Revenue Vehicles



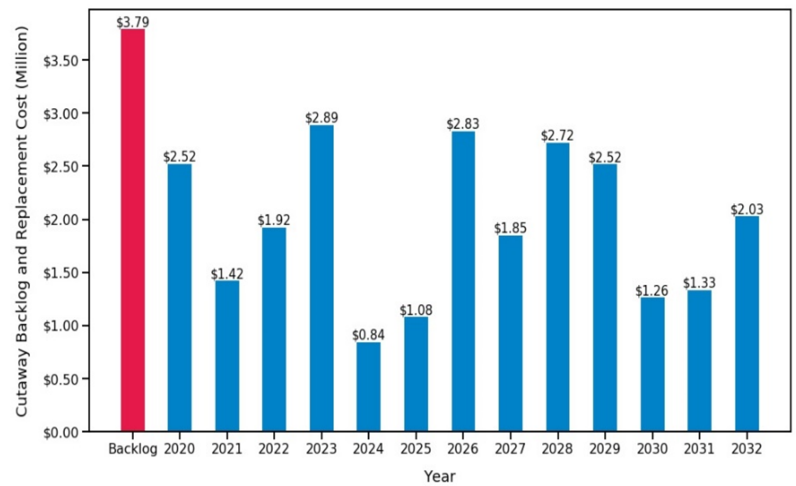
Backlog and Projected Replacement of Buses



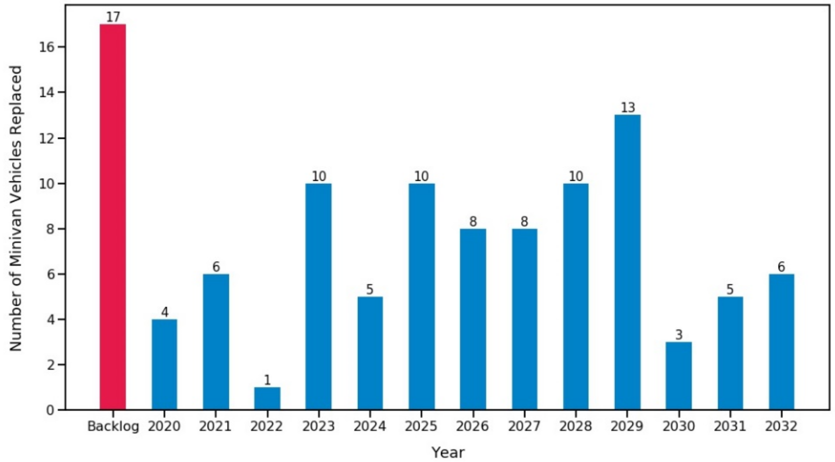
Backlog and Projected Replacement Cost for Buses



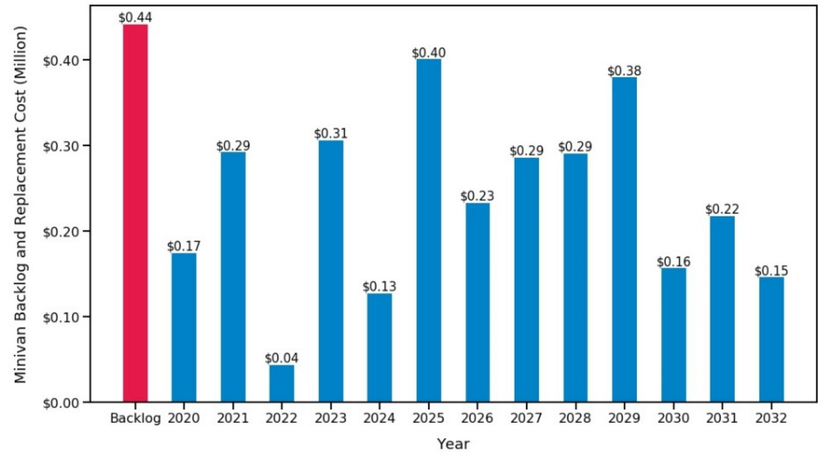
Backlog and Projected Replacement of Cutaways



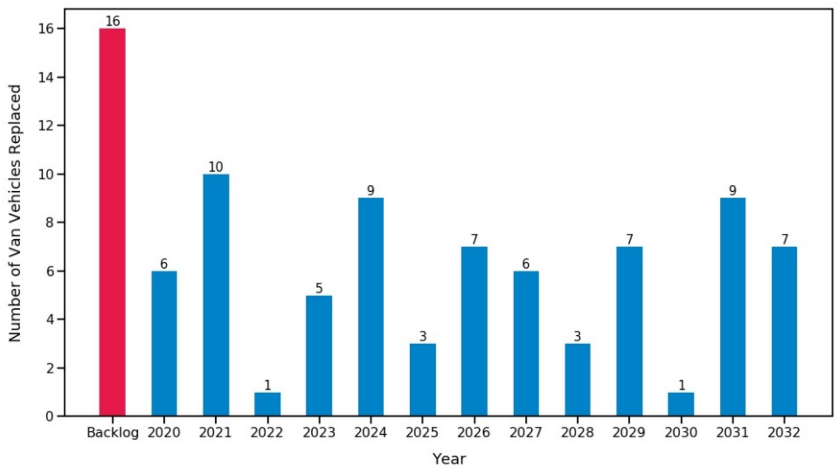
Backlog and Projected Replacement Cost for Cutaways



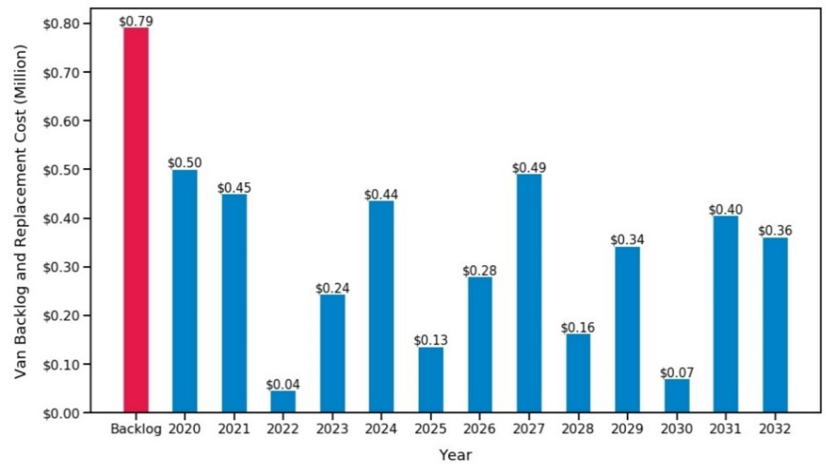
Backlog and Projected Replacement of Minivans



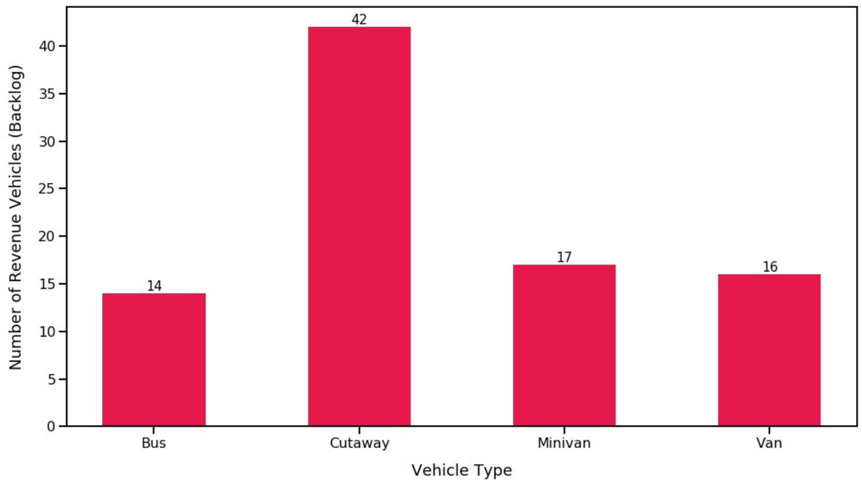
Backlog and Projected Replacement Cost for Minivans



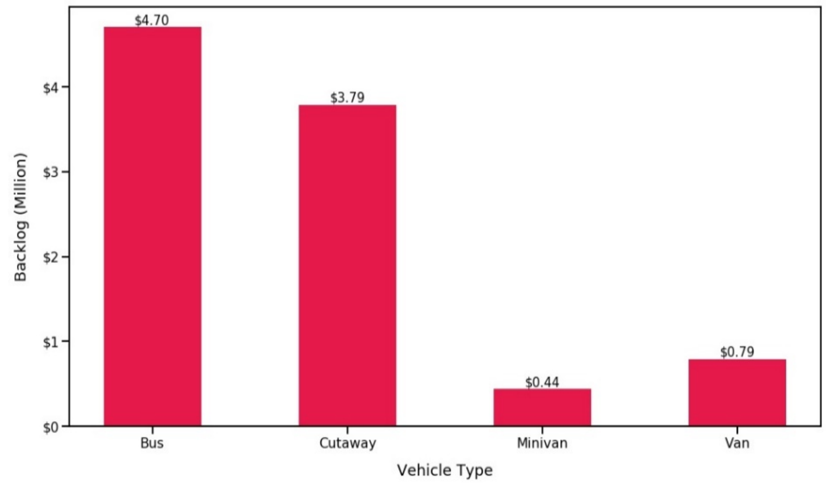
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

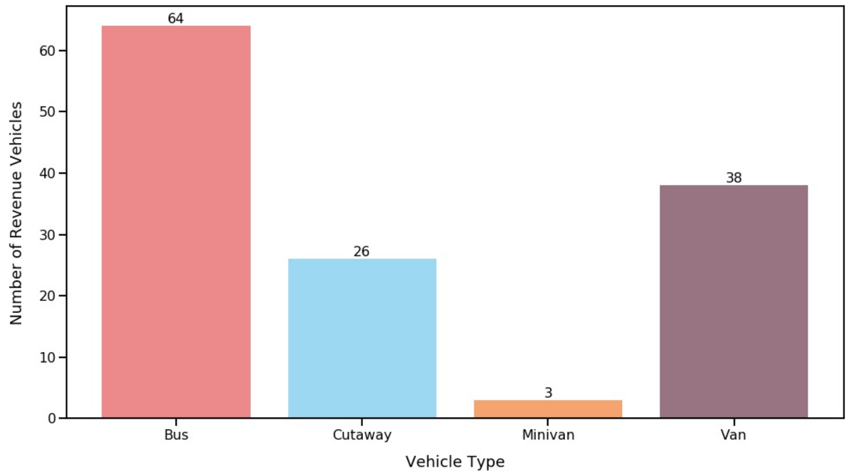


Backlog of the Revenue Vehicles by Vehicle Type

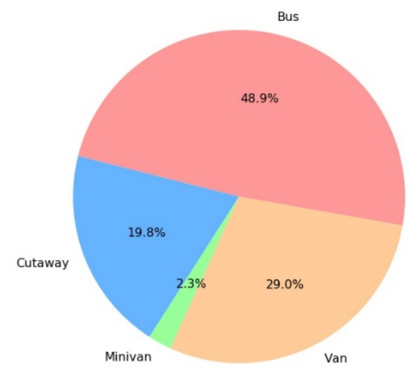


Funds Needed for Backlog by Vehicle Type

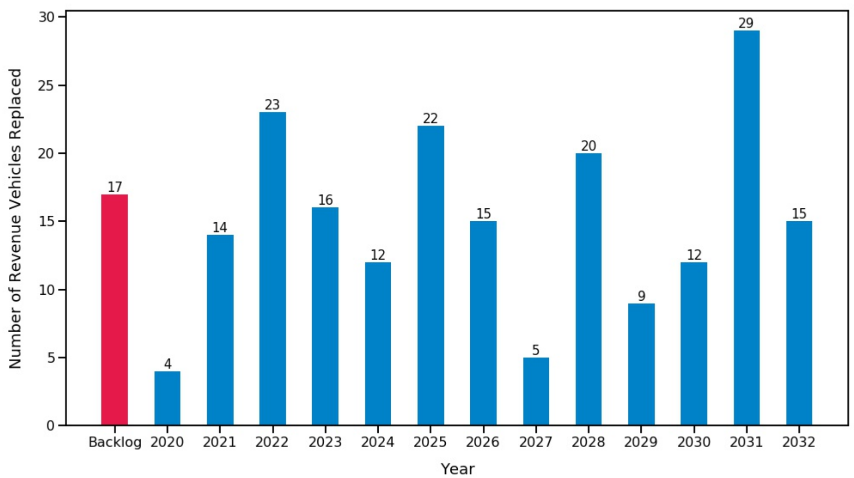
18 MA – Revenue Vehicles Information for Massachusetts's Small Urban and Rural Transit Systems (NTD 2017)



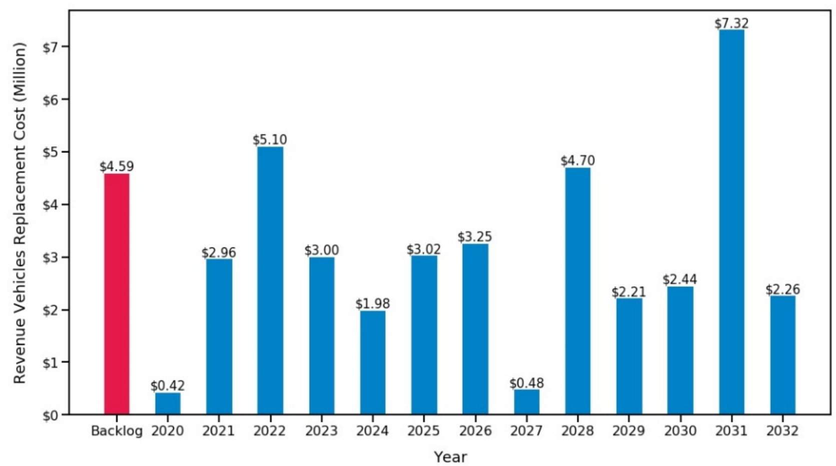
Number of Revenue Vehicles by Vehicle Type



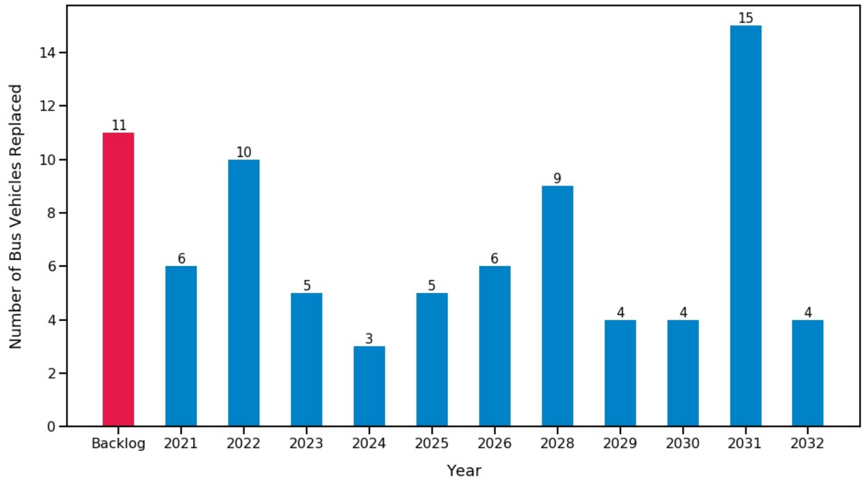
Percentage of Revenue Vehicles



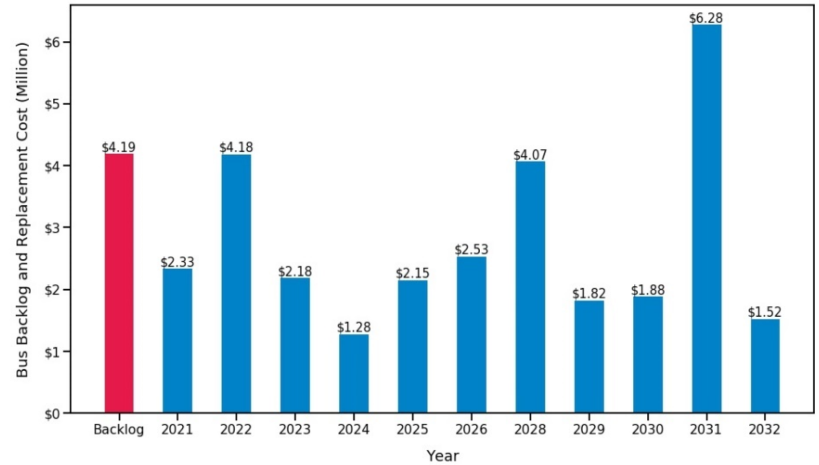
Backlog and Projected Replacement of Revenue Vehicles



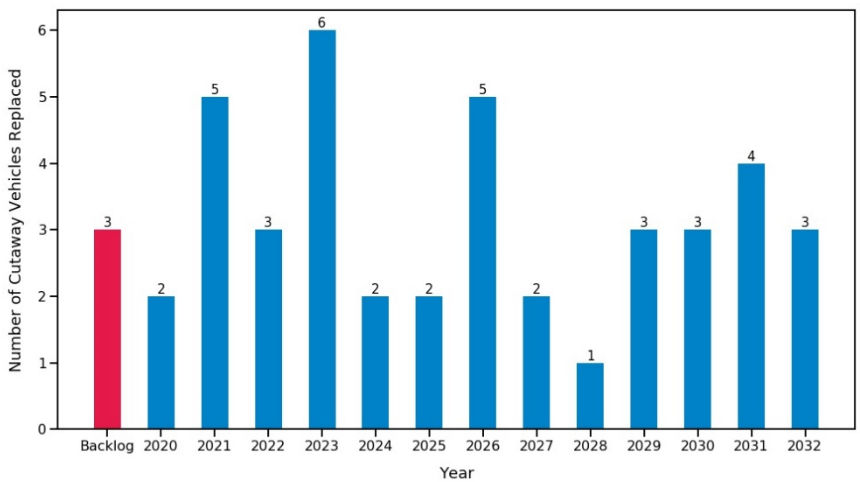
Backlog and Projected Replacement Costs for Revenue Vehicles



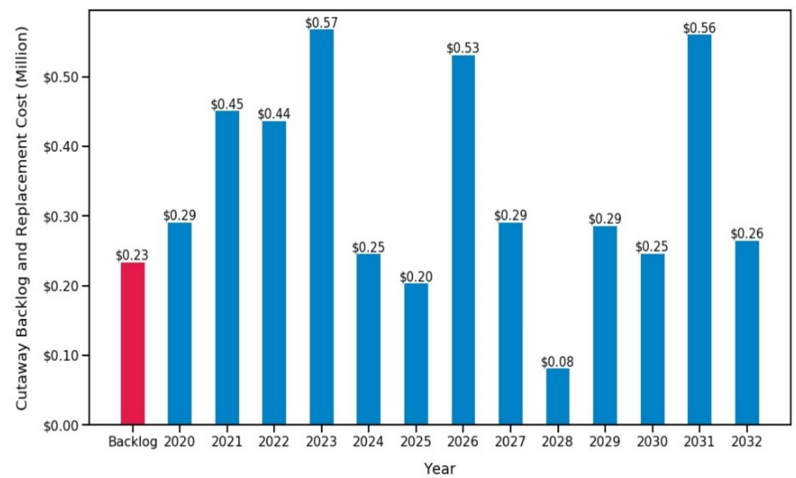
Backlog and Projected Replacement of Buses



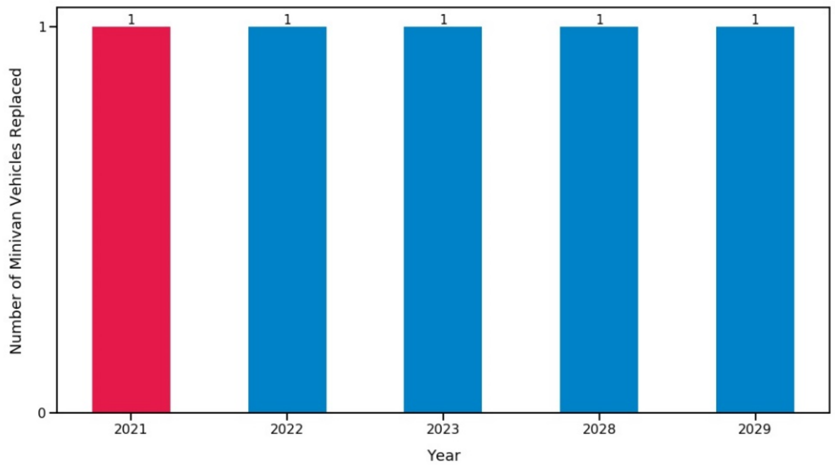
Backlog and Projected Replacement Cost for Buses

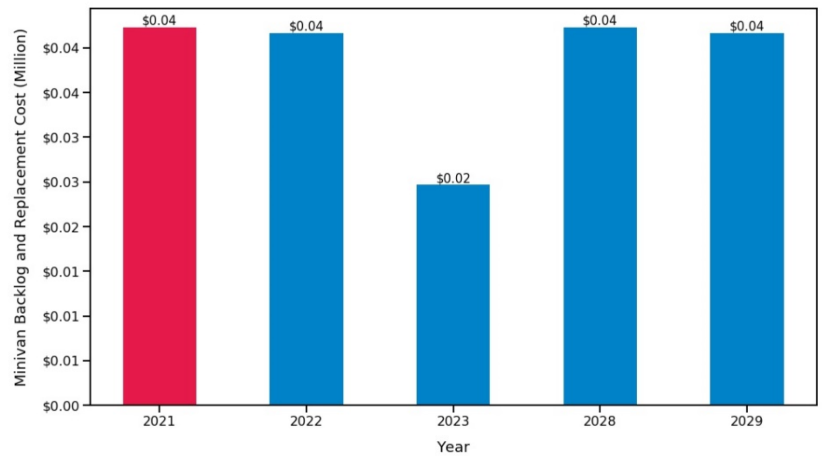


Backlog and Projected Replacement of Cutaways



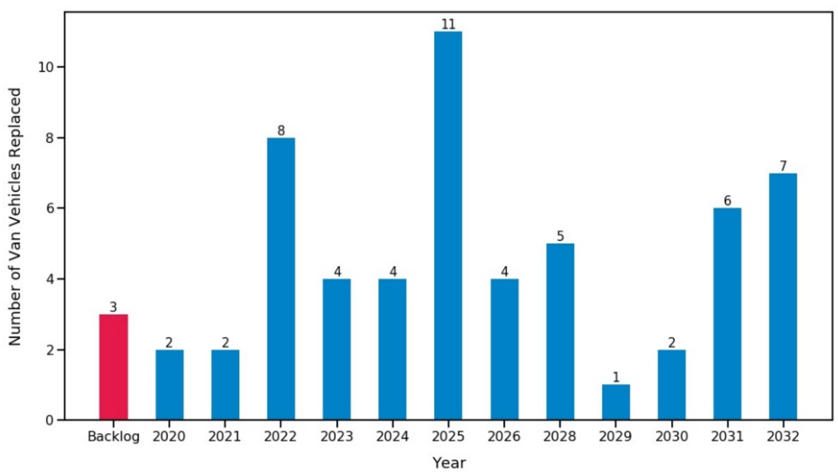
Backlog and Projected Replacement Cost for Cutaways

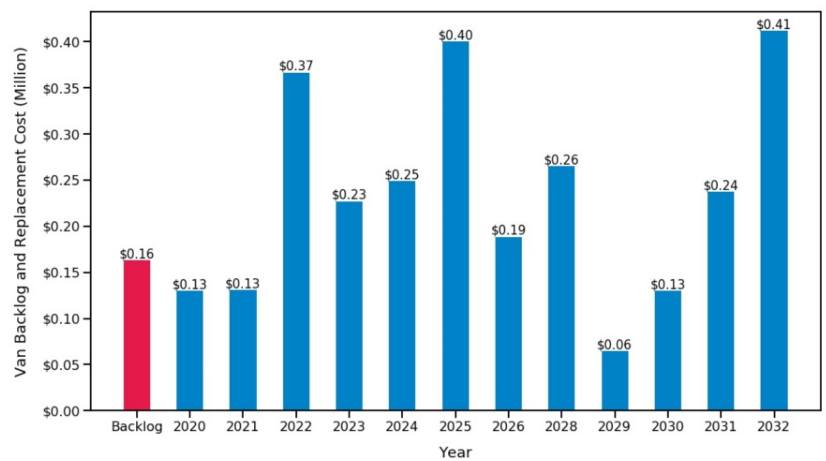




Backlog and Projected Replacement of Minivans

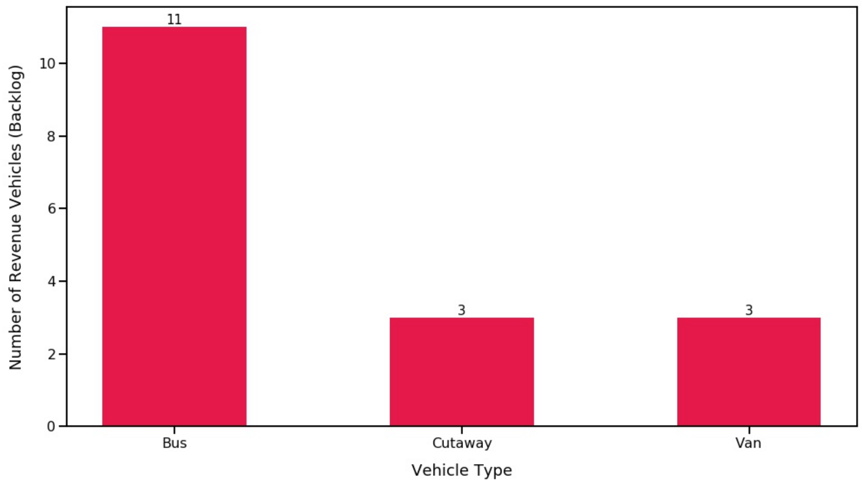
Backlog and Projected Replacement Cost for Minivans



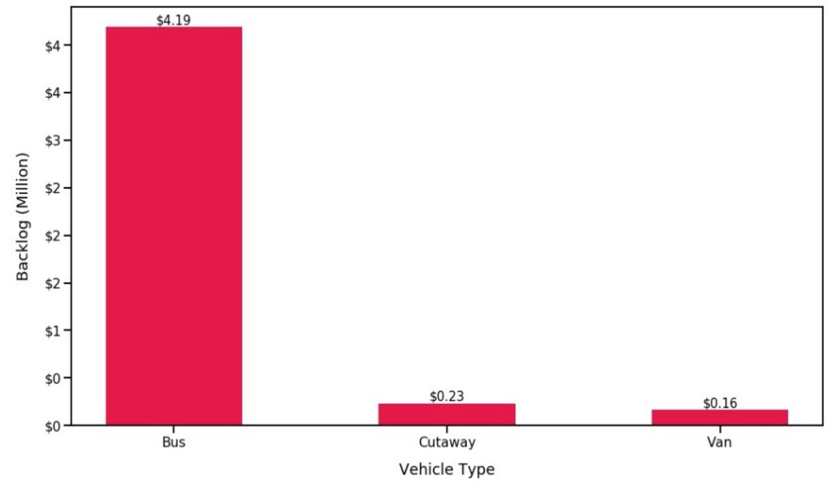


Backlog and Projected Replacement of Vans

Backlog and Projected Replacement Cost for Vans

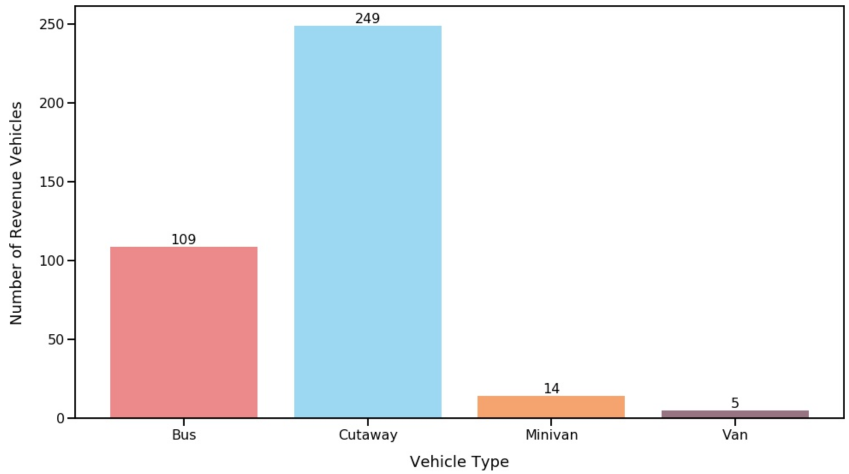


Backlog of the Revenue Vehicles by Vehicle Type

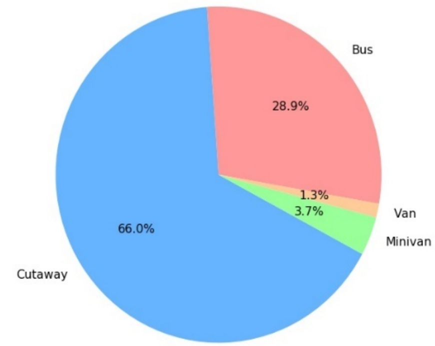


Funds Needed for Backlog by Vehicle Type

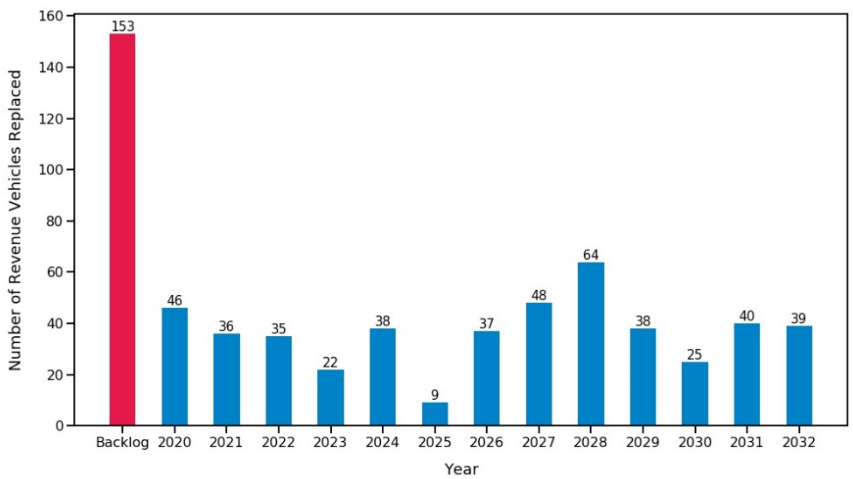
19 MD – Revenue Vehicles Information for Maryland's Small Urban and Rural Transit Systems (NTD 2017)



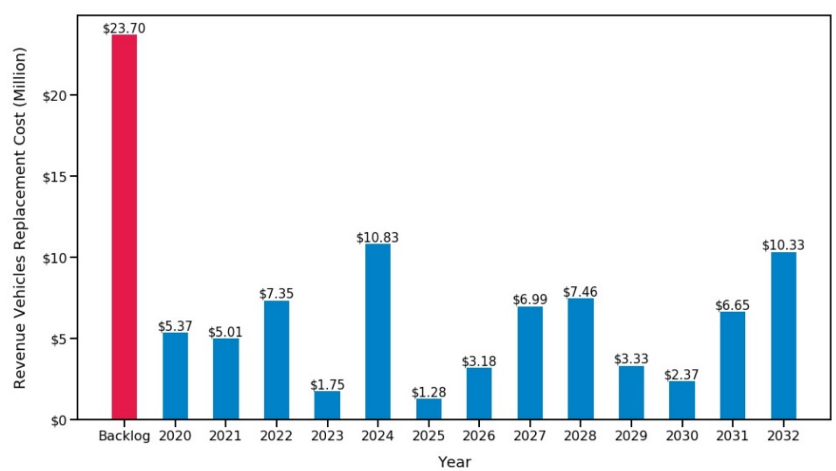
Number of Revenue Vehicles by Vehicle Type



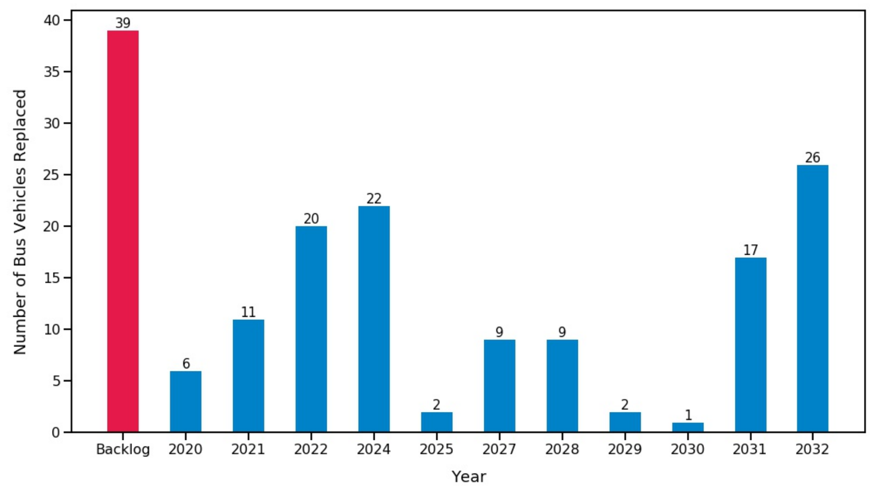
Percentage of Revenue Vehicles



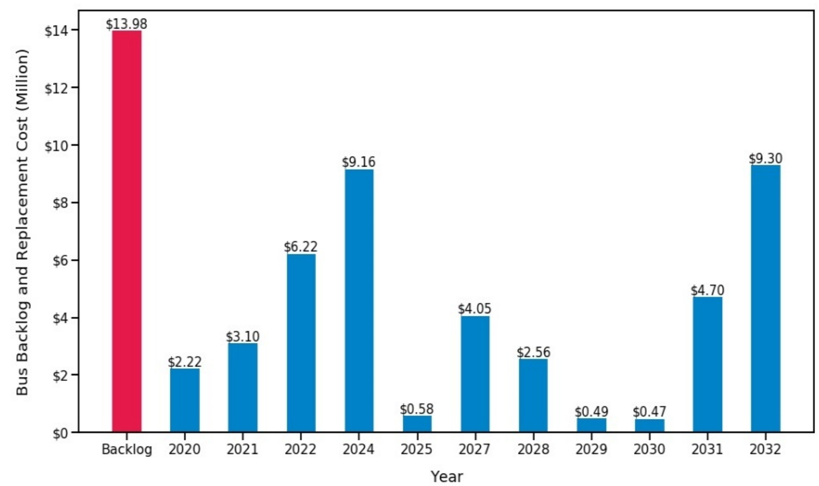
Backlog and Projected Replacement of Revenue Vehicles



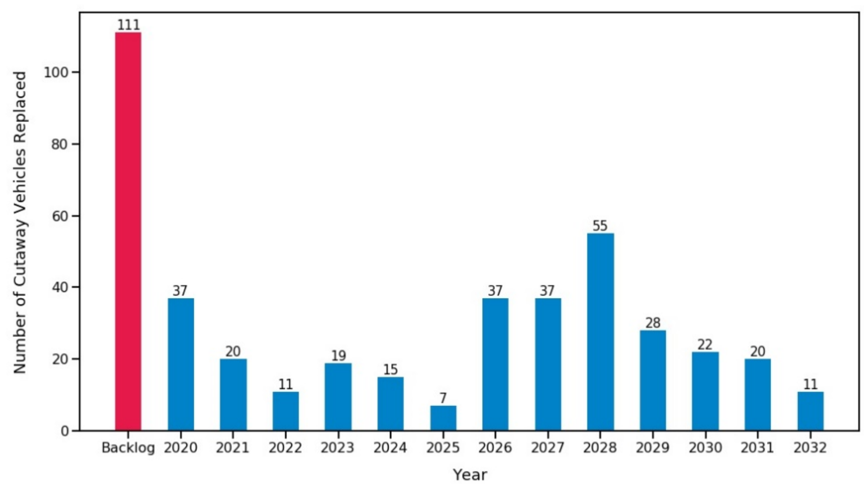
Backlog and Projected Replacement Costs for Revenue Vehicles



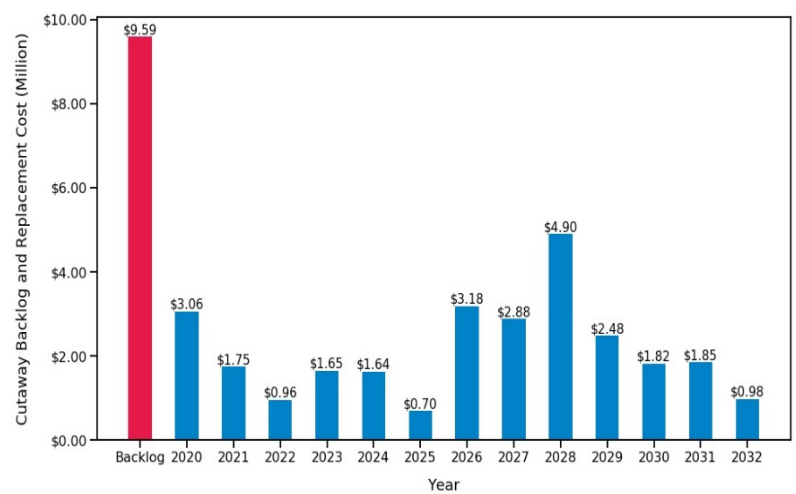
Backlog and Projected Replacement of Buses



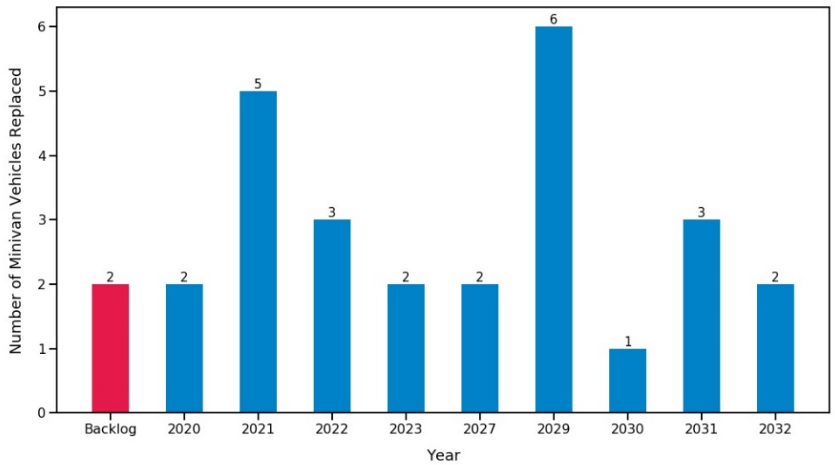
Backlog and Projected Replacement Cost for Buses



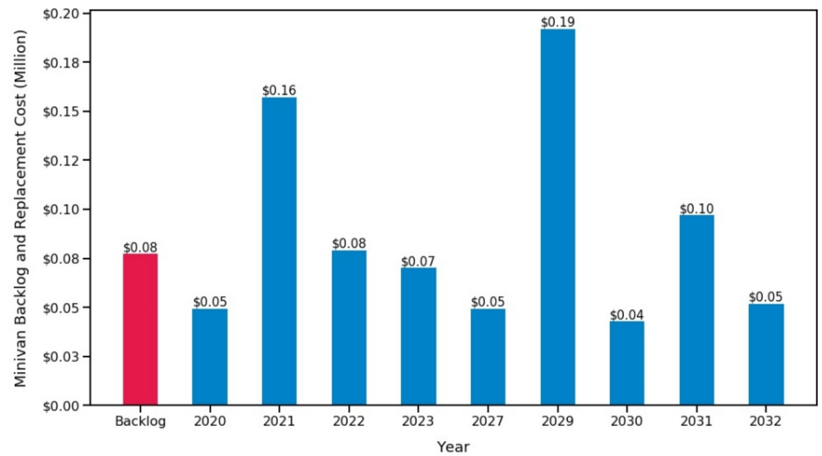
Backlog and Projected Replacement of Cutaways



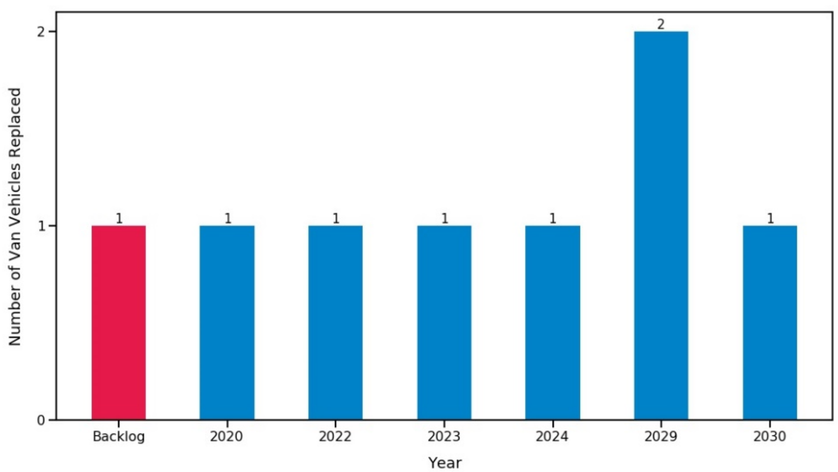
Backlog and Projected Replacement Cost for Cutaways



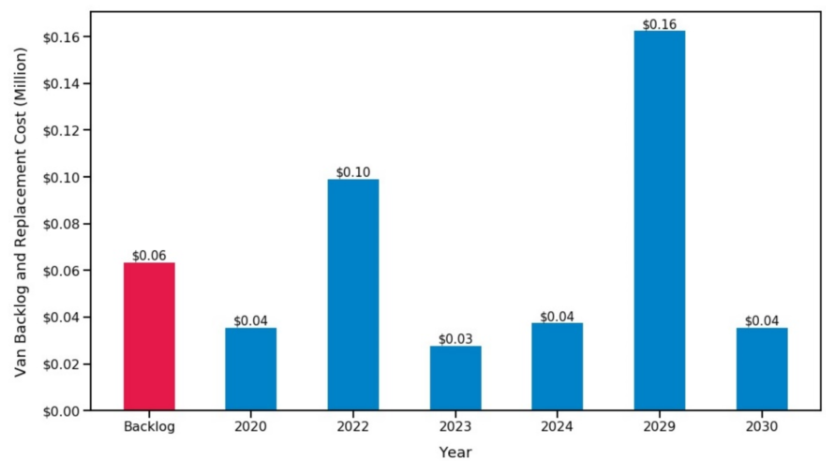
Backlog and Projected Replacement of Minivans



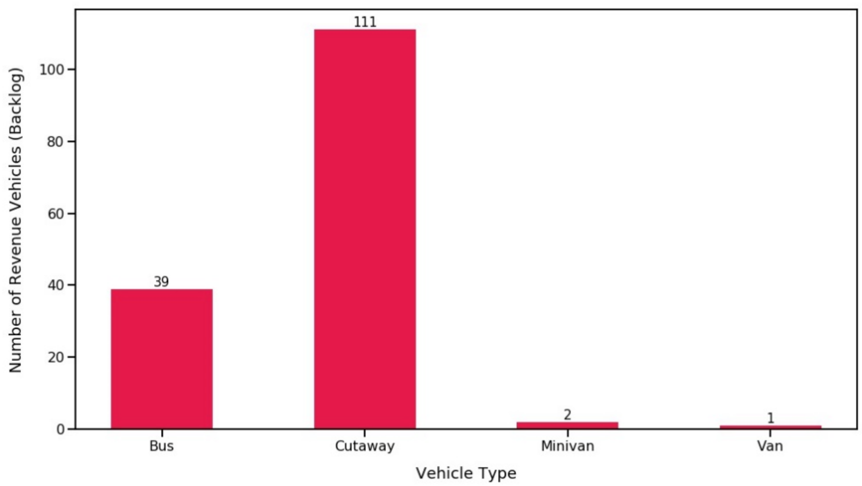
Backlog and Projected Replacement Cost for Minivans



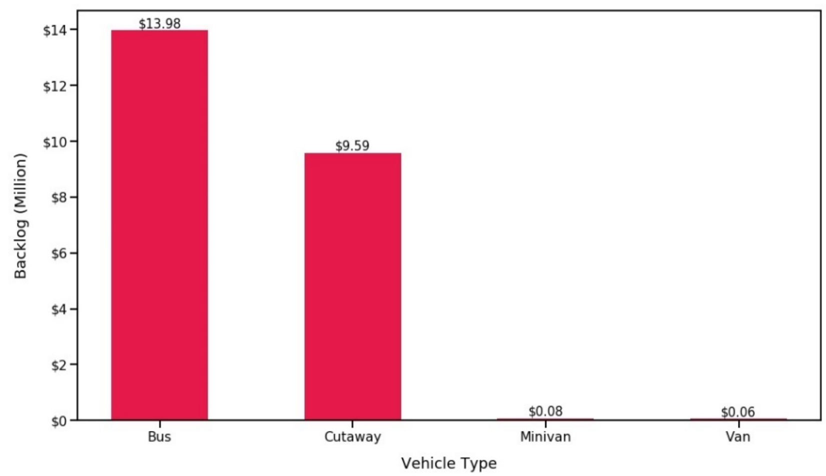
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

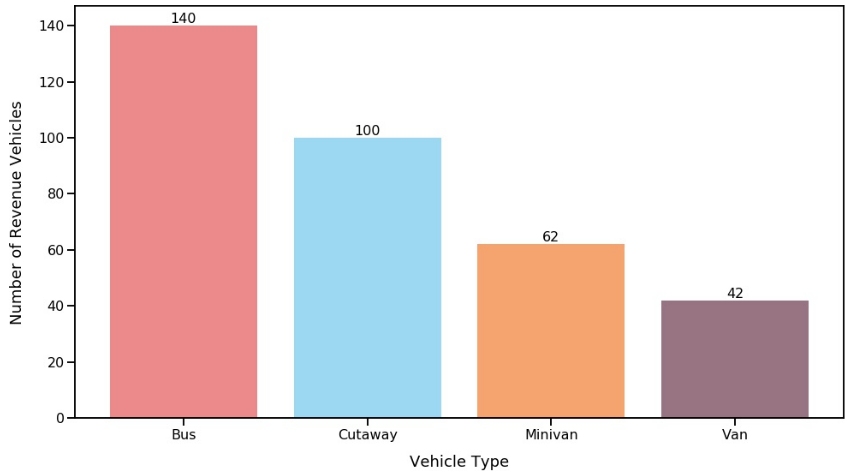


Backlog of the Revenue Vehicles by Vehicle Type

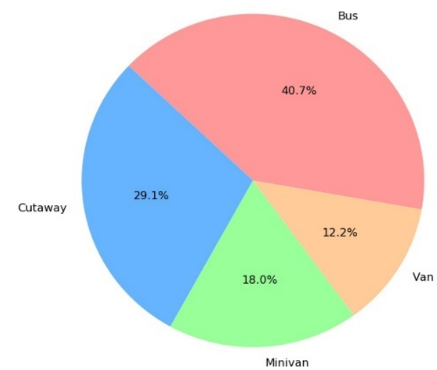


Funds Needed for Backlog by Vehicle Type

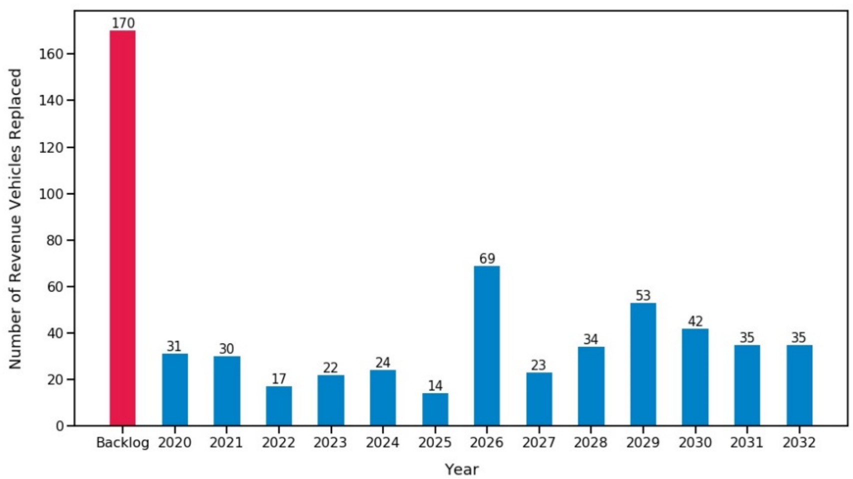
20 ME – Revenue Vehicles Information for Maine's Small Urban and Rural Transit Systems (NTD 2017)



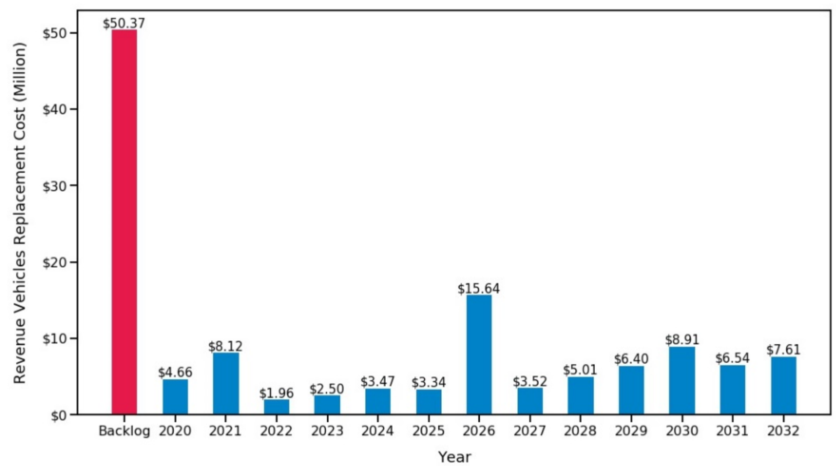
Number of Revenue Vehicles by Vehicle Type



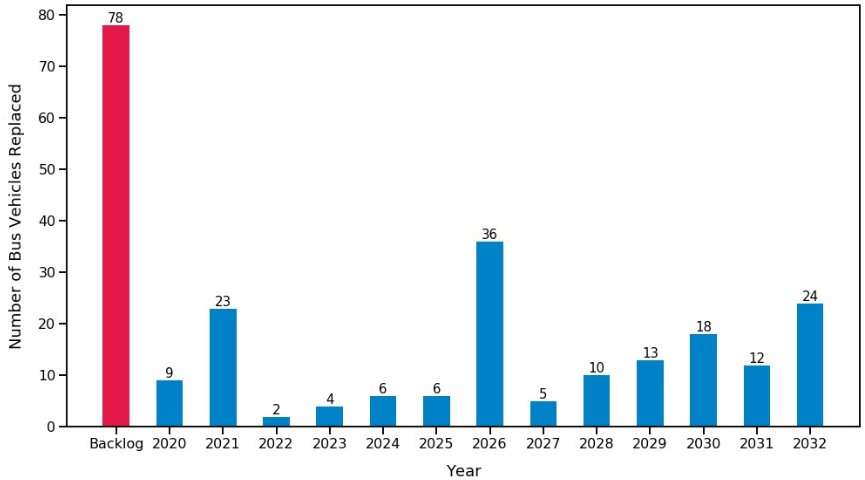
Percentage of Revenue Vehicles



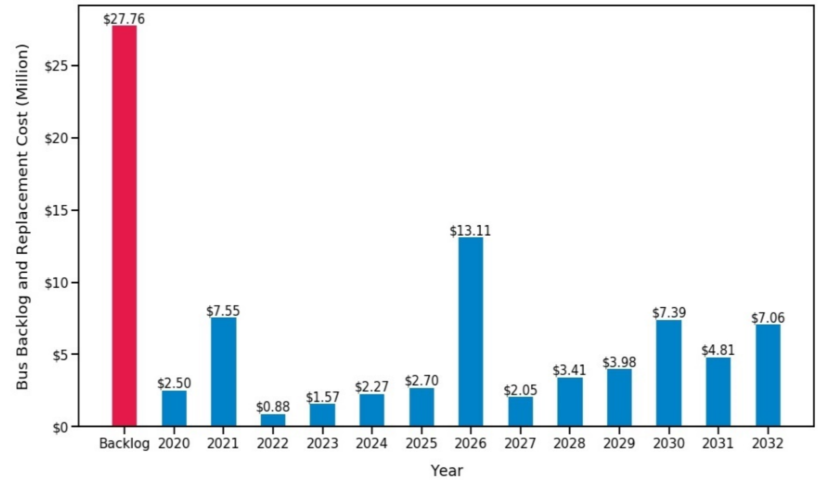
Backlog and Projected Replacement of Revenue Vehicles



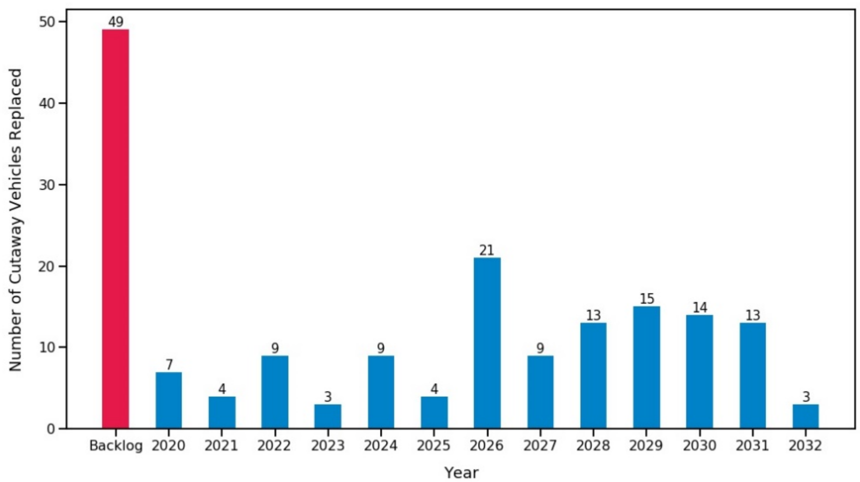
Backlog and Projected Replacement Costs for Revenue Vehicles



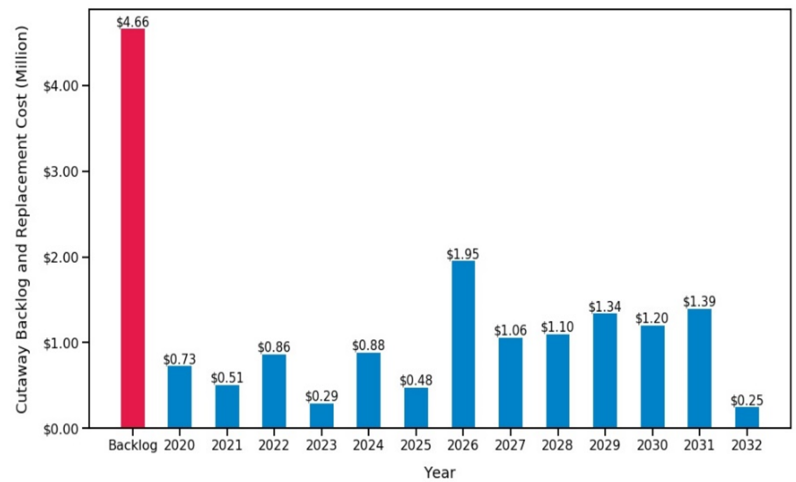
Backlog and Projected Replacement of Buses



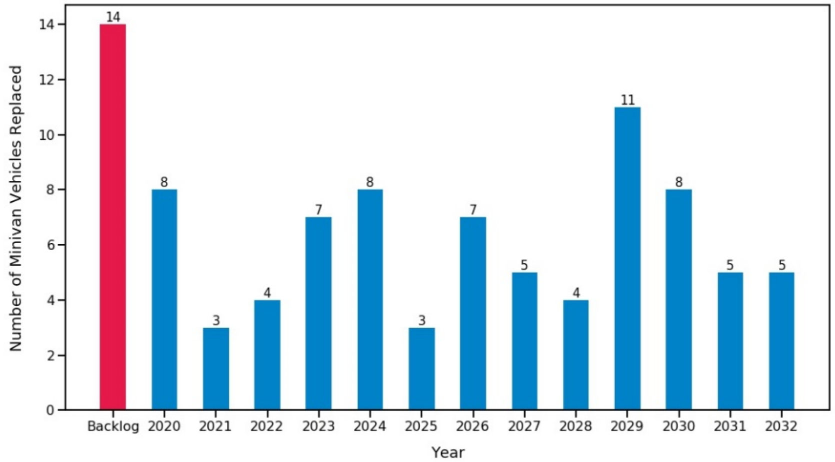
Backlog and Projected Replacement Cost for Buses



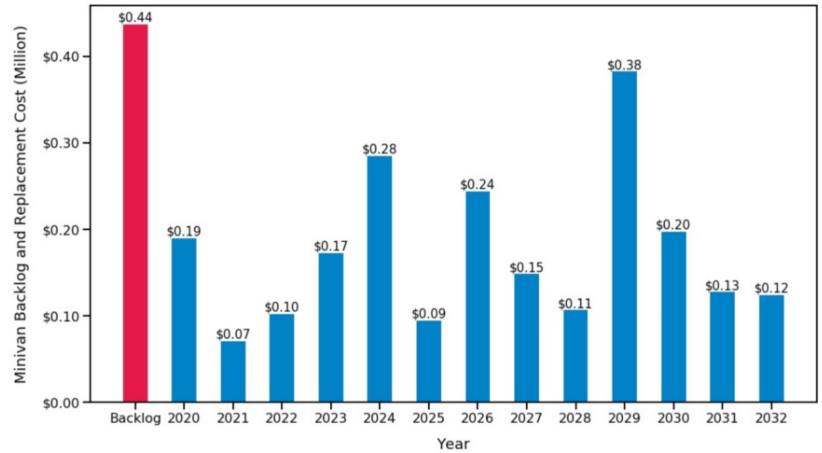
Backlog and Projected Replacement of Cutaways



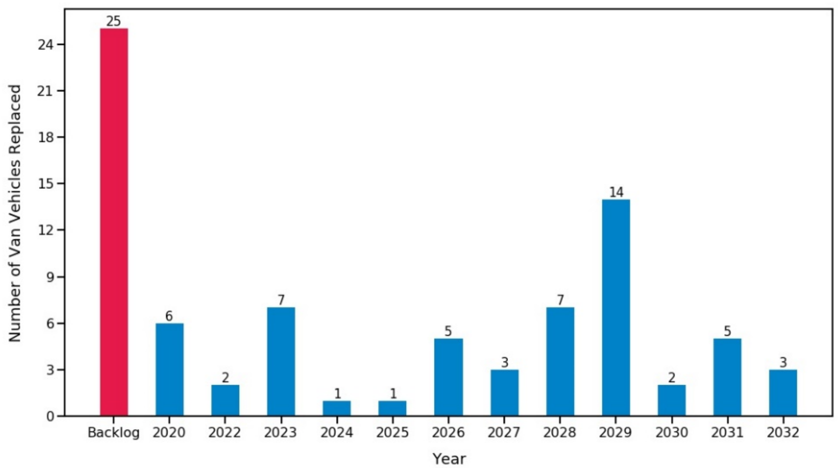
Backlog and Projected Replacement Cost for Cutaways



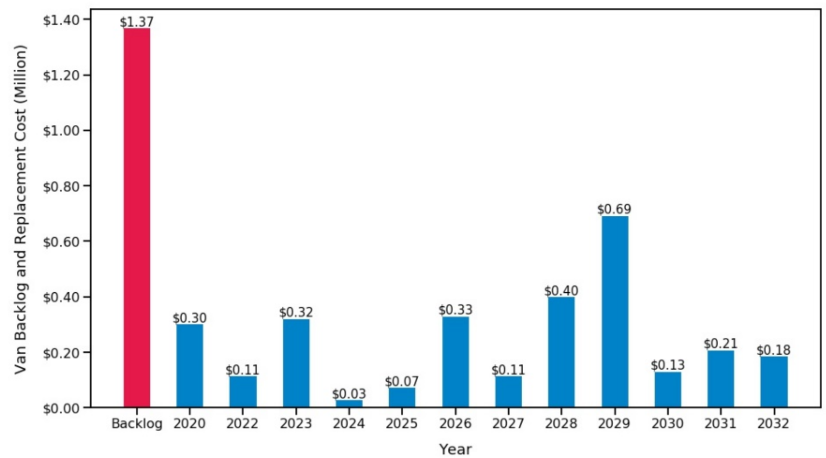
Backlog and Projected Replacement of Minivans



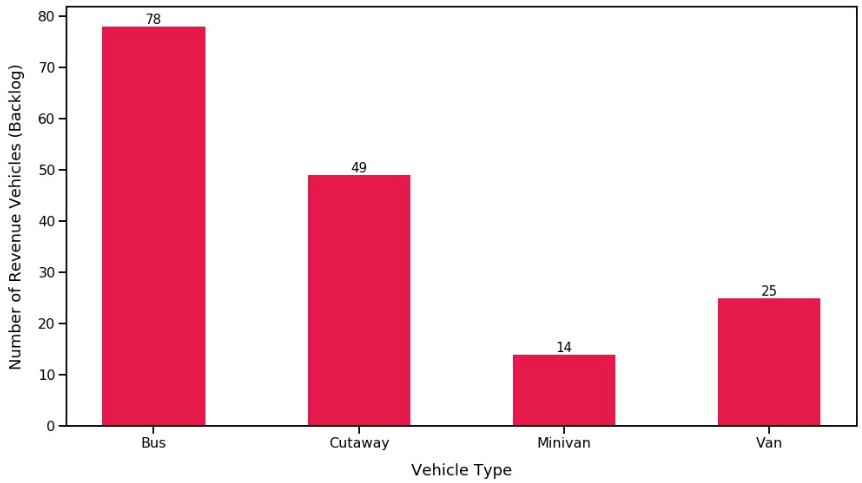
Backlog and Projected Replacement Cost for Minivans



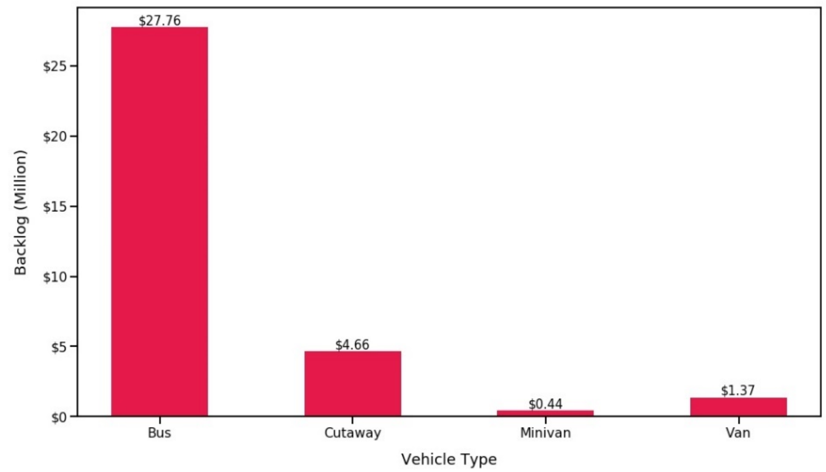
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

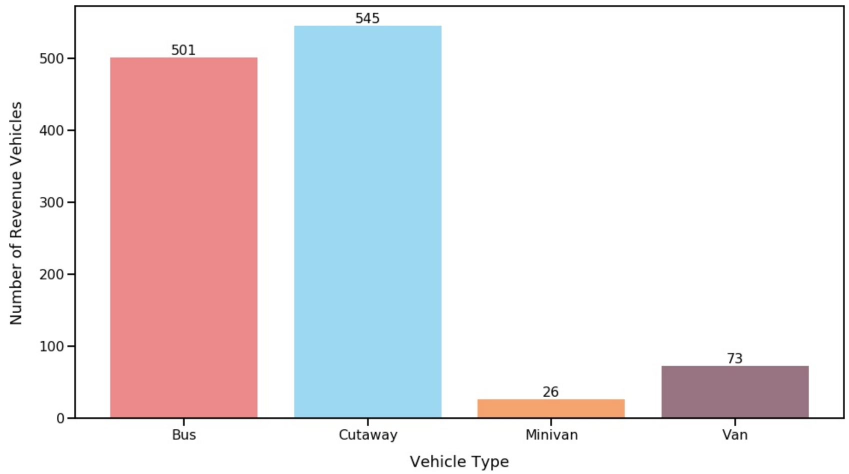


Backlog of the Revenue Vehicles by Vehicle Type

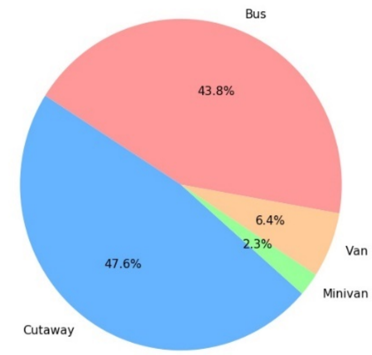


Funds Needed for Backlog by Vehicle Type

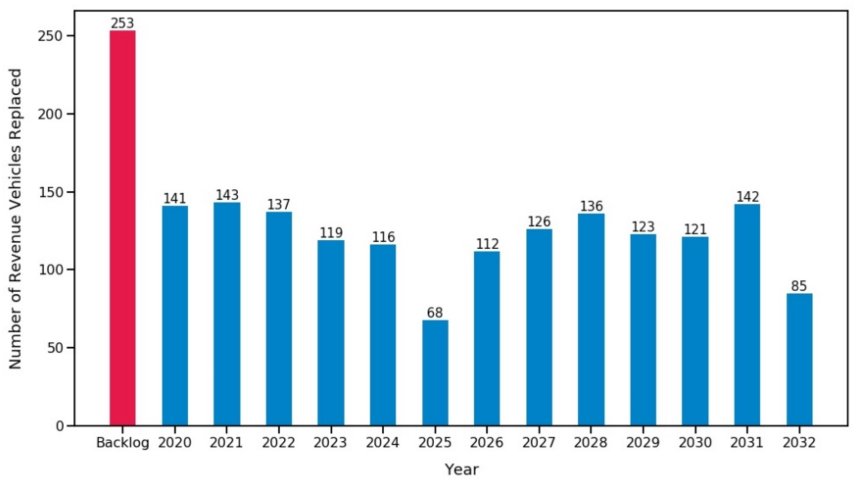
21 MI – Revenue Vehicles Information for Michigan's Small Urban and Rural Transit Systems (NTD 2017)



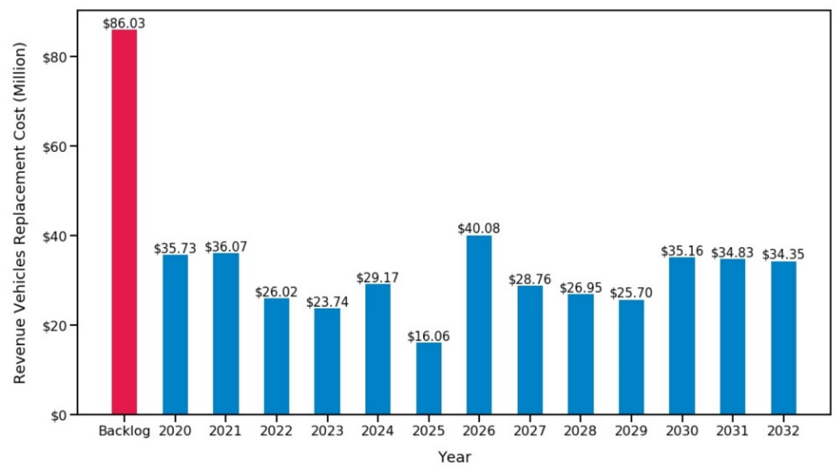
Number of Revenue Vehicles by Vehicle Type



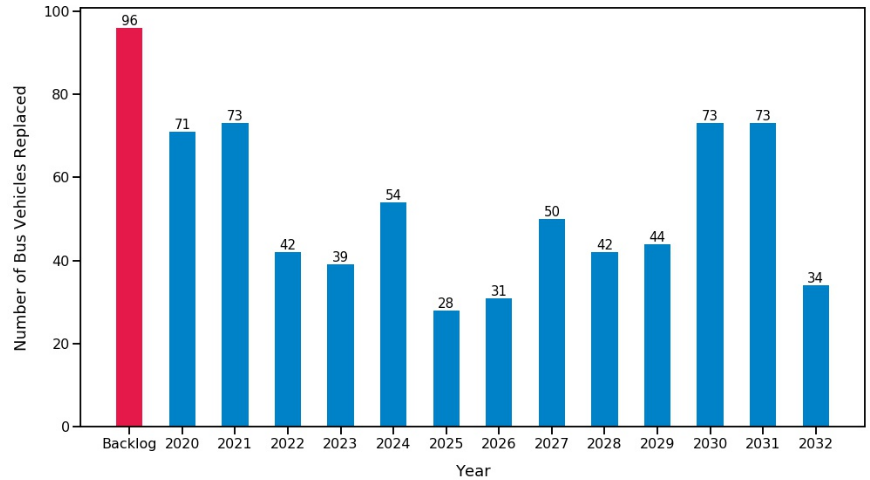
Percentage of Revenue Vehicles



Backlog and Projected Replacement of Revenue Vehicles

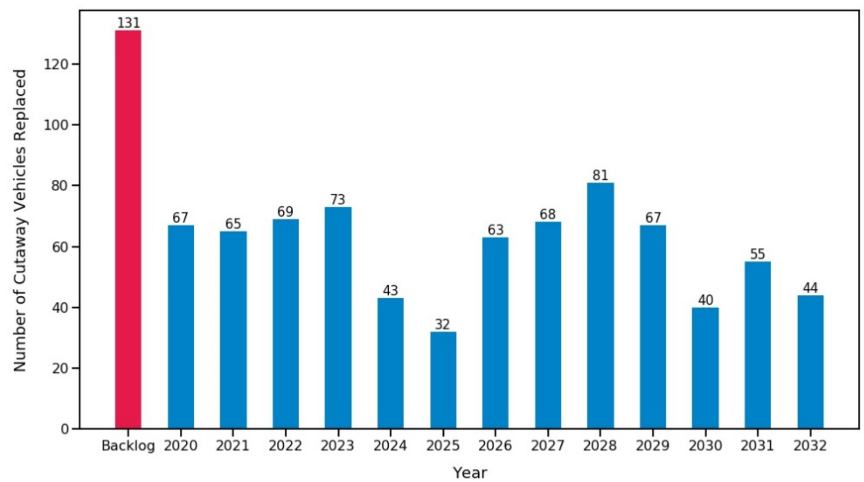


Backlog and Projected Replacement Costs for Revenue Vehicles

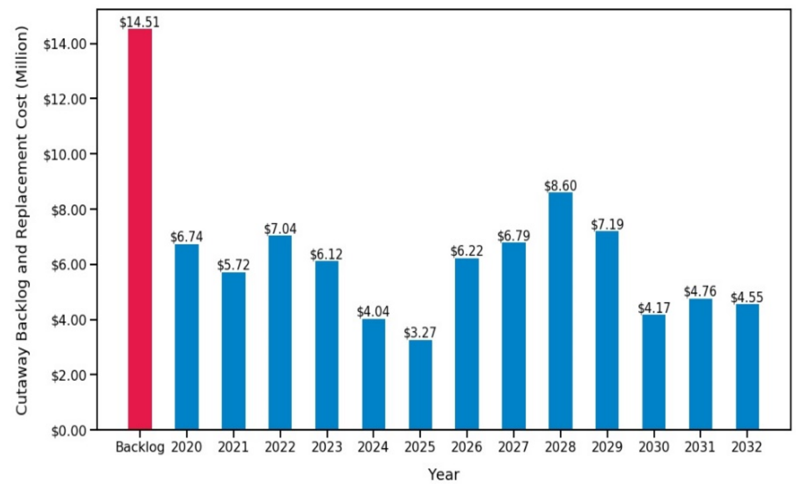


Backlog and Projected Replacement of Buses

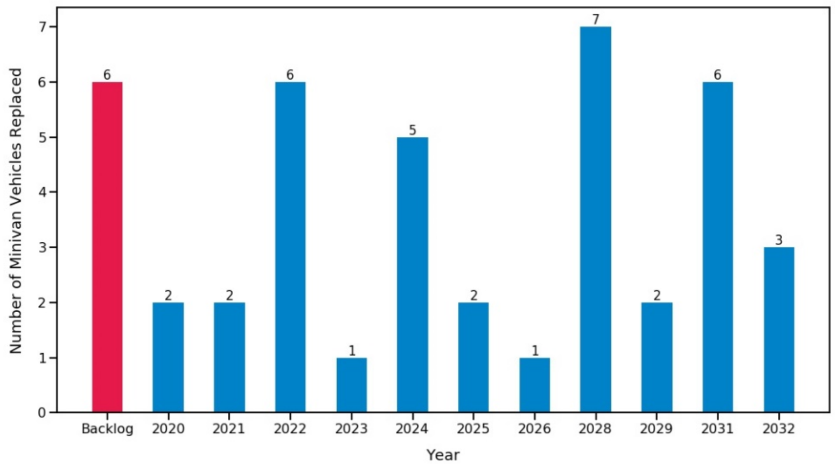
Backlog and Projected Replacement Cost for Buses



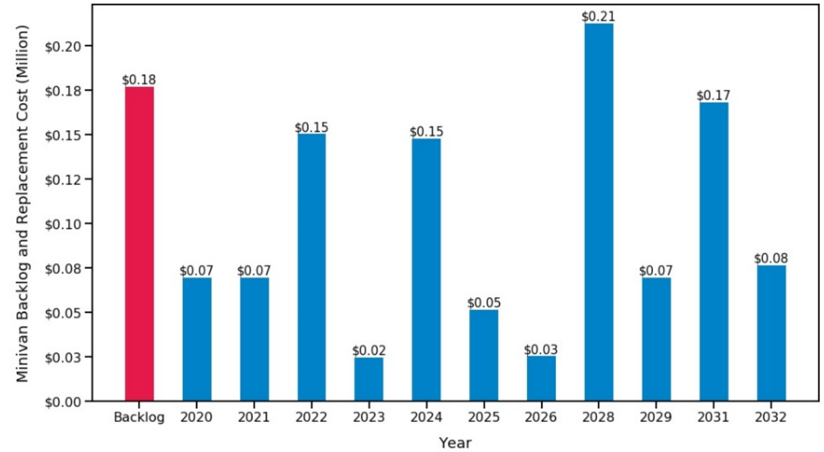
Backlog and Projected Replacement of Cutaways



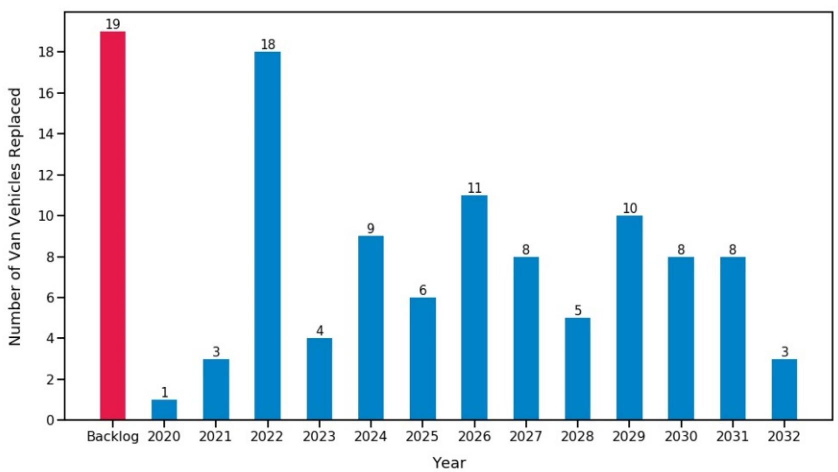
Backlog and Projected Replacement Cost for Cutaways



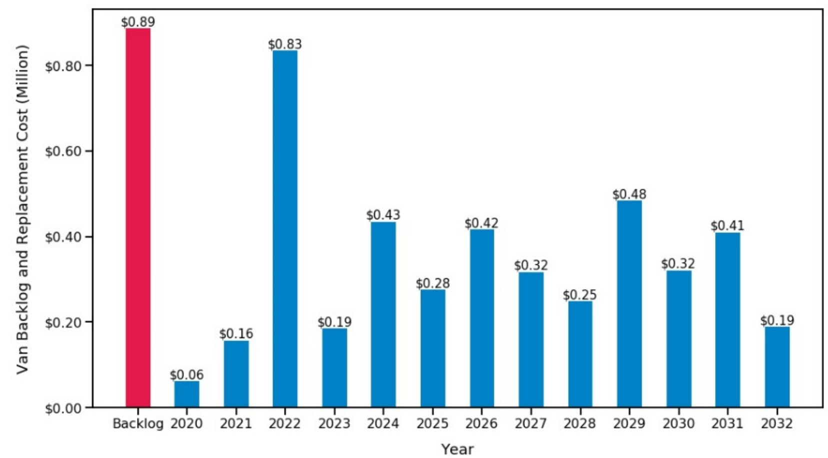
Backlog and Projected Replacement of Minivans



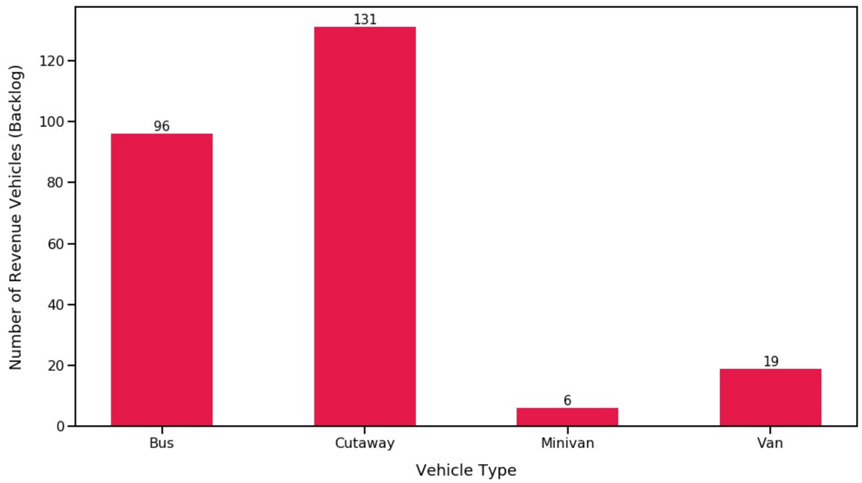
Backlog and Projected Replacement Cost for Minivans



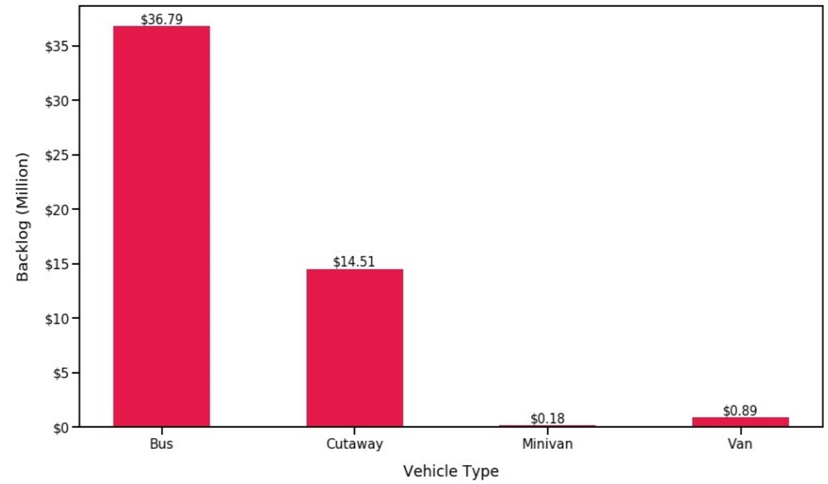
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

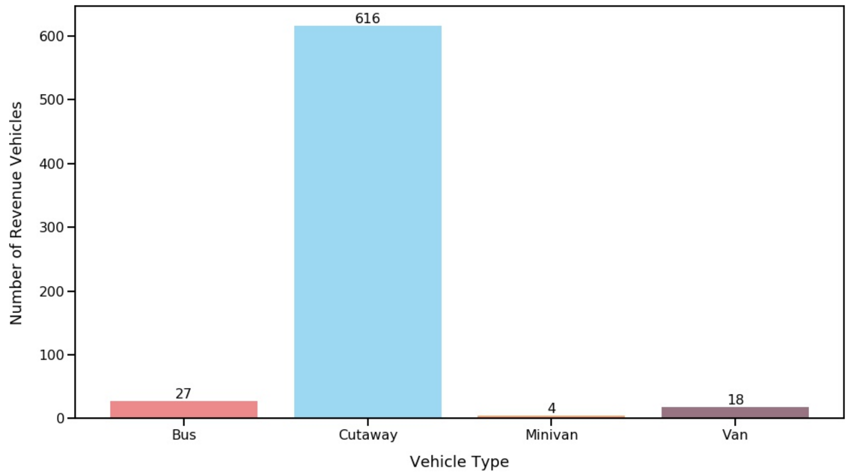


Backlog of the Revenue Vehicles by Vehicle Type

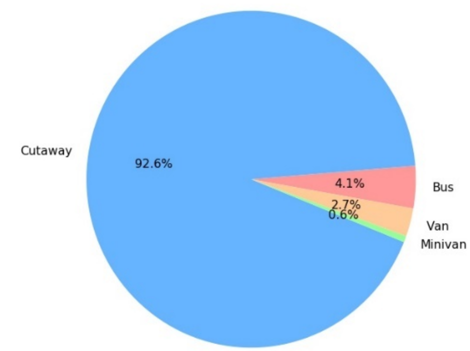


Funds Needed for Backlog by Vehicle Type

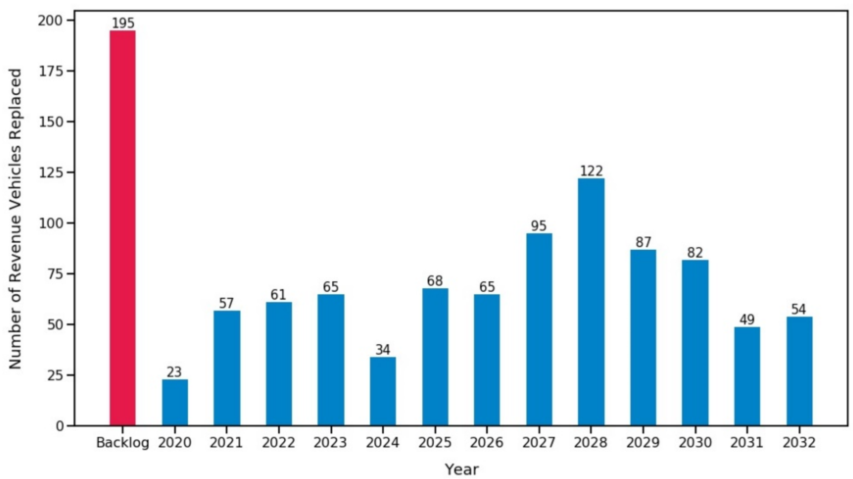
22 MN – Revenue Vehicles Information for Minnesota's Small Urban and Rural Transit Systems (NTD 2017)



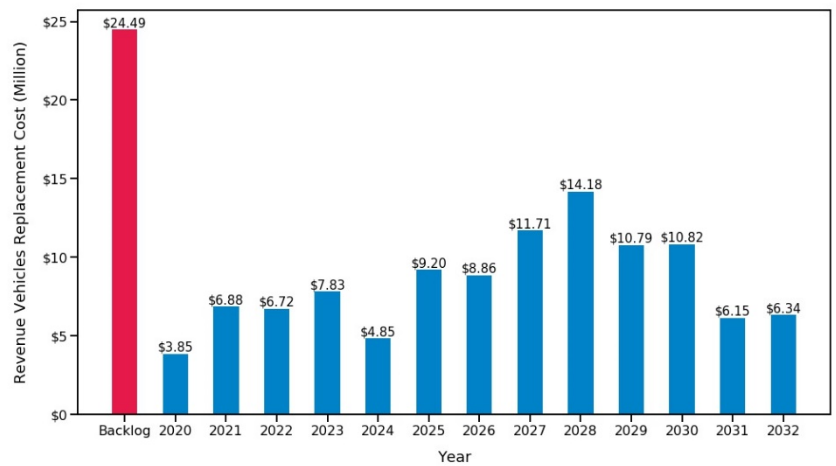
Number of Revenue Vehicles by Vehicle Type



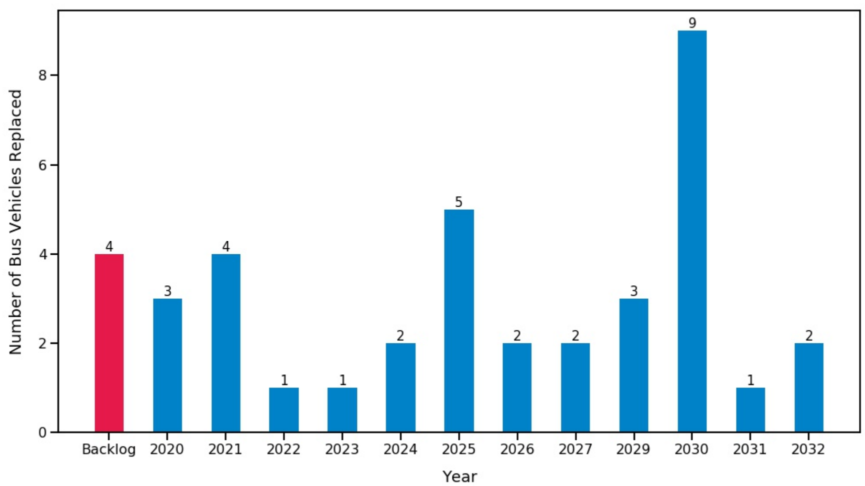
Percentage of Revenue Vehicles



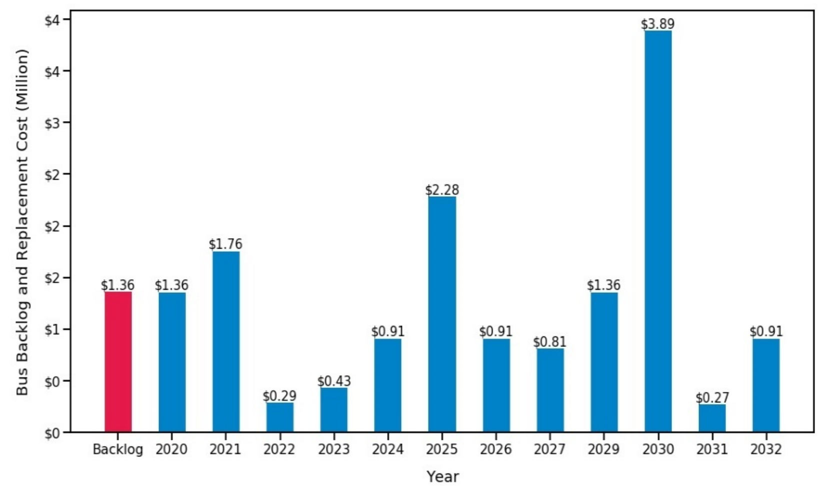
Backlog and Projected Replacement of Revenue Vehicles



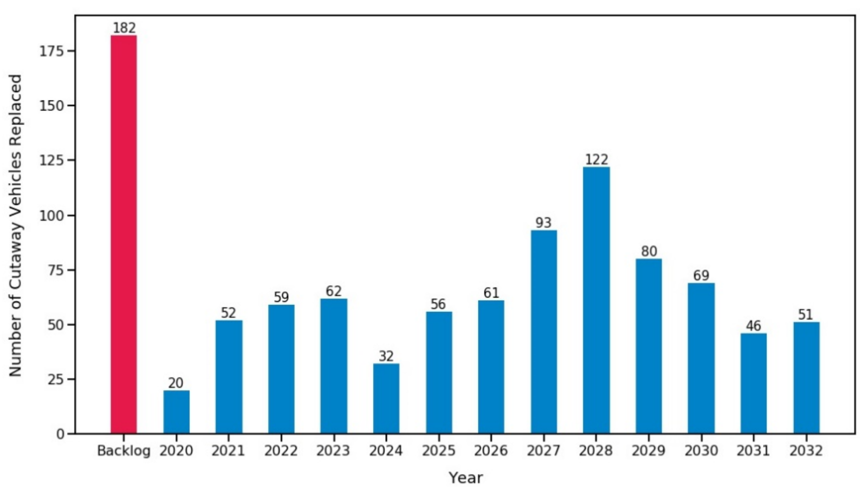
Backlog and Projected Replacement Costs for Revenue Vehicles



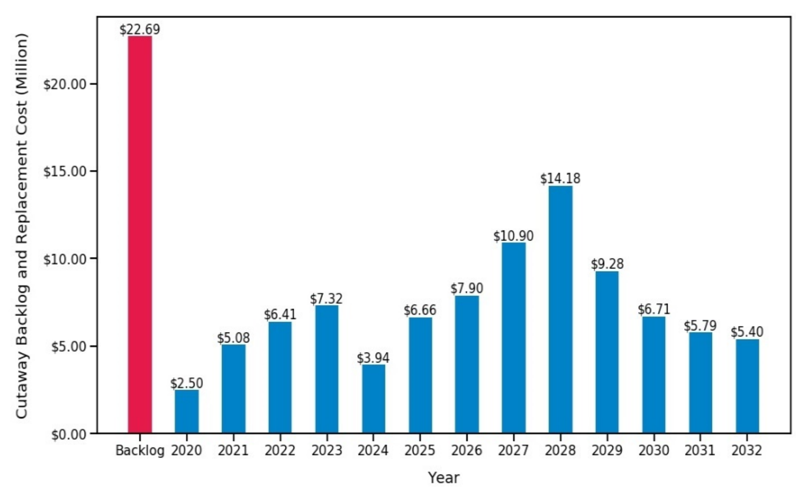
Backlog and Projected Replacement of Buses



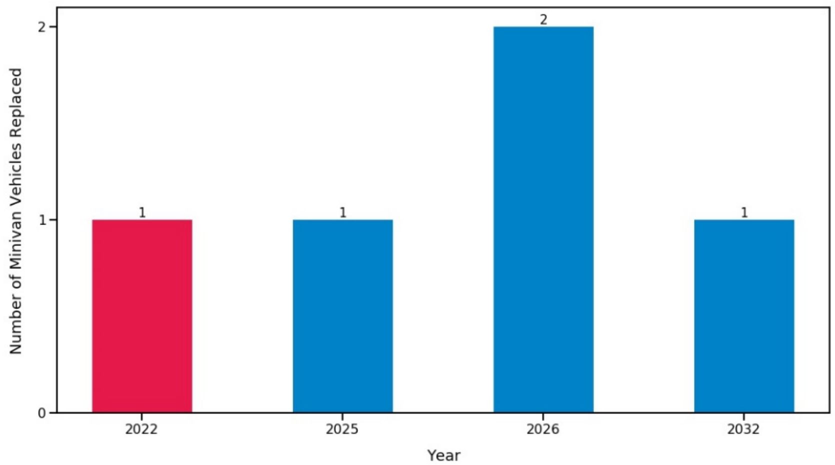
Backlog and Projected Replacement Cost for Buses



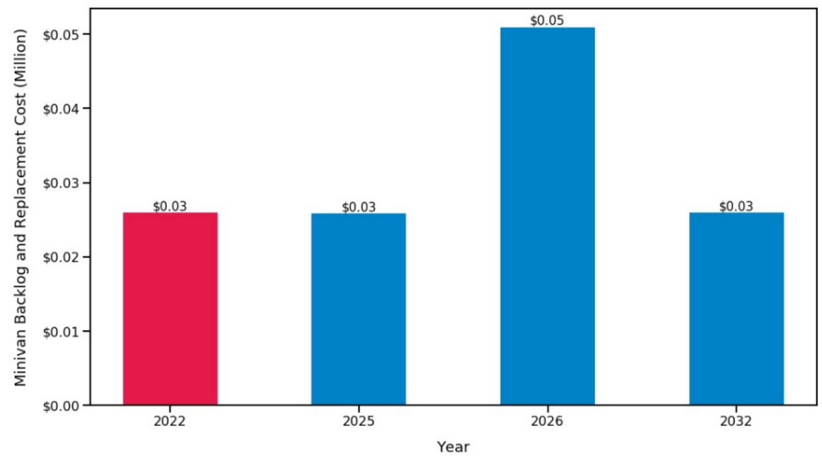
Backlog and Projected Replacement of Cutaways



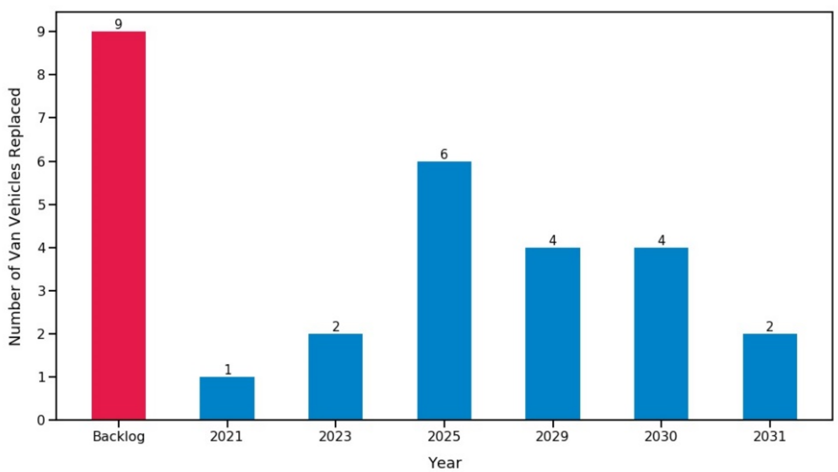
Backlog and Projected Replacement Cost for Cutaways



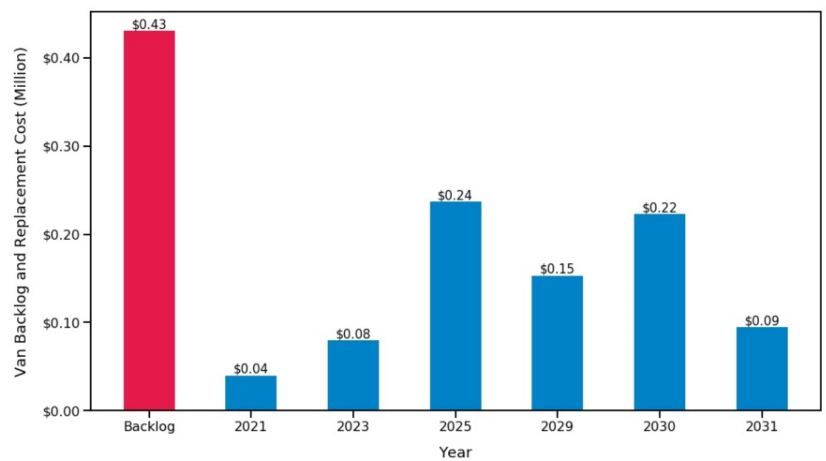
Backlog and Projected Replacement of Minivans



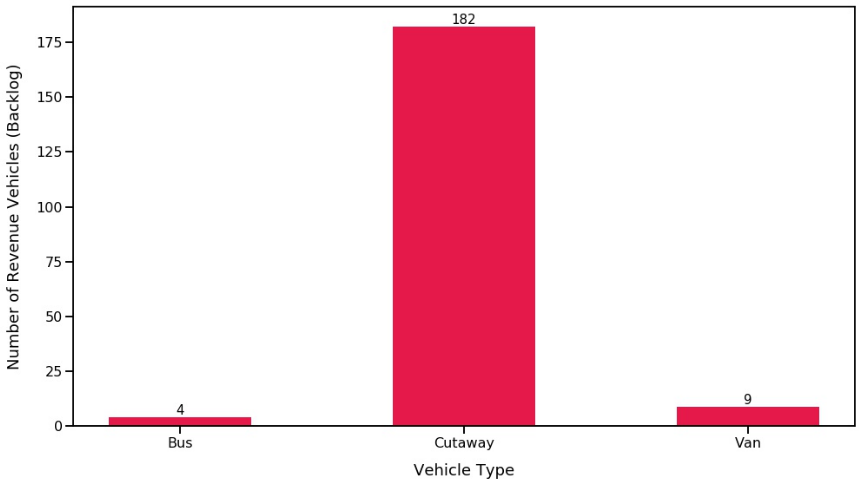
Backlog and Projected Replacement Cost for Minivans



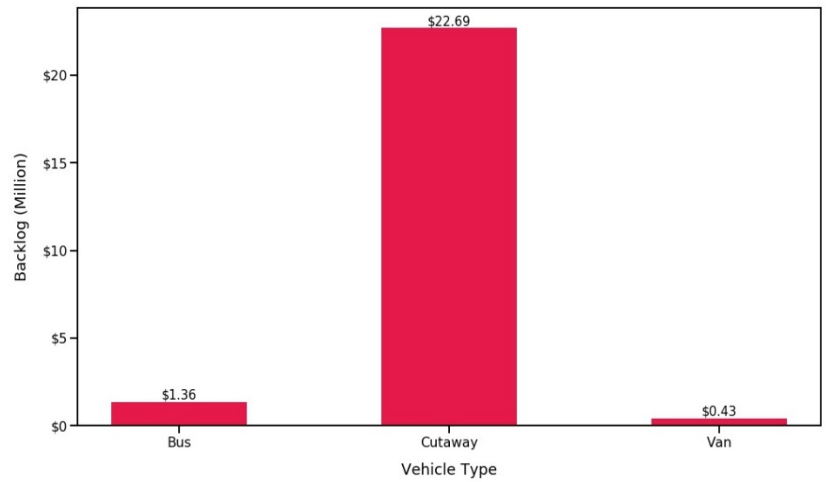
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

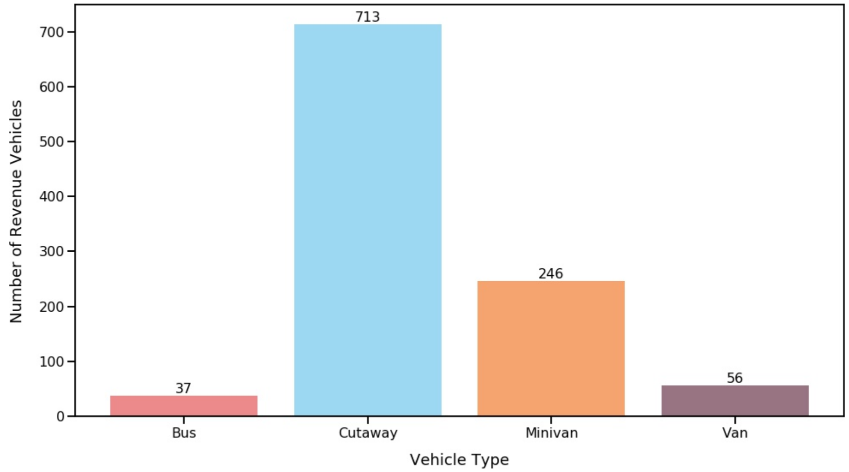


Backlog of the Revenue Vehicles by Vehicle Type

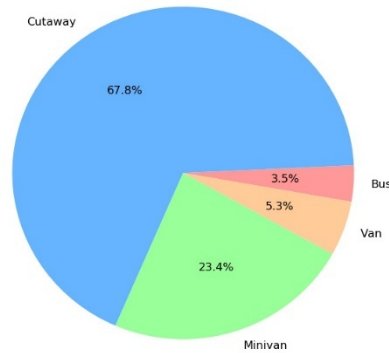


Funds Needed for Backlog by Vehicle Type

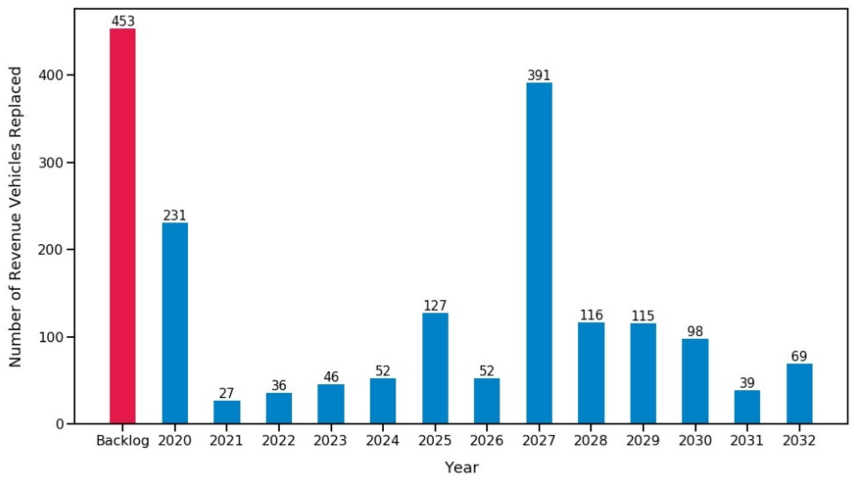
23 MO – Revenue Vehicles Information for Missouri's Small Urban and Rural Transit Systems (NTD 2017)



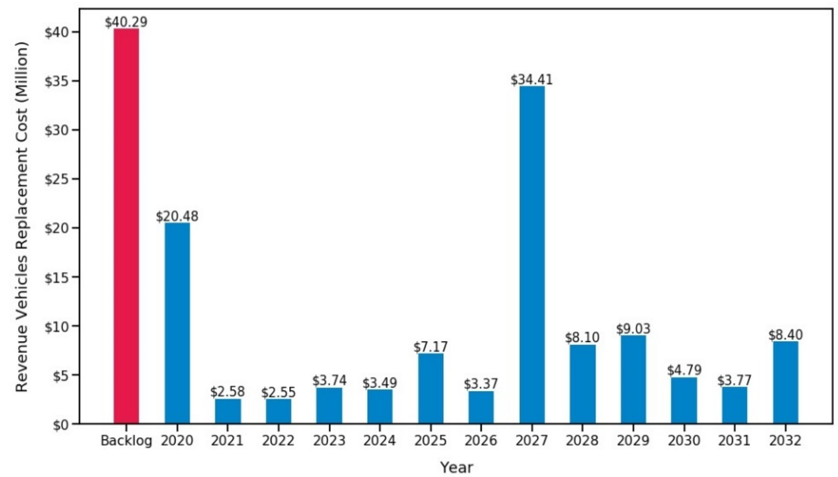
Number of Revenue Vehicles by Vehicle Type



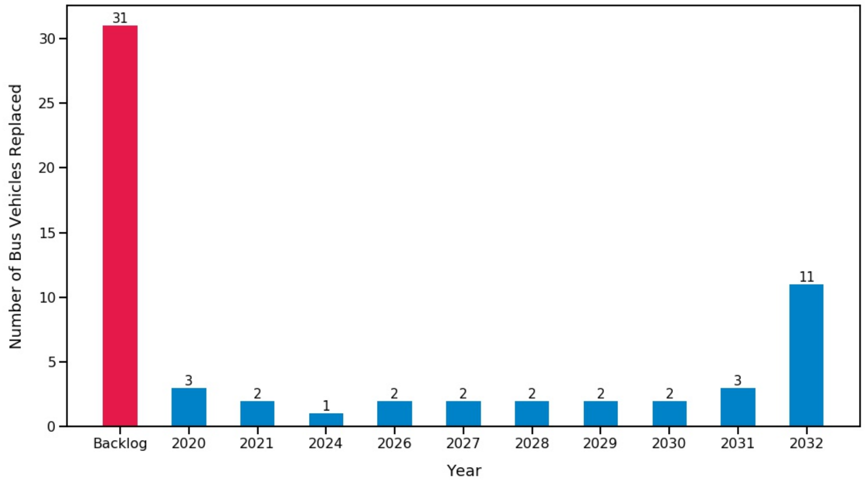
Percentage of Revenue Vehicles



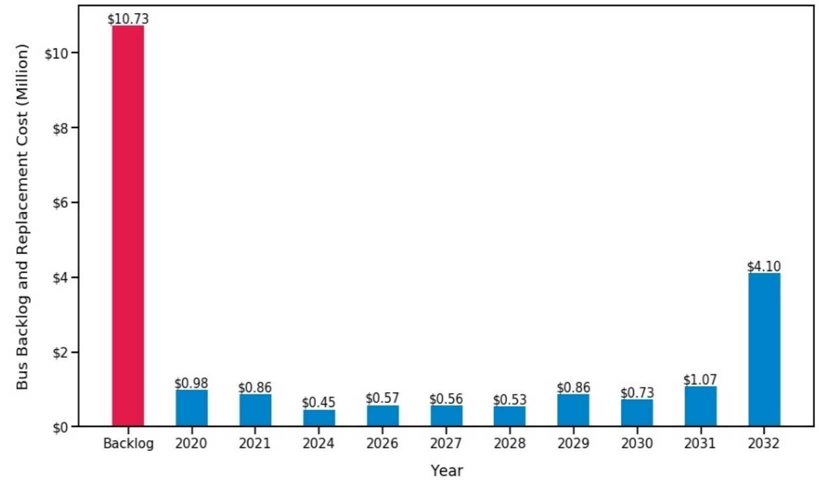
Backlog and Projected Replacement of Revenue Vehicles



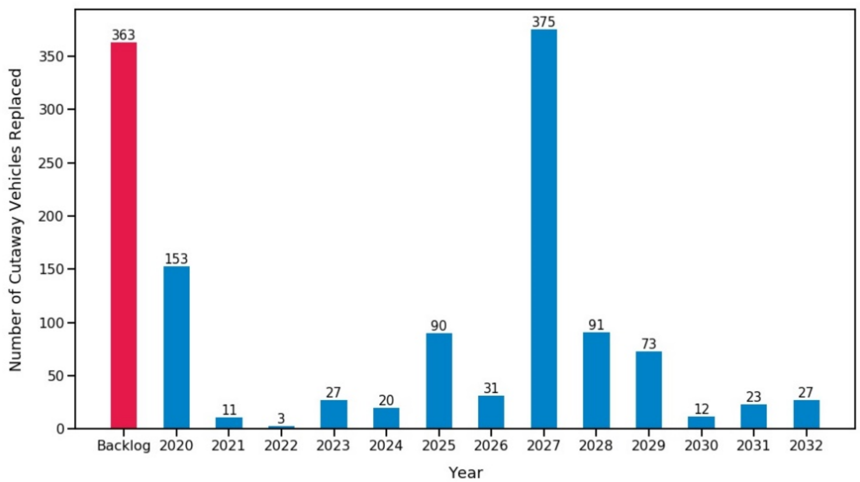
Backlog and Projected Replacement Costs for Revenue Vehicles



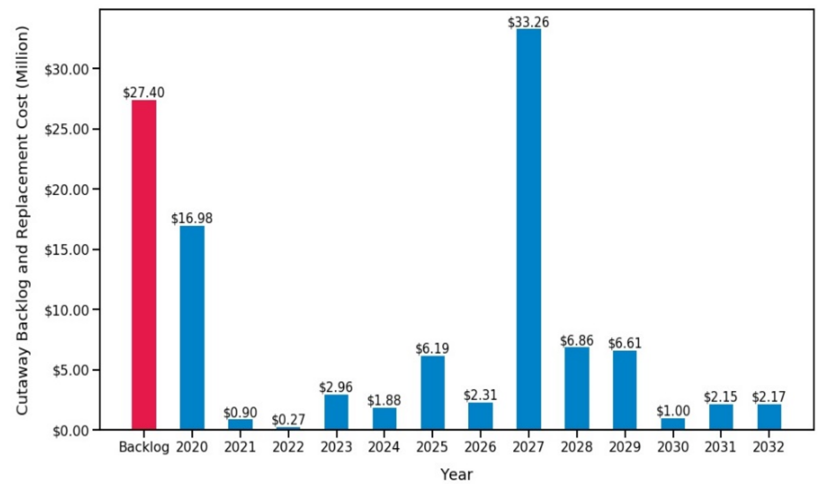
Backlog and Projected Replacement of Buses



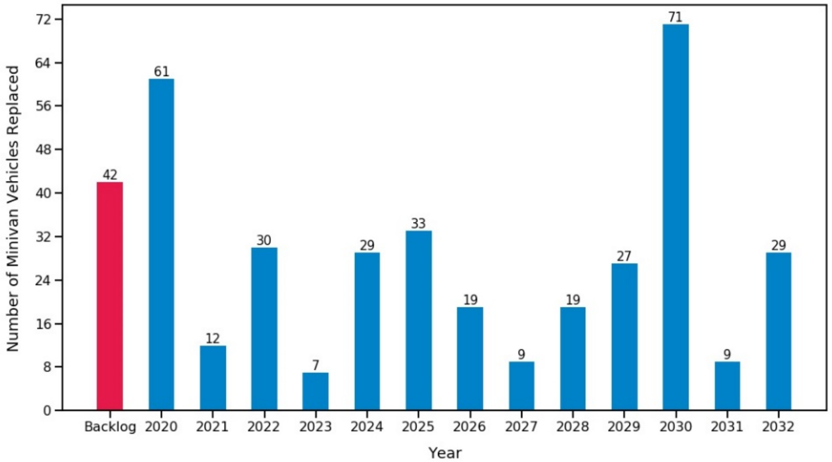
Backlog and Projected Replacement Cost for Buses



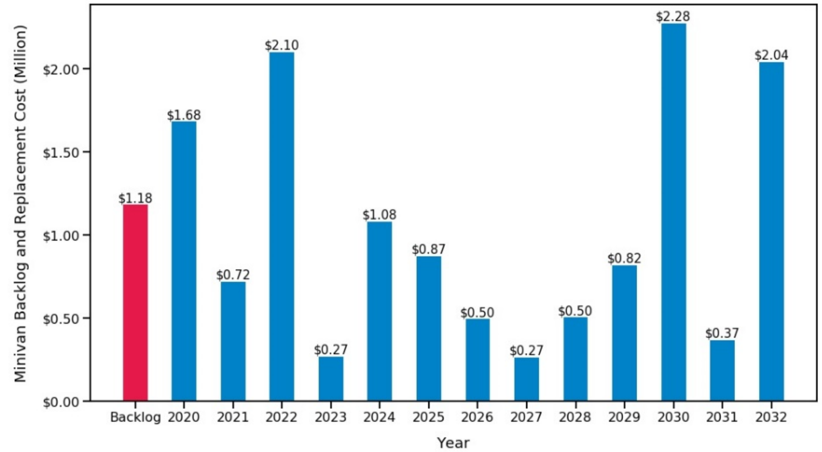
Backlog and Projected Replacement of Cutaways



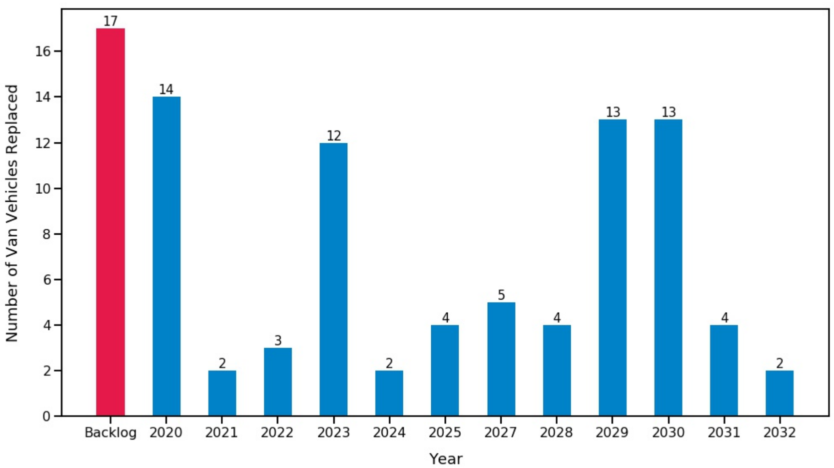
Backlog and Projected Replacement Cost for Cutaways



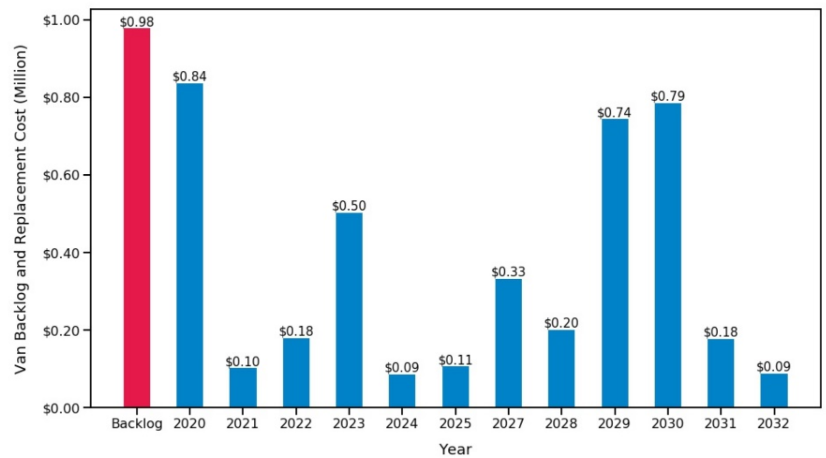
Backlog and Projected Replacement of Minivans



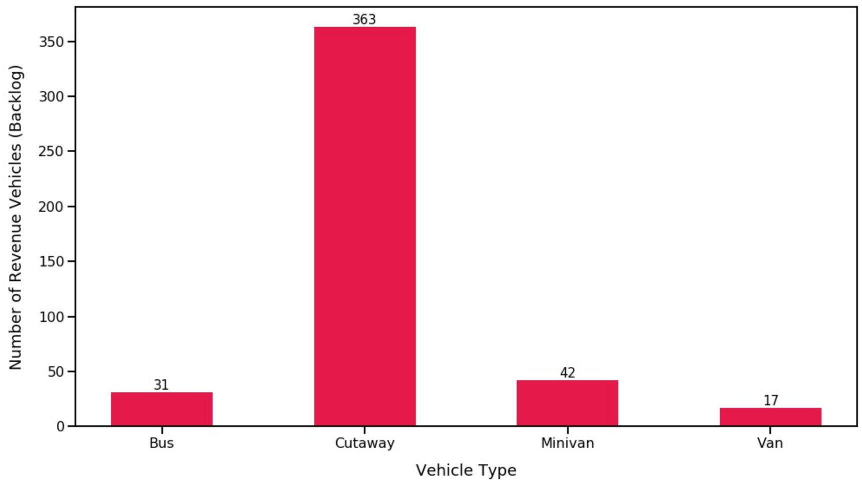
Backlog and Projected Replacement Cost for Minivans



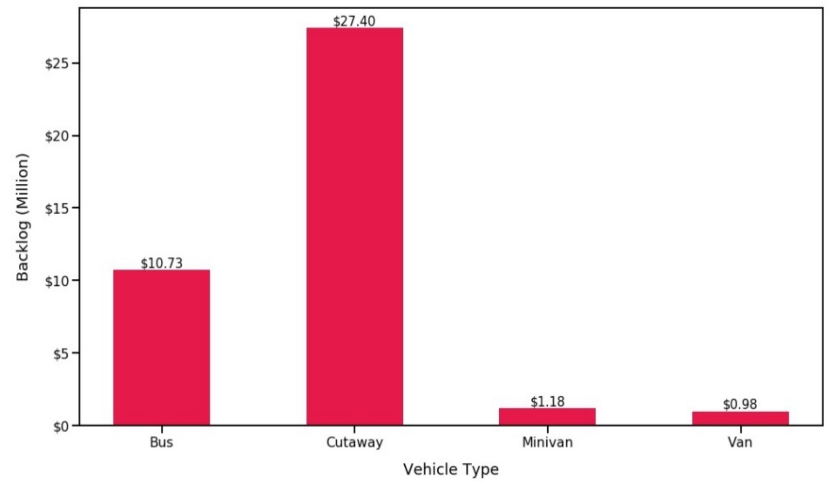
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

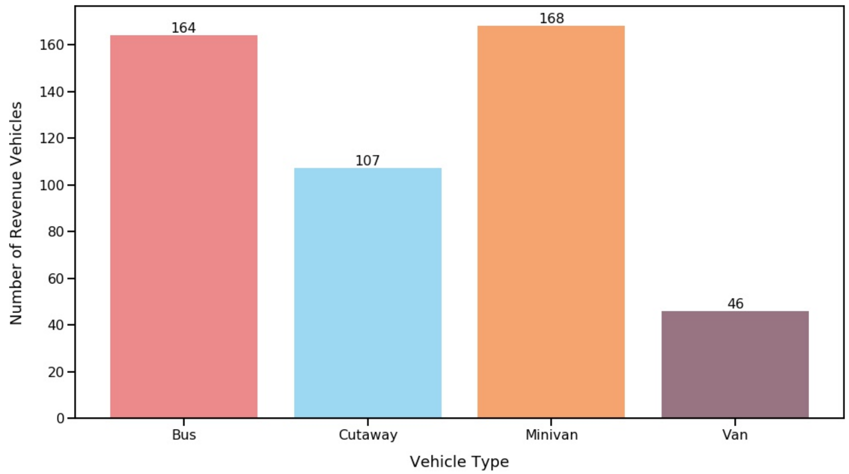


Backlog of the Revenue Vehicles by Vehicle Type

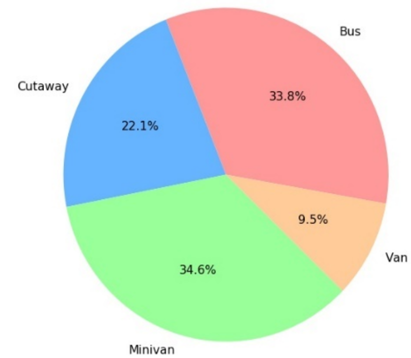


Funds Needed for Backlog by Vehicle Type

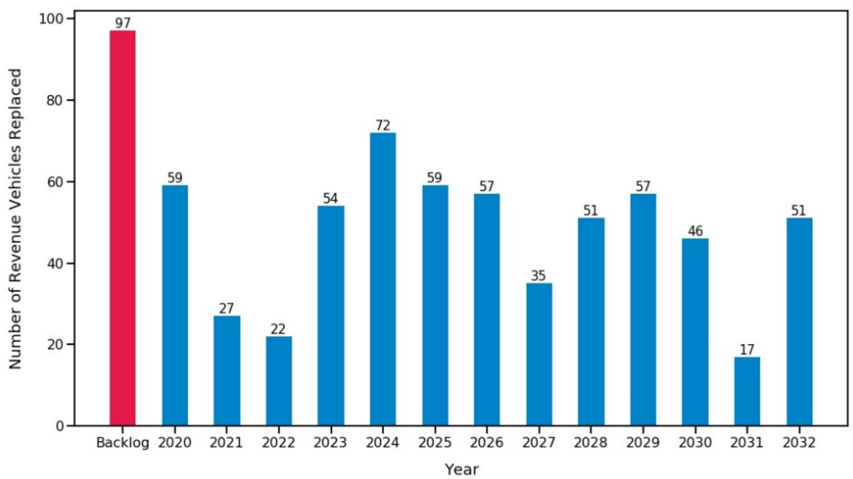
24 MS – Revenue Vehicles Information for Mississippi's Small Urban and Rural Transit Systems (NTD 2017)



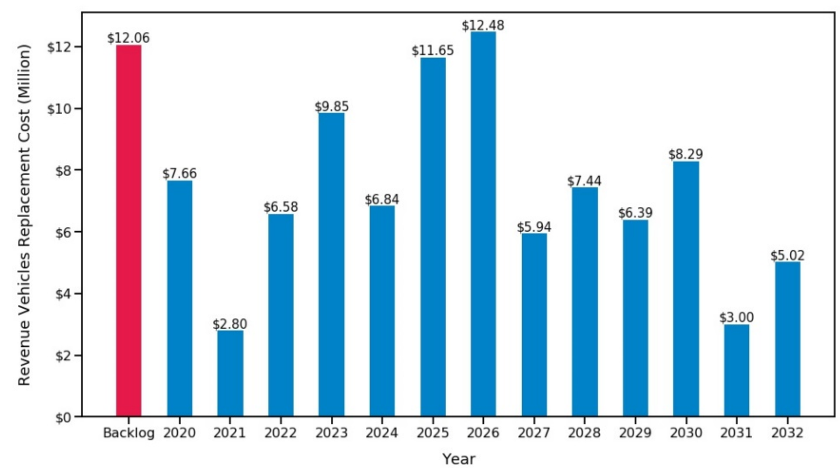
Number of Revenue Vehicles by Vehicle Type



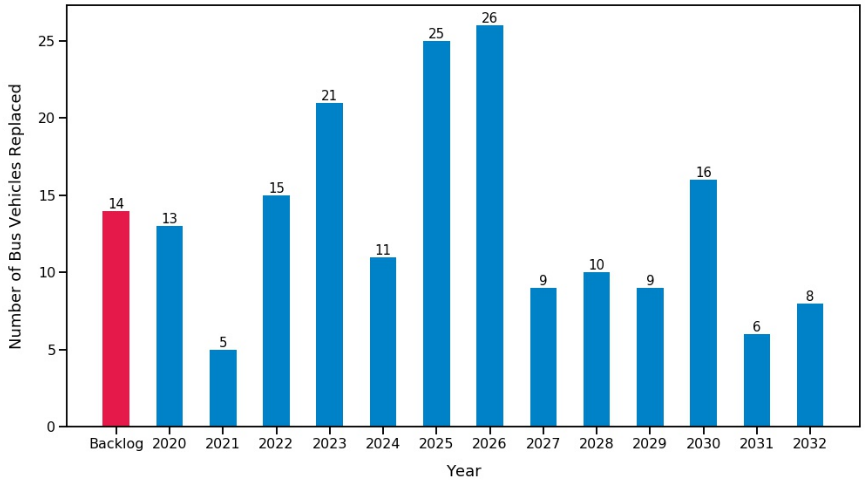
Percentage of Revenue Vehicles



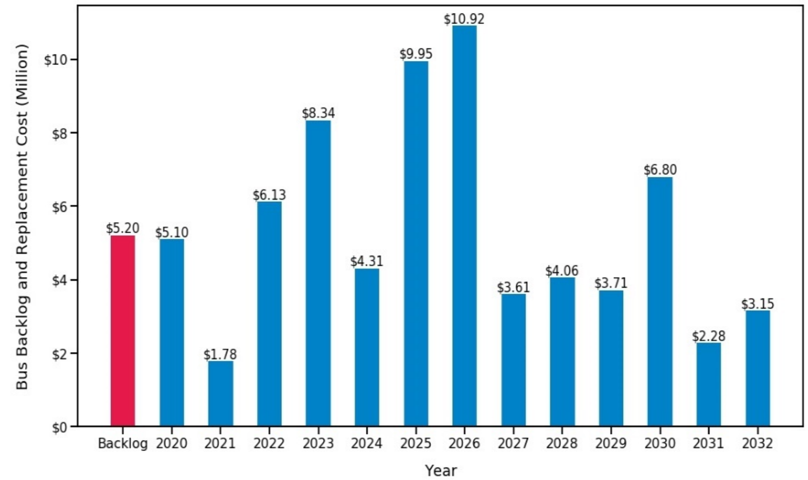
Backlog and Projected Replacement of Revenue Vehicles



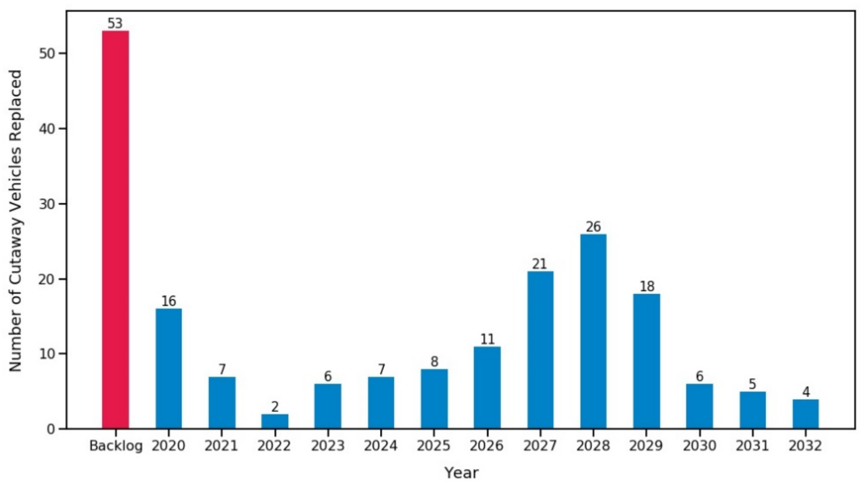
Backlog and Projected Replacement Costs for Revenue Vehicles



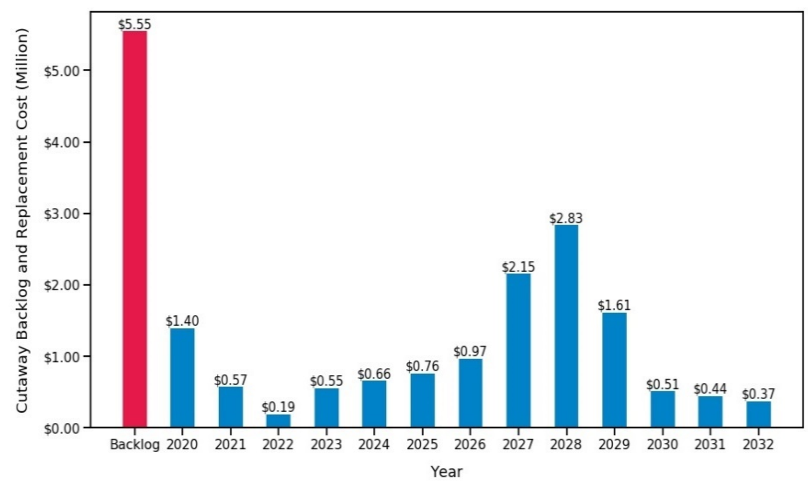
Backlog and Projected Replacement of Buses



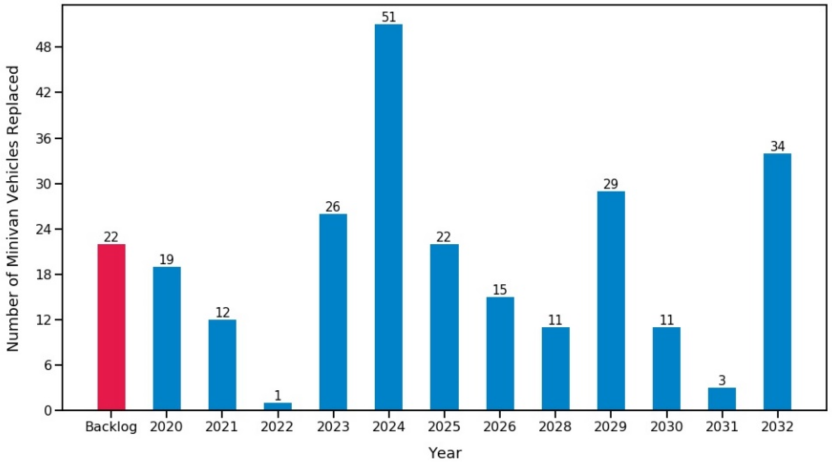
Backlog and Projected Replacement Cost for Buses



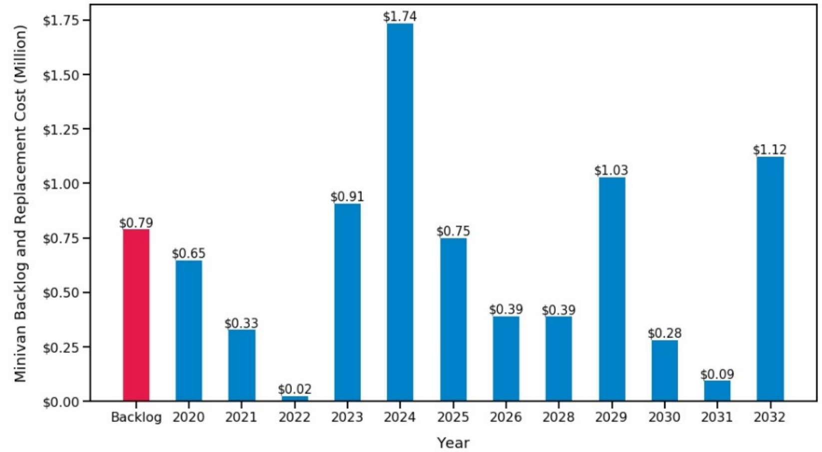
Backlog and Projected Replacement of Cutaways



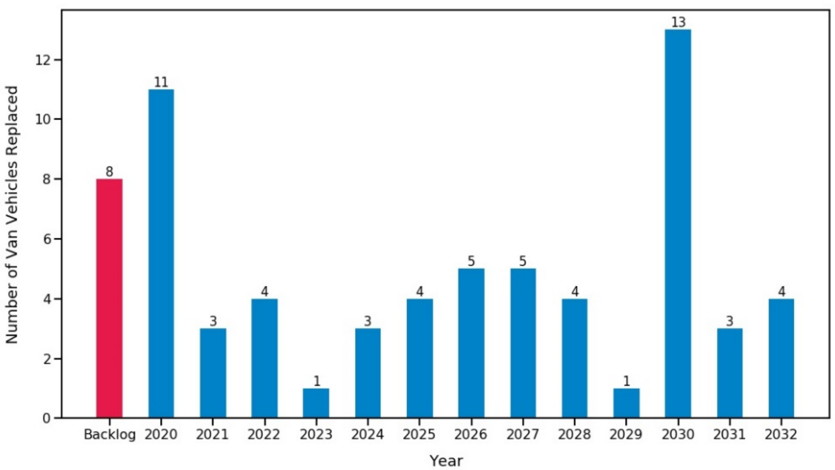
Backlog and Projected Replacement Cost for Cutaways



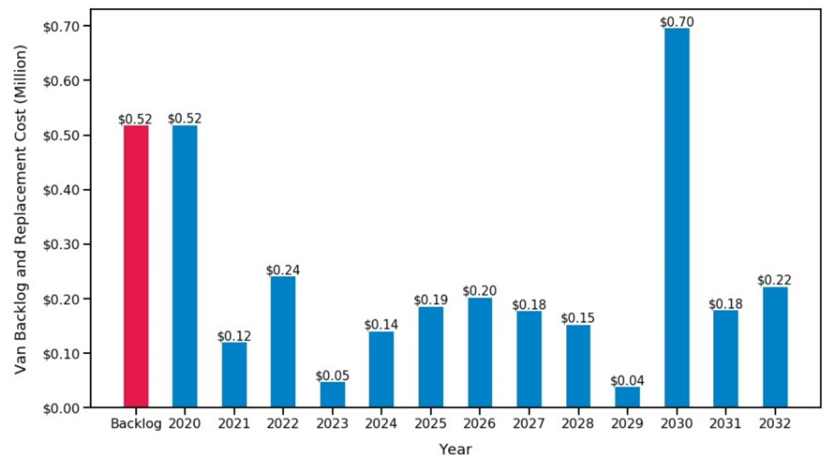
Backlog and Projected Replacement of Minivans



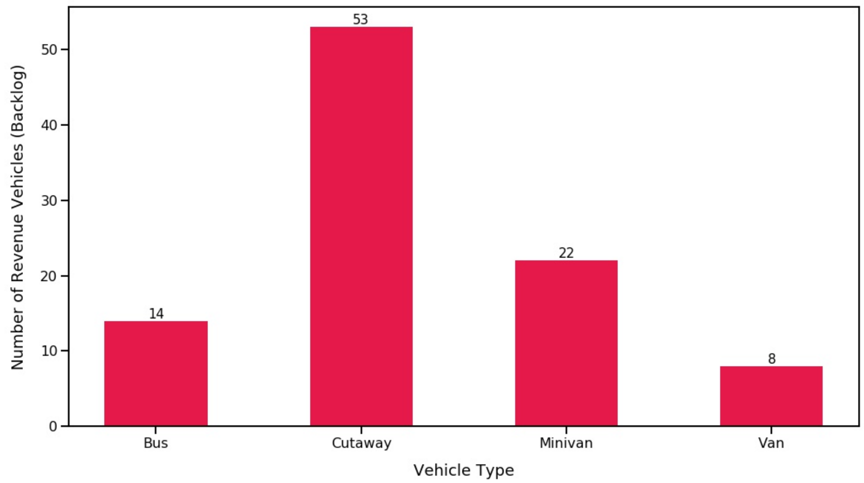
Backlog and Projected Replacement Cost for Minivans



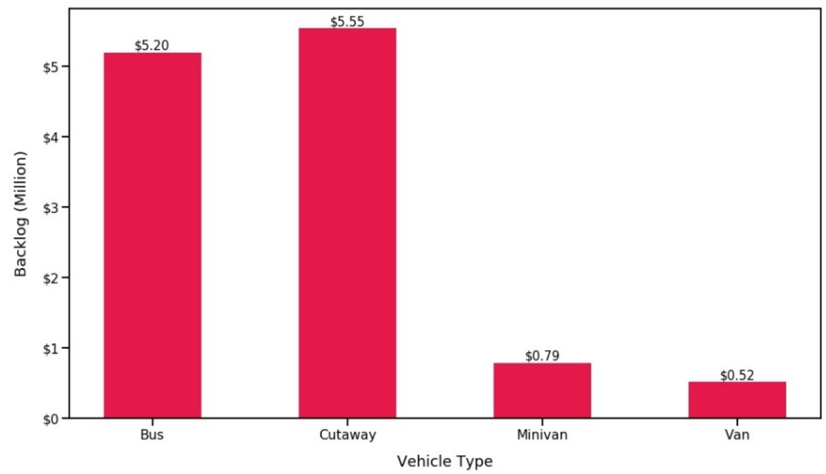
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

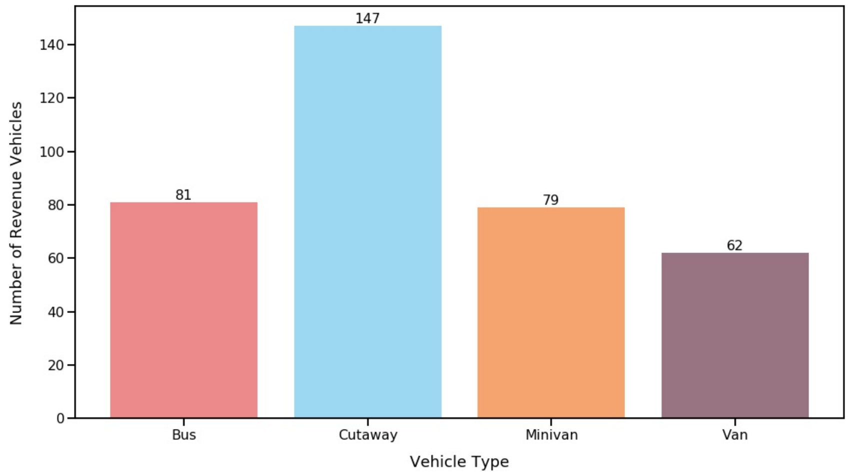


Backlog of the Revenue Vehicles by Vehicle Type

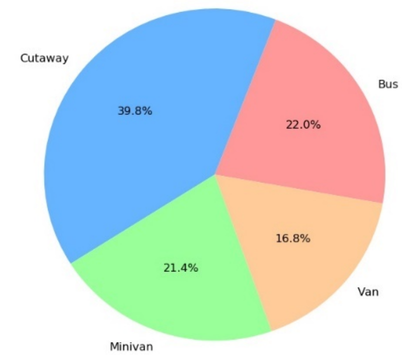


Funds Needed for Backlog by Vehicle Type

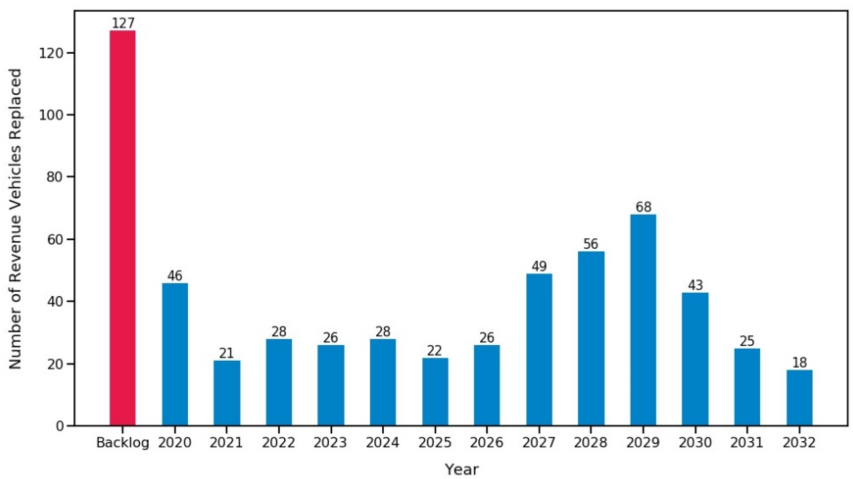
25 MT – Revenue Vehicles Information for Montana's Small Urban and Rural Transit Systems (NTD 2017)



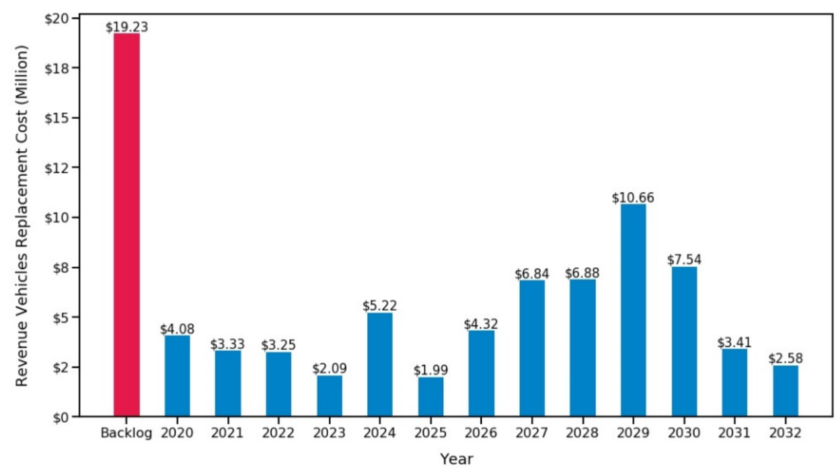
Number of Revenue Vehicles by Vehicle Type



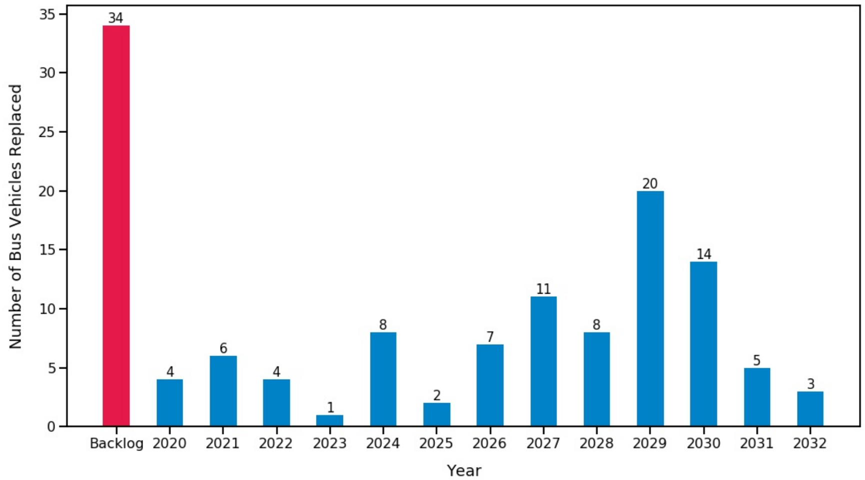
Percentage of Revenue Vehicles



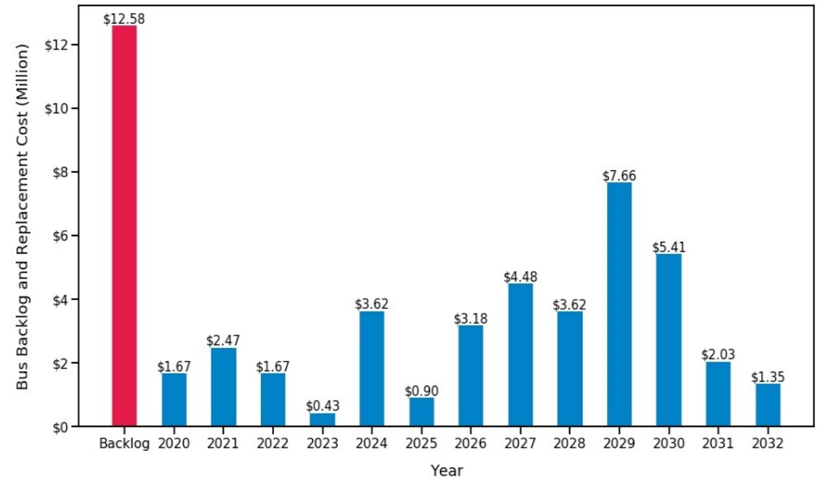
Backlog and Projected Replacement of Revenue Vehicles



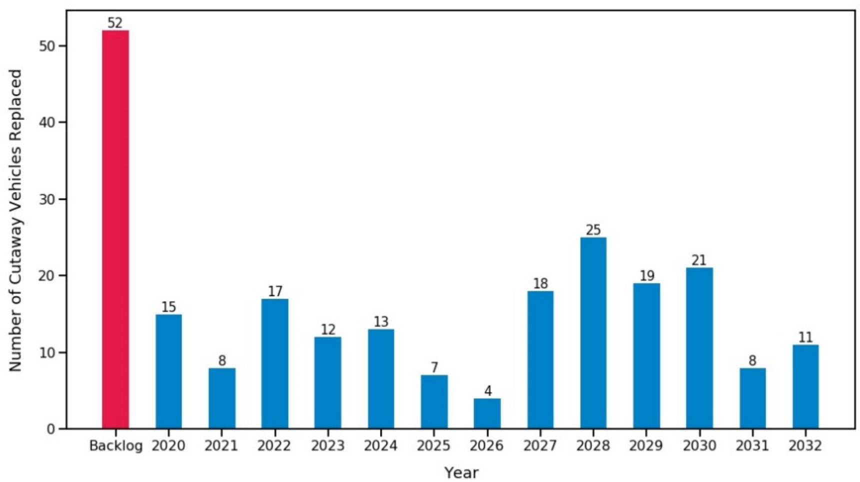
Backlog and Projected Replacement Costs for Revenue Vehicles



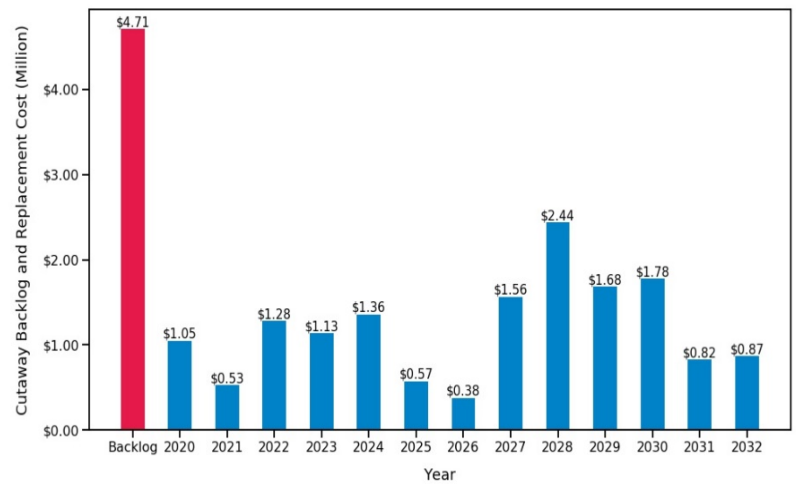
Backlog and Projected Replacement of Buses



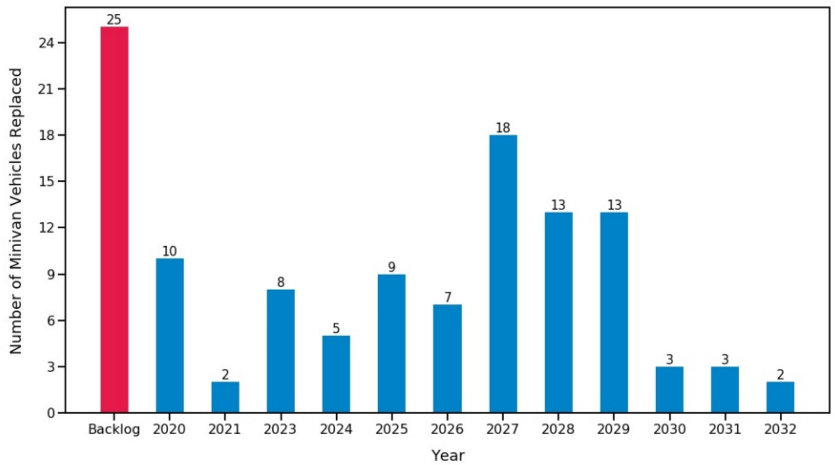
Backlog and Projected Replacement Cost for Buses



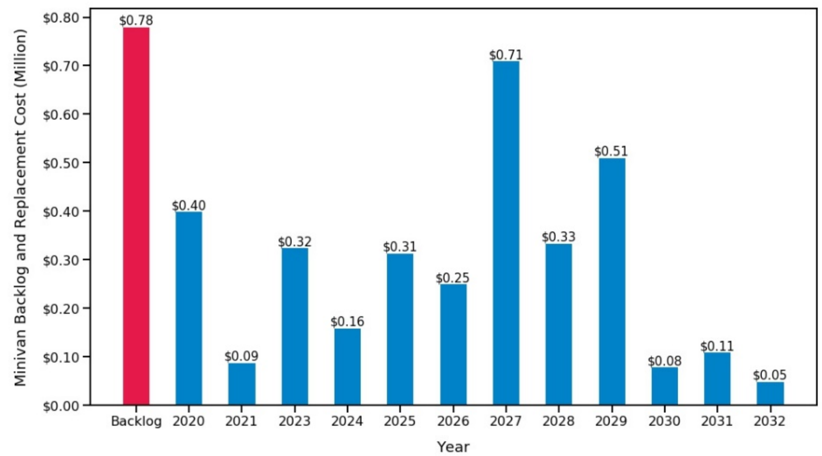
Backlog and Projected Replacement of Cutaways



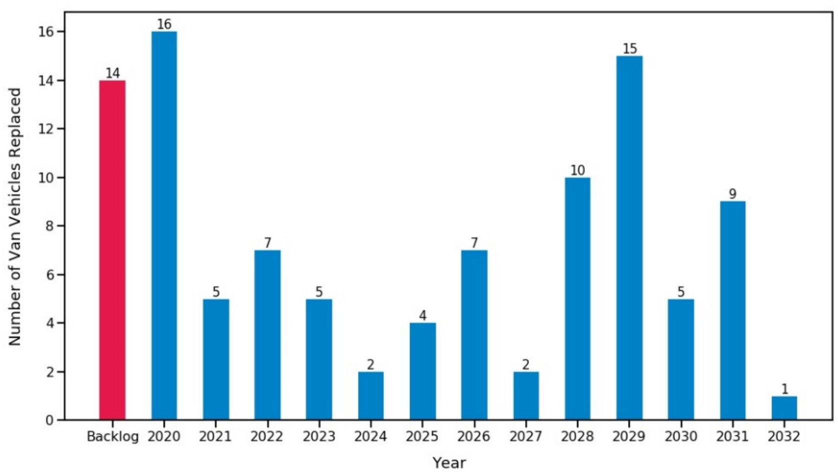
Backlog and Projected Replacement Cost for Cutaways



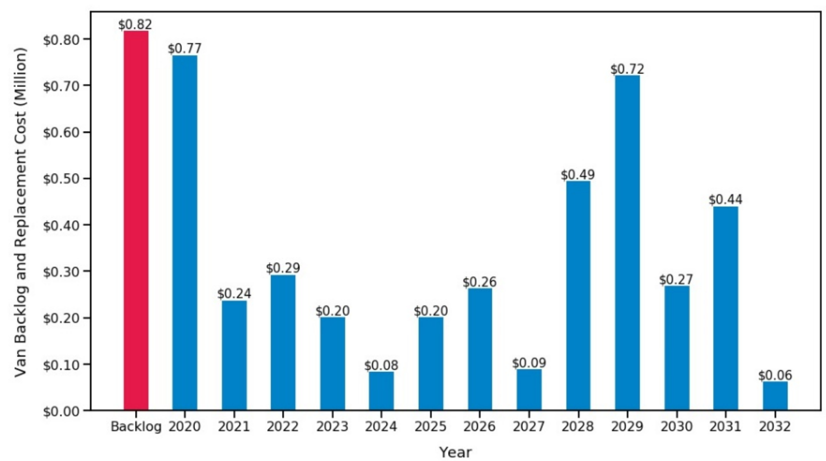
Backlog and Projected Replacement of Minivans



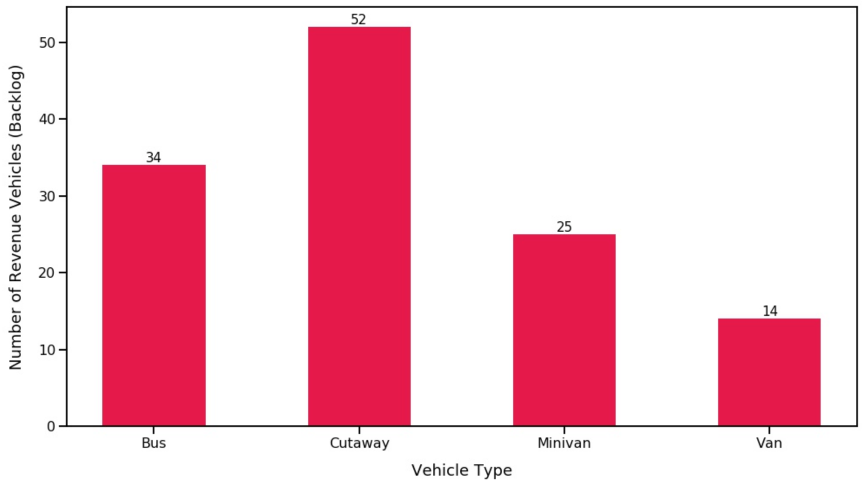
Backlog and Projected Replacement Cost for Minivans



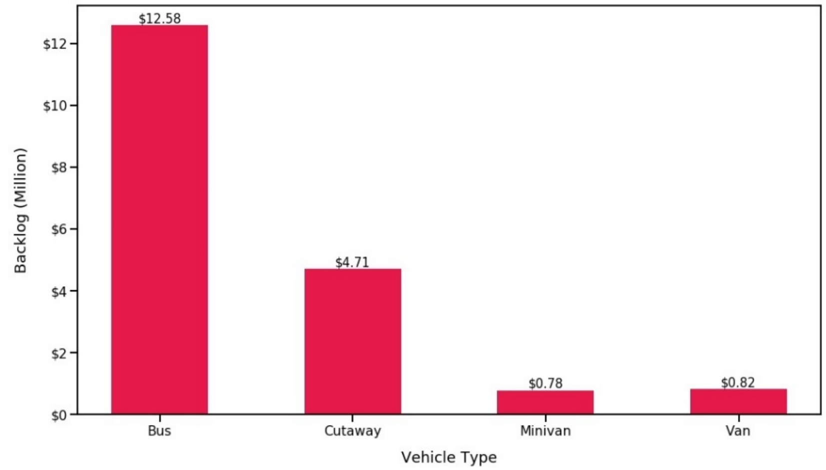
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

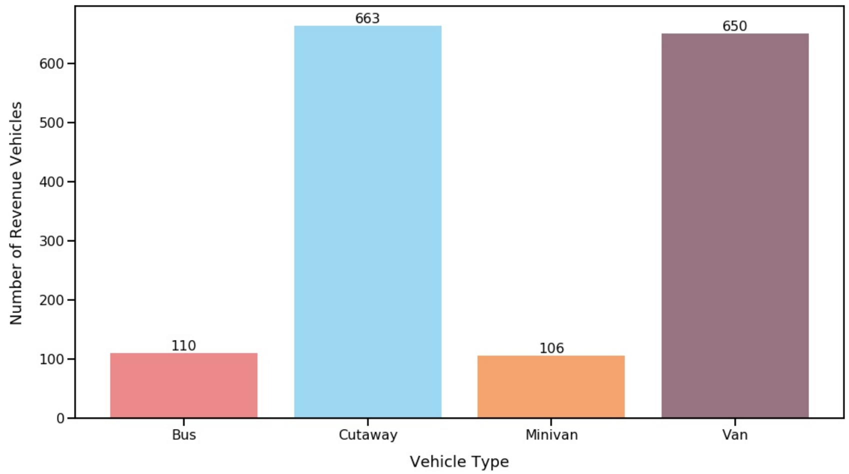


Backlog of the Revenue Vehicles by Vehicle Type

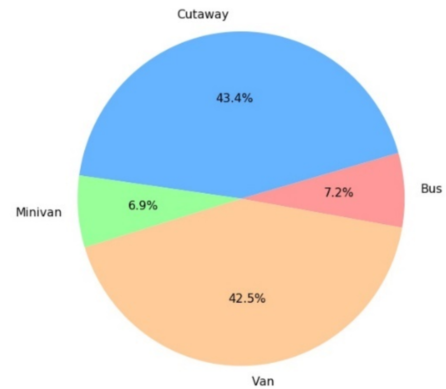


Funds Needed for Backlog by Vehicle Type

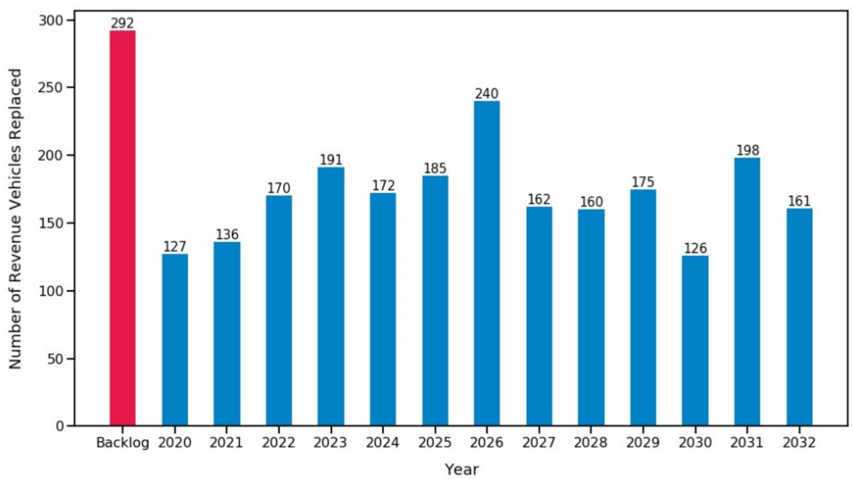
26 NC – Revenue Vehicles Information for North Carolina's Small Urban and Rural Transit Systems (NTD 2017)



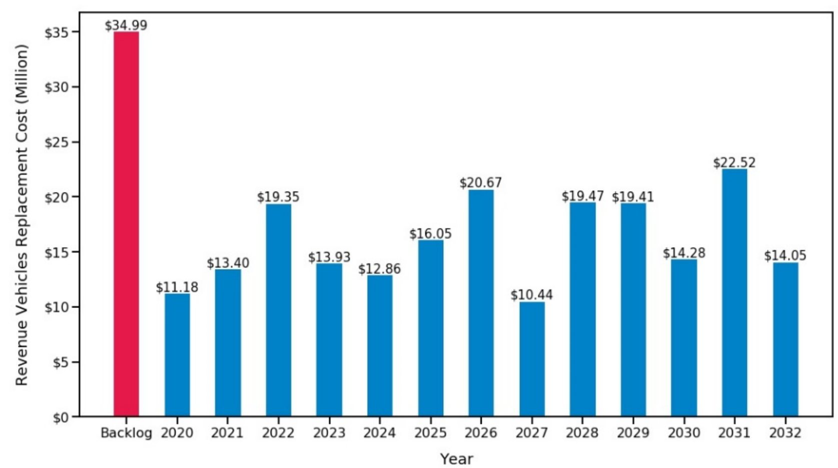
Number of Revenue Vehicles by Vehicle Type



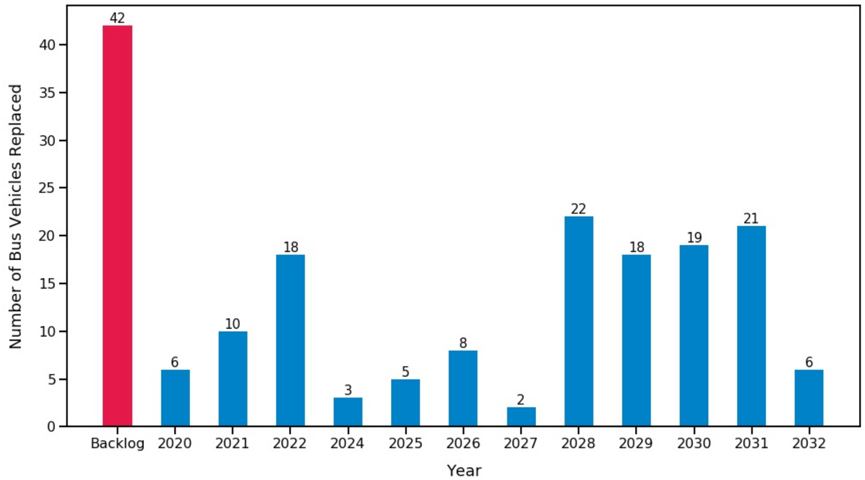
Percentage of Revenue Vehicles



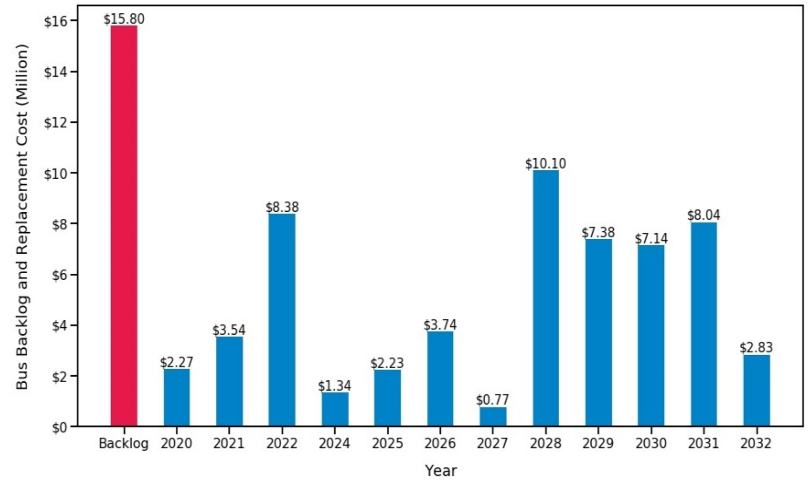
Backlog and Projected Replacement of Revenue Vehicles



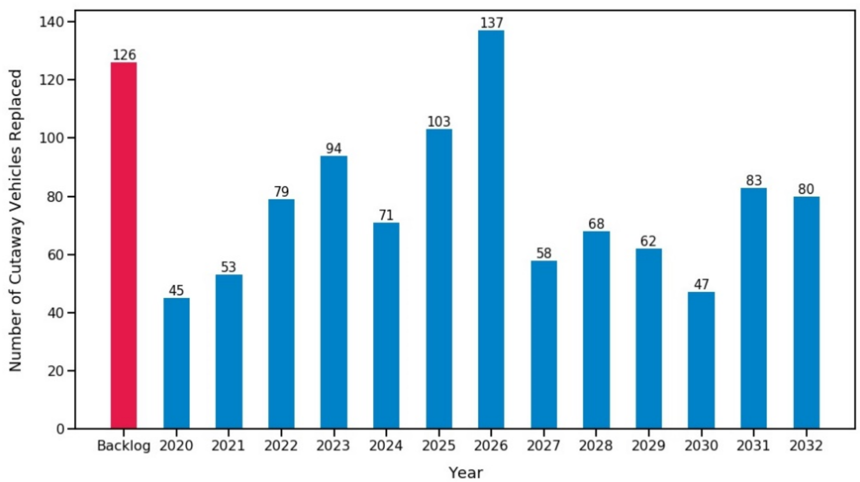
Backlog and Projected Replacement Costs for Revenue Vehicles



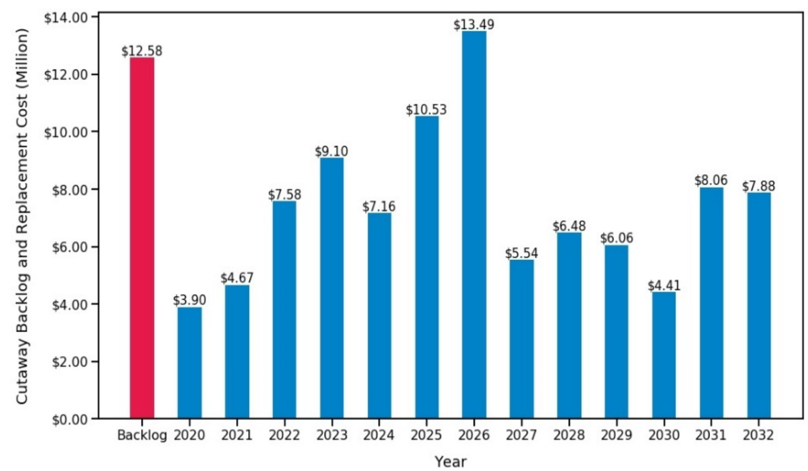
Backlog and Projected Replacement of Buses



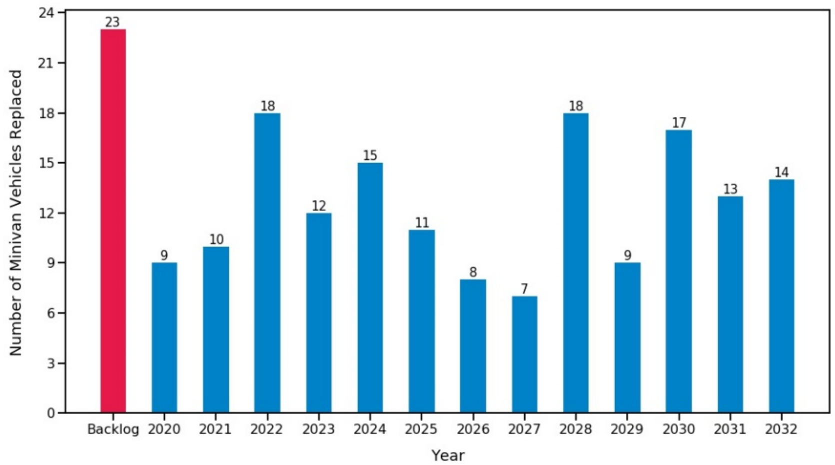
Backlog and Projected Replacement Cost for Buses



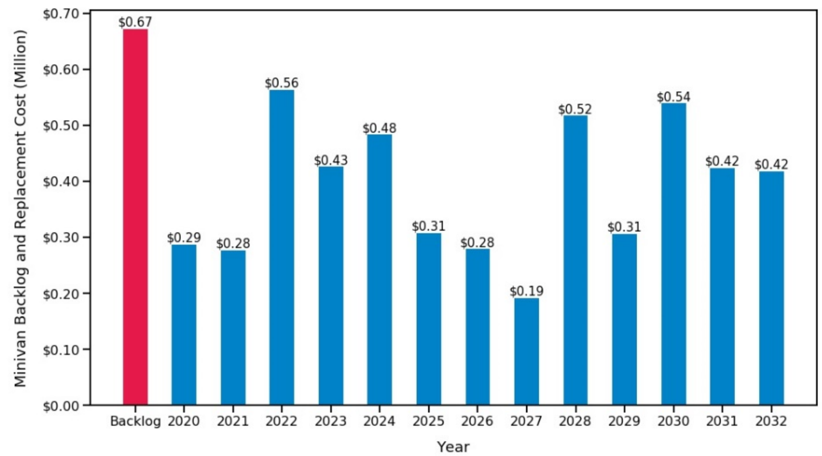
Backlog and Projected Replacement of Cutaways



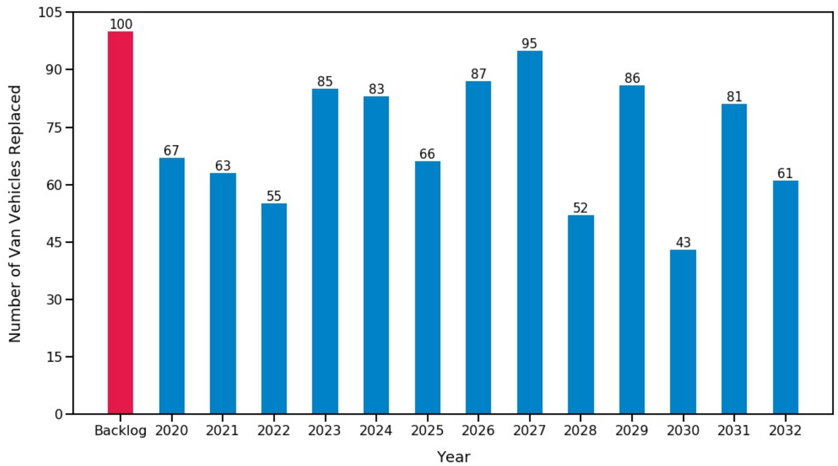
Backlog and Projected Replacement Cost for Cutaways



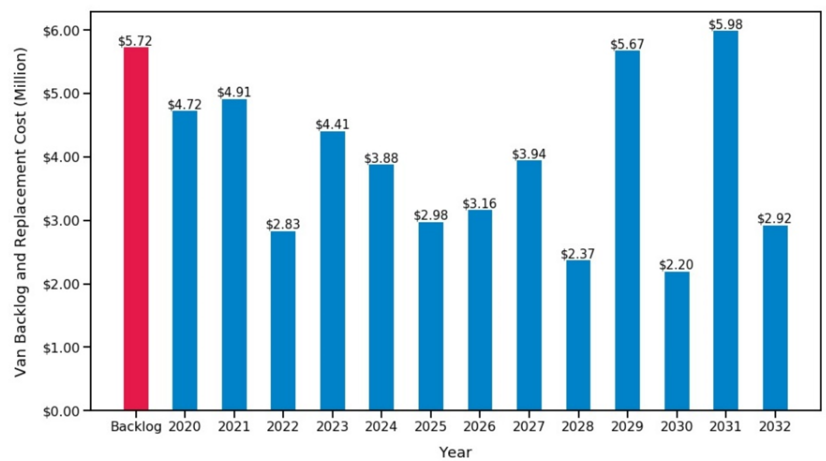
Backlog and Projected Replacement of Minivans



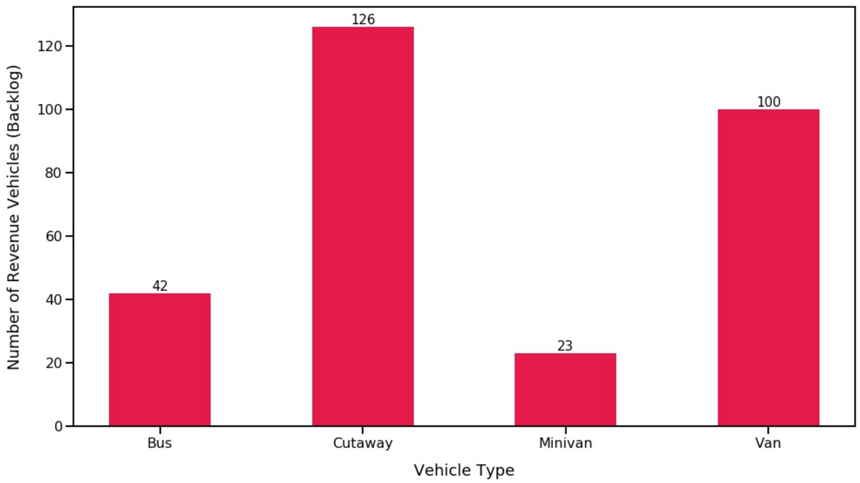
Backlog and Projected Replacement Cost for Minivans

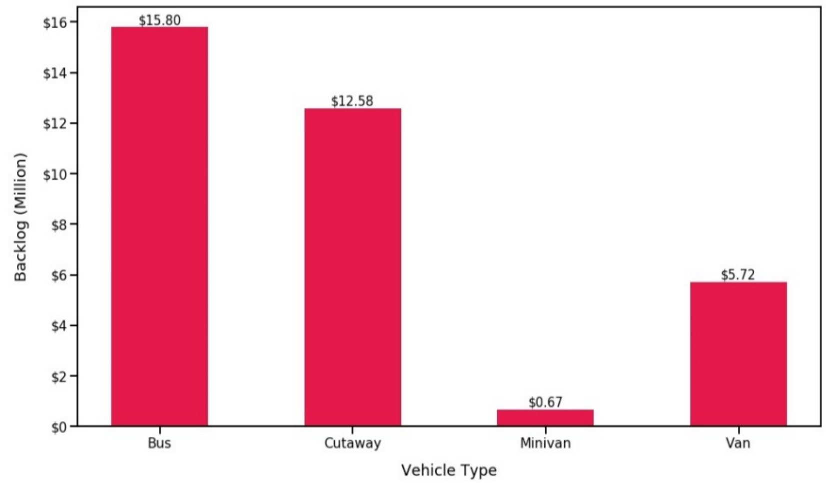


Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

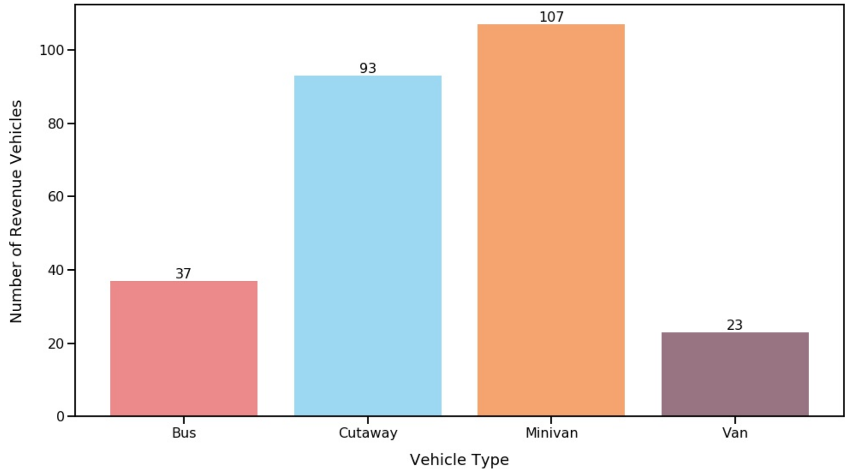




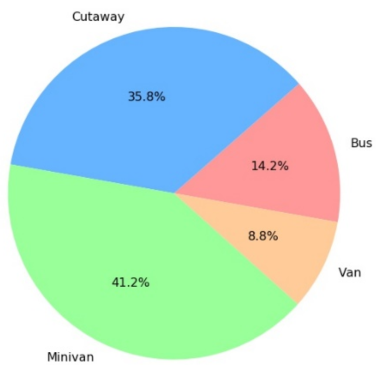
Backlog of the Revenue Vehicles by Vehicle Type

Funds Needed for Backlog by Vehicle Type

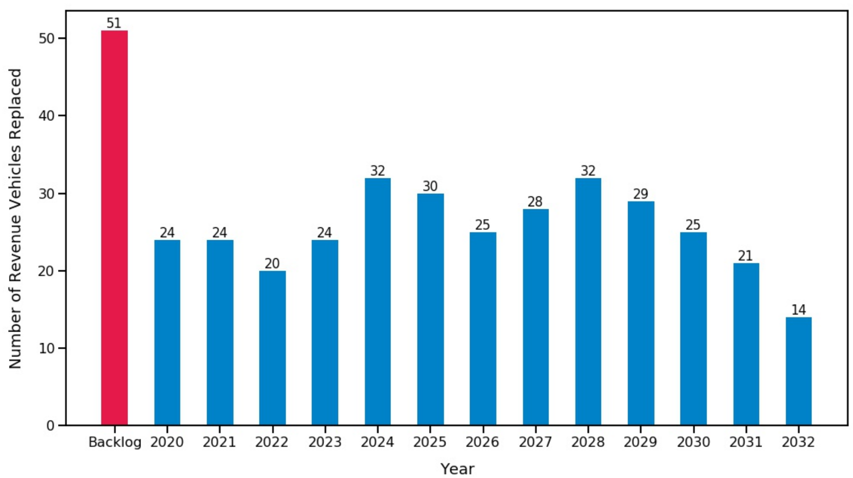
27 ND – Revenue Vehicles Information for North Dakota's Small Urban and Rural Transit Systems (NTD 2017)



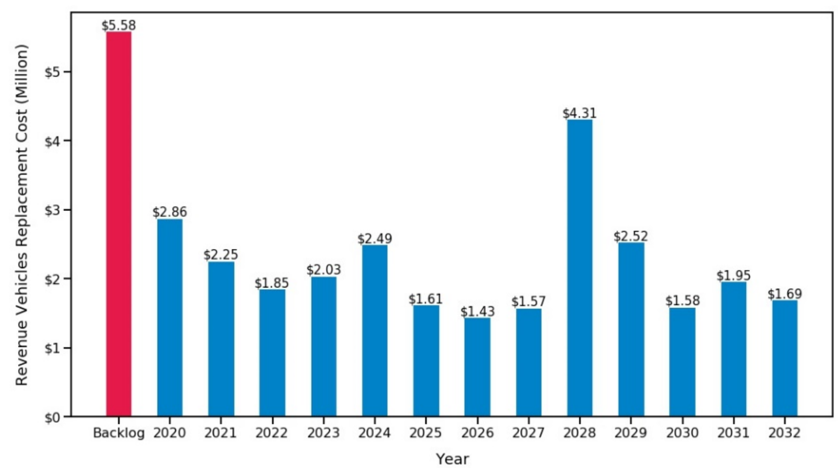
Number of Revenue Vehicles by Vehicle Type



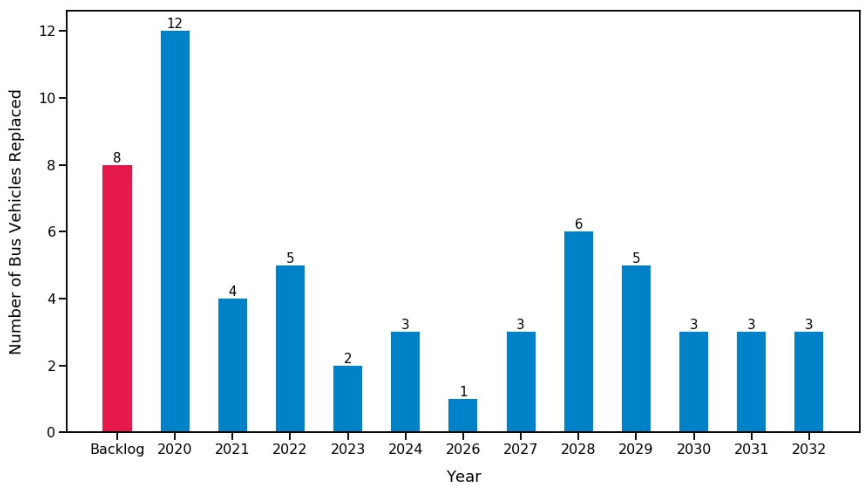
Percentage of Revenue Vehicles



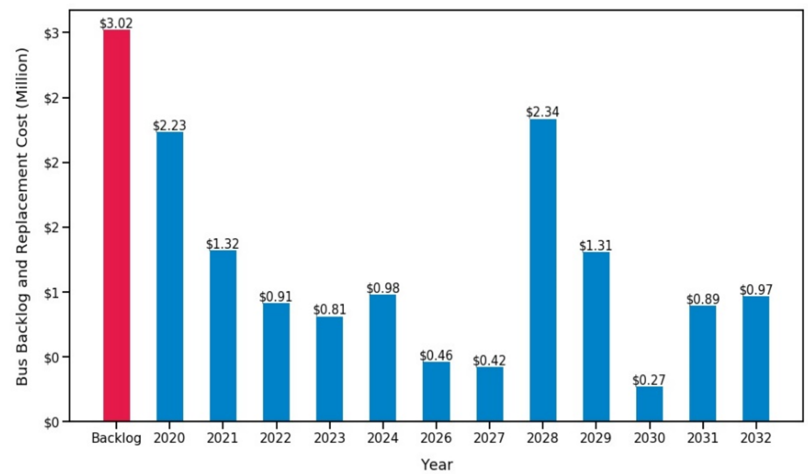
Backlog and Projected Replacement of Revenue Vehicles



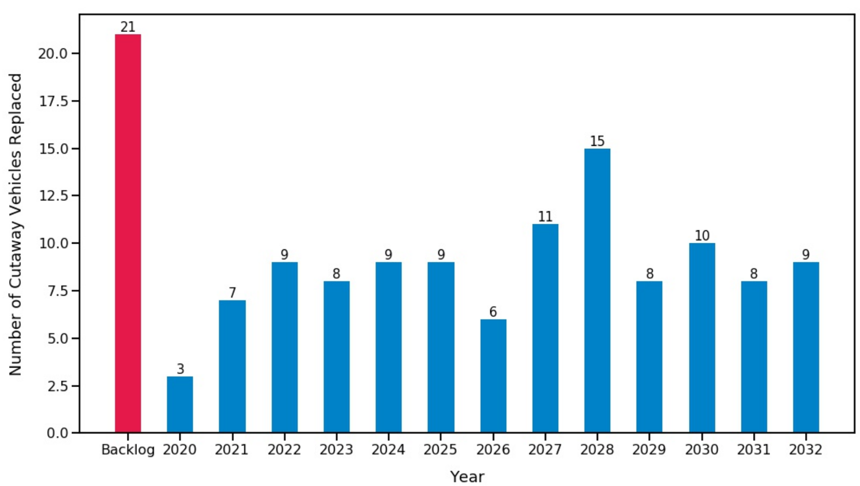
Backlog and Projected Replacement Costs for Revenue Vehicles



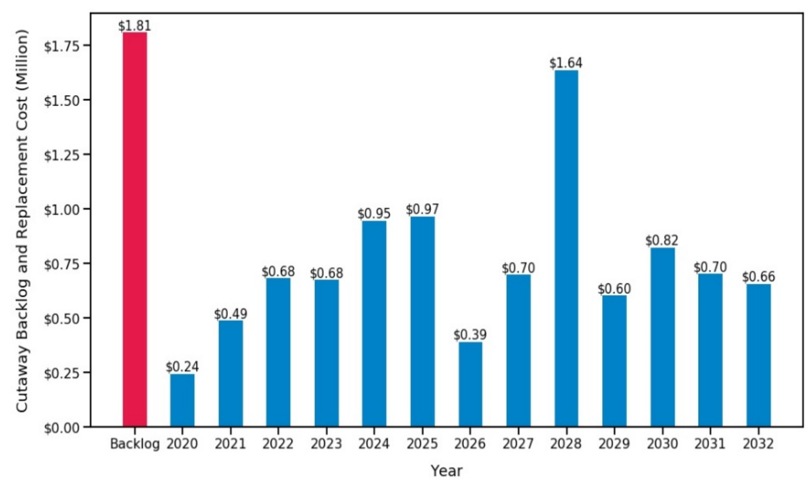
Backlog and Projected Replacement of Buses



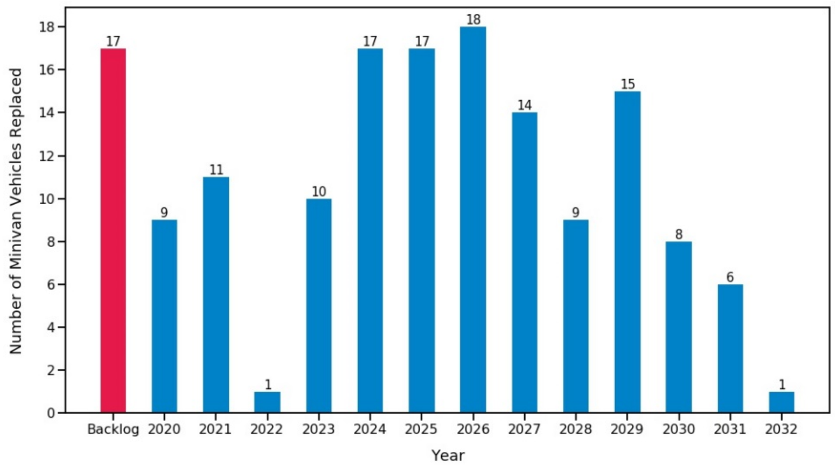
Backlog and Projected Replacement Cost for Buses



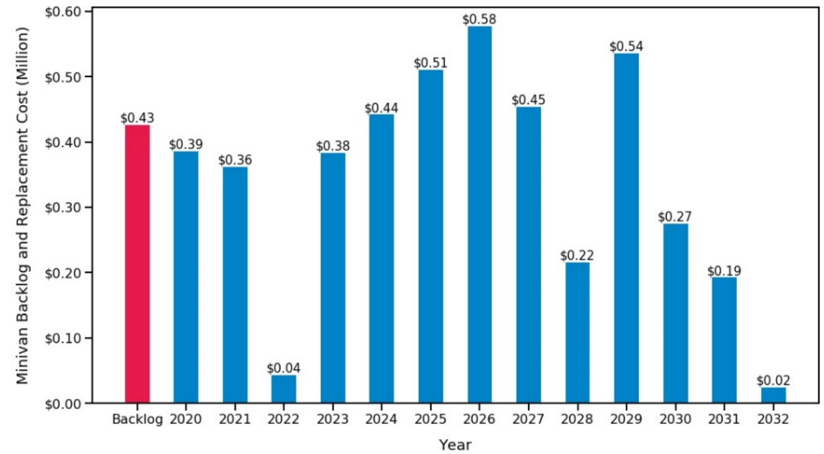
Backlog and Projected Replacement of Cutaways



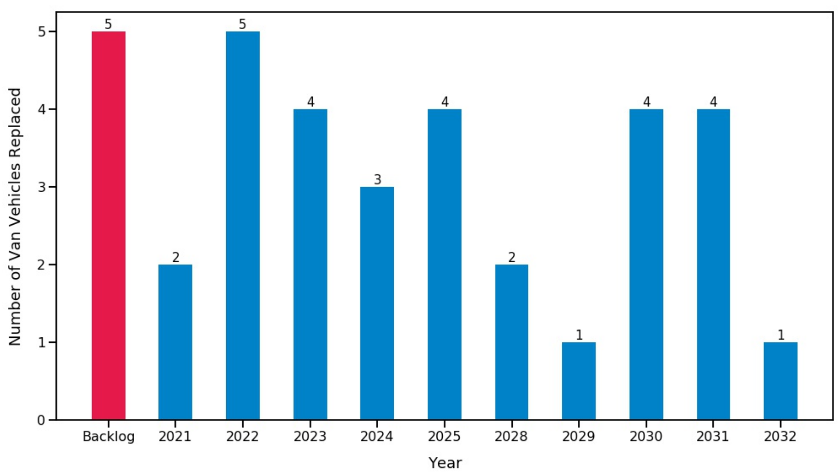
Backlog and Projected Replacement Cost for Cutaways



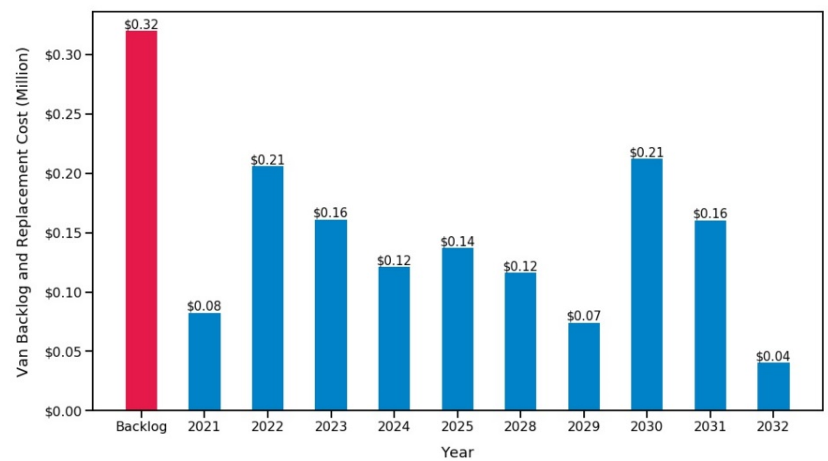
Backlog and Projected Replacement of Minivans



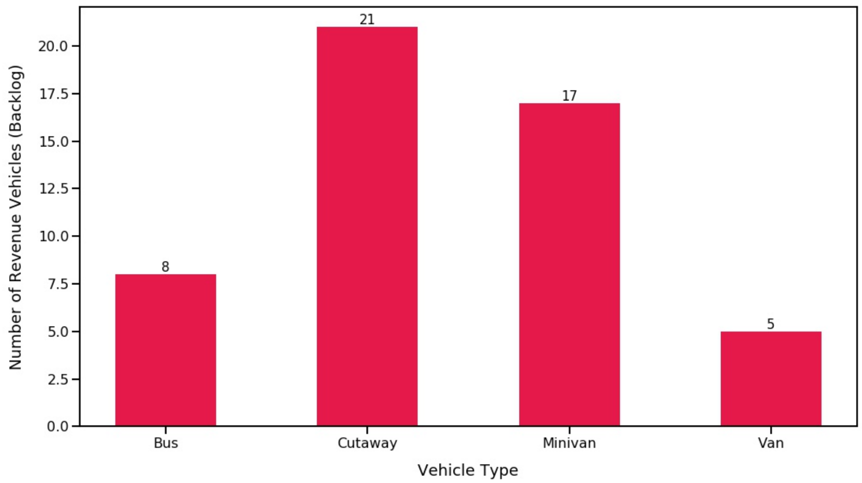
Backlog and Projected Replacement Cost for Minivans



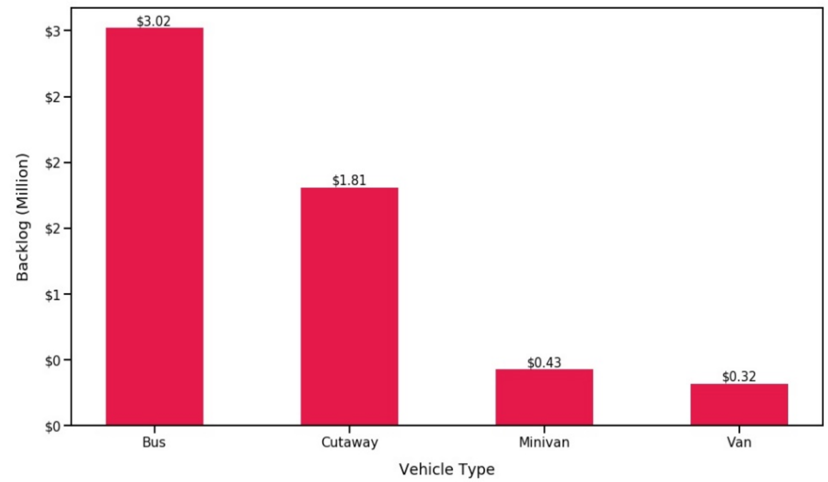
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

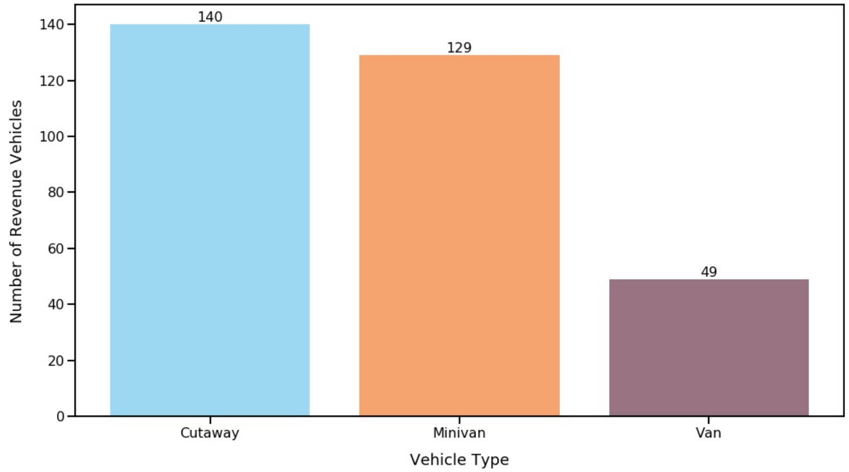


Backlog of the Revenue Vehicles by Vehicle Type

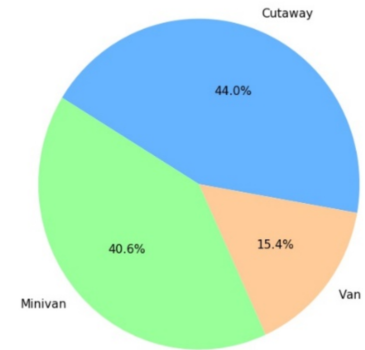


Funds Needed for Backlog by Vehicle Type

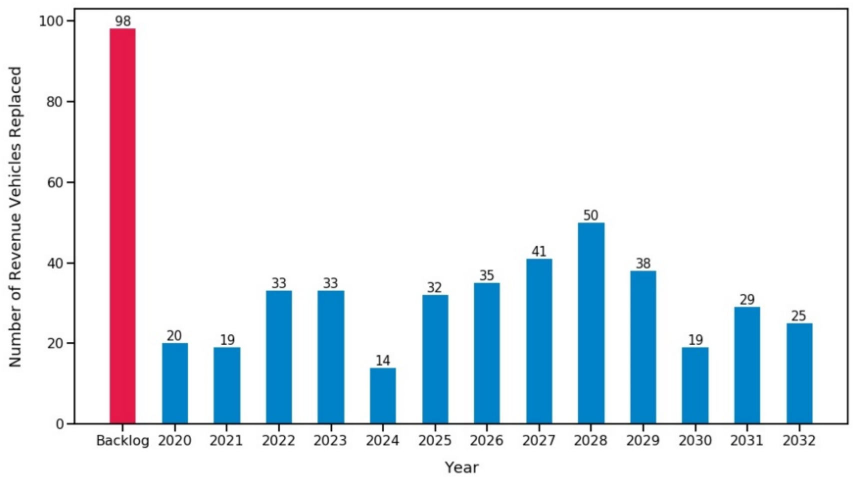
28 NE – Revenue Vehicles Information for Nebraska's Small Urban and Rural Transit Systems (NTD 2017)



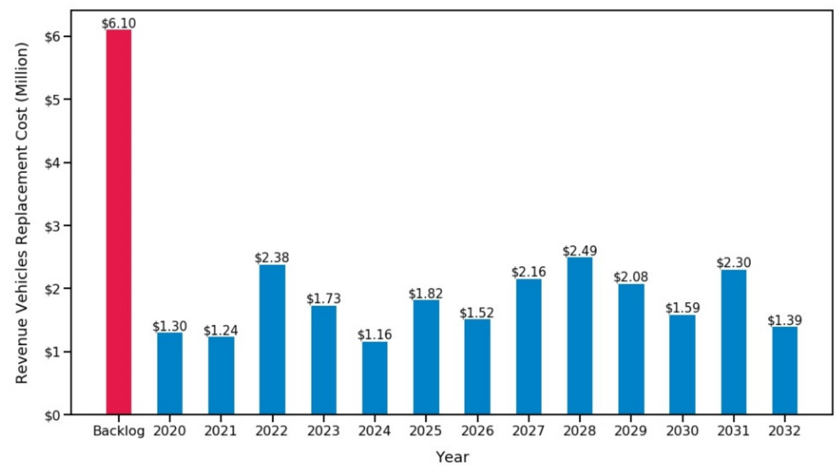
Number of Revenue Vehicles by Vehicle Type



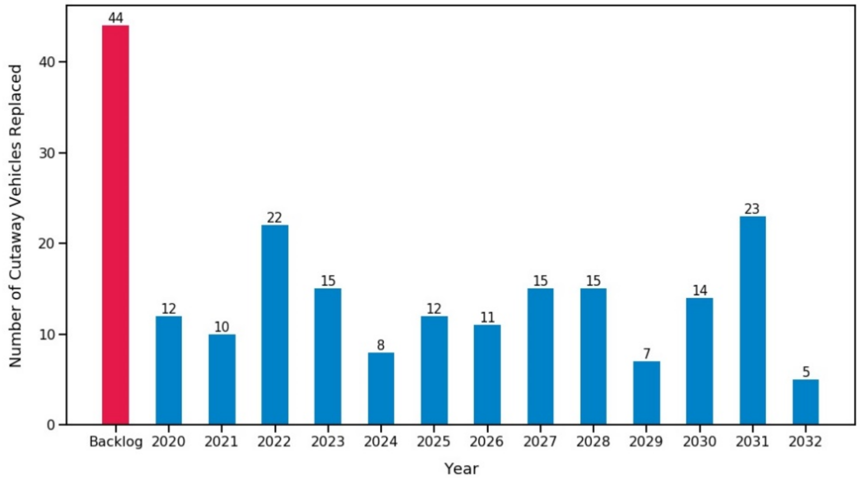
Percentage of Revenue Vehicles



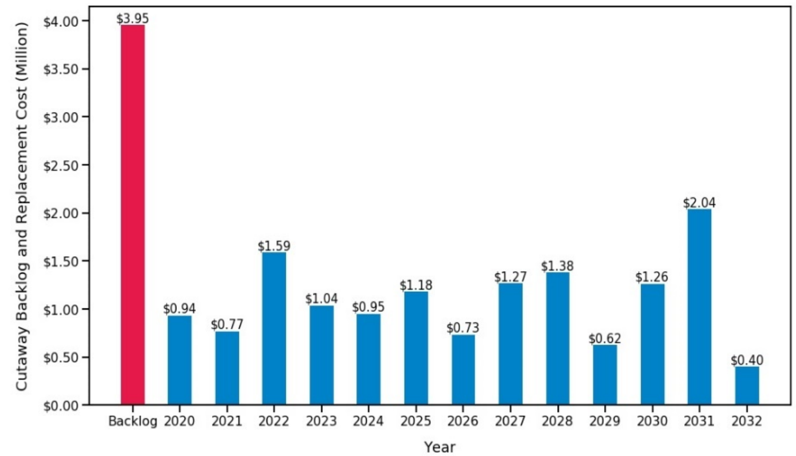
Backlog and Projected Replacement of Revenue Vehicles



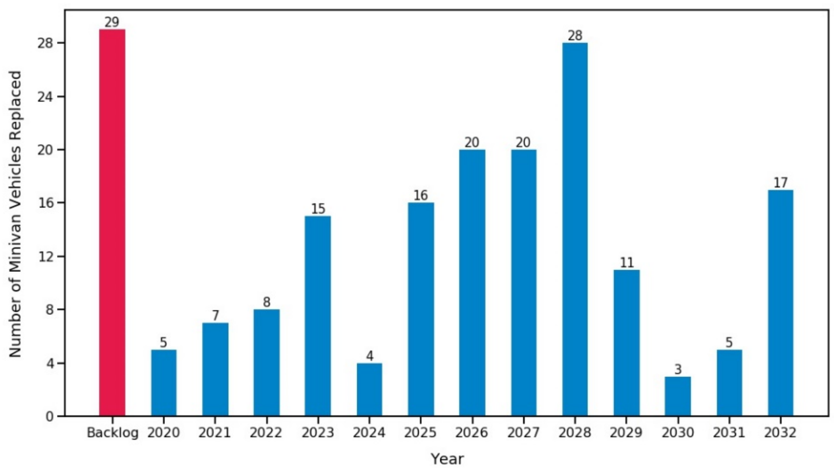
Backlog and Projected Replacement Costs for Revenue Vehicles



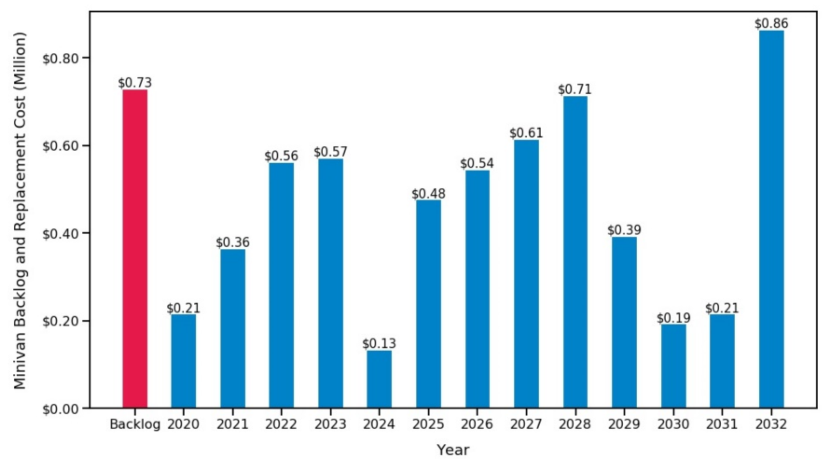
Backlog and Projected Replacement of Cutaways



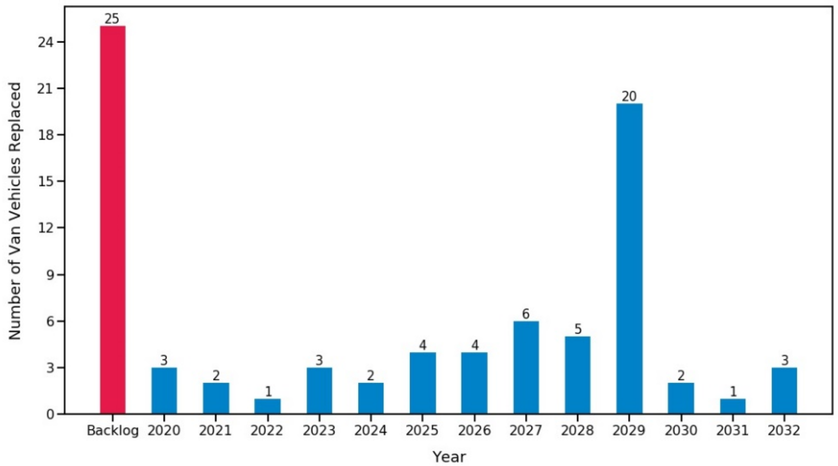
Backlog and Projected Replacement Cost for Cutaways



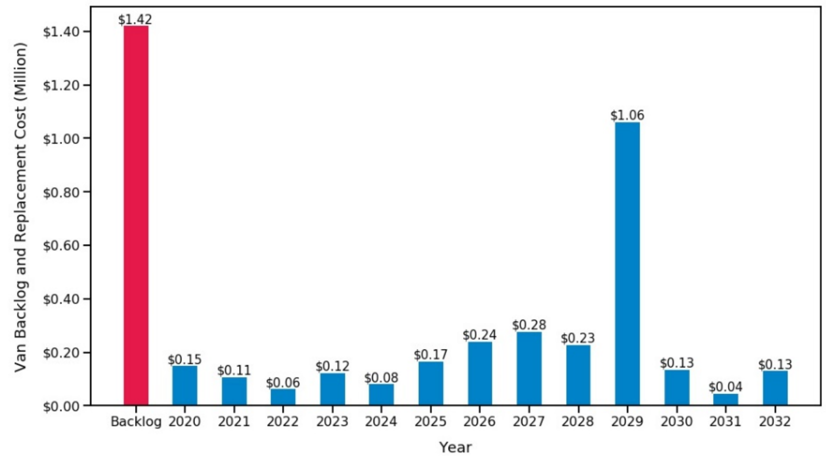
Backlog and Projected Replacement of Minivans



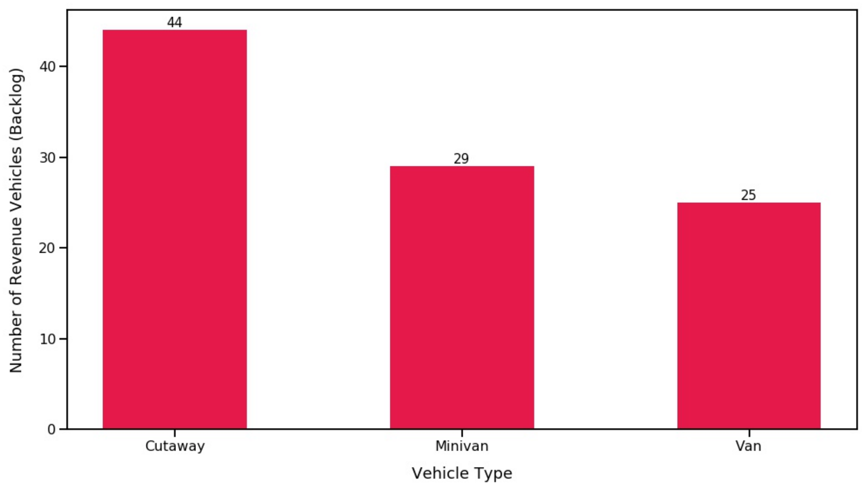
Backlog and Projected Replacement Cost for Minivans



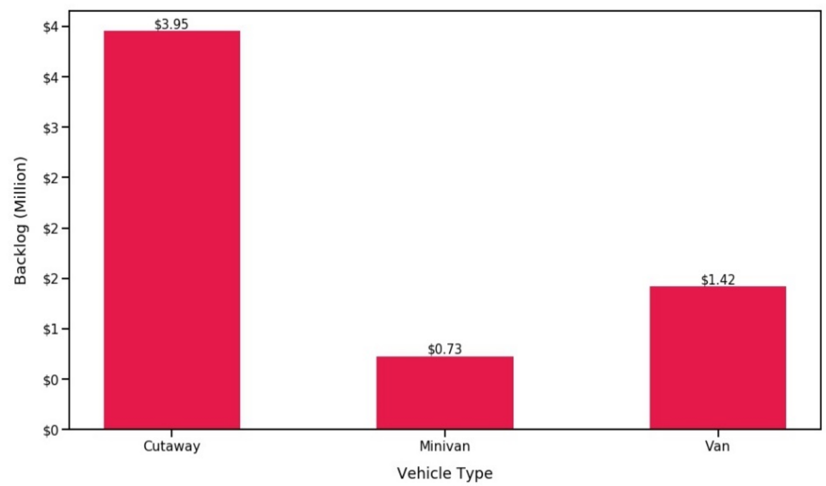
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

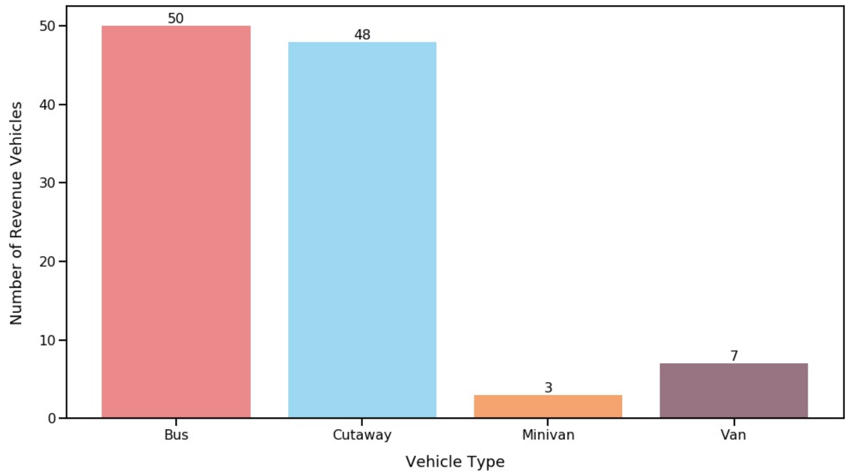


Backlog of the Revenue Vehicles by Vehicle Type

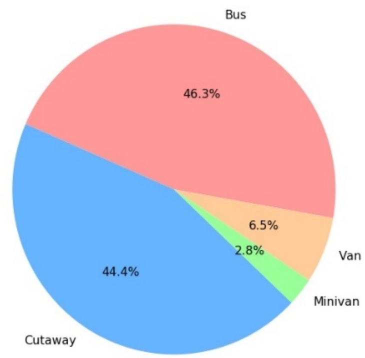


Funds Needed for Backlog by Vehicle Type

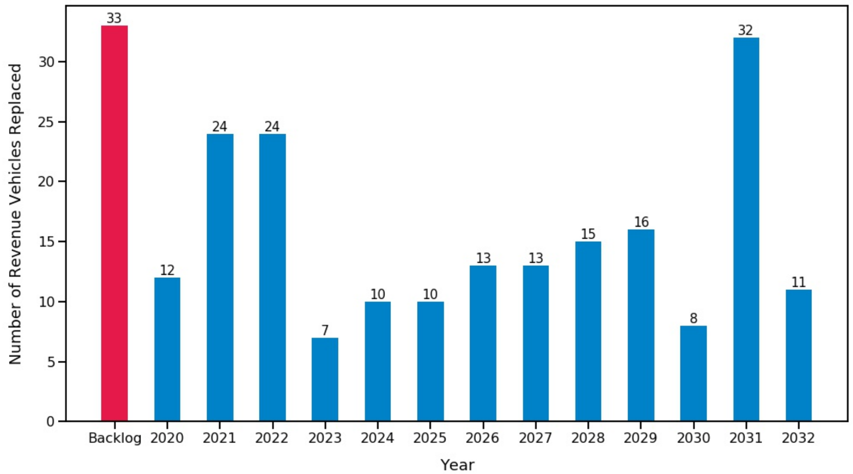
29 NH – Revenue Vehicles Information for New Hampshire's Small Urban and Rural Transit Systems (NTD 2017)



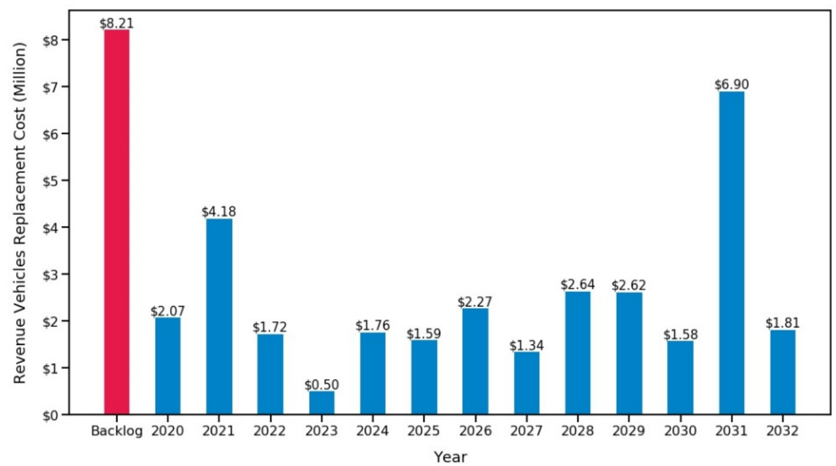
Number of Revenue Vehicles by Vehicle Type



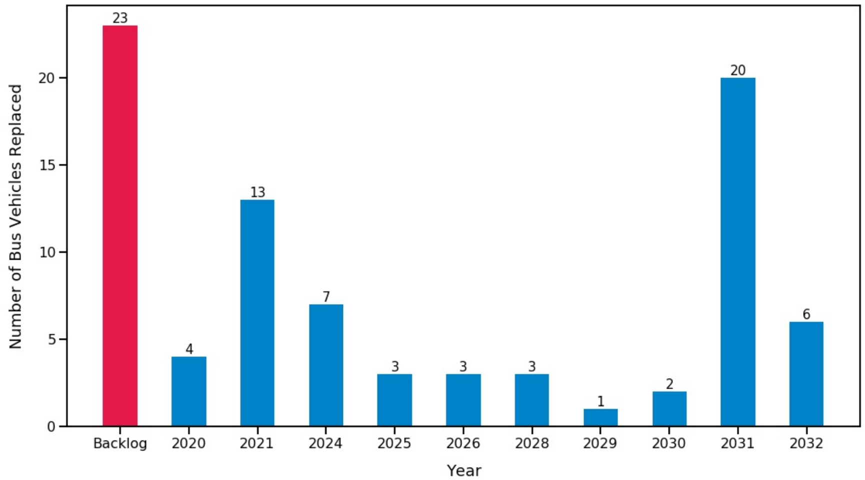
Percentage of Revenue Vehicles



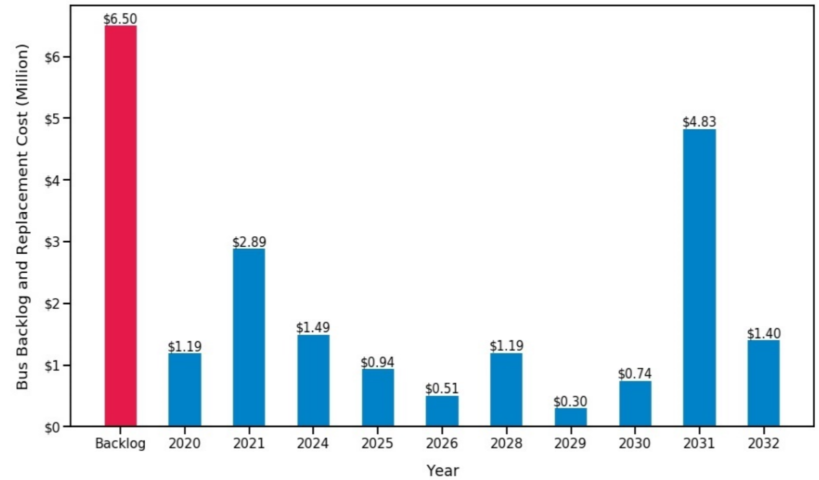
Backlog and Projected Replacement of Revenue Vehicles



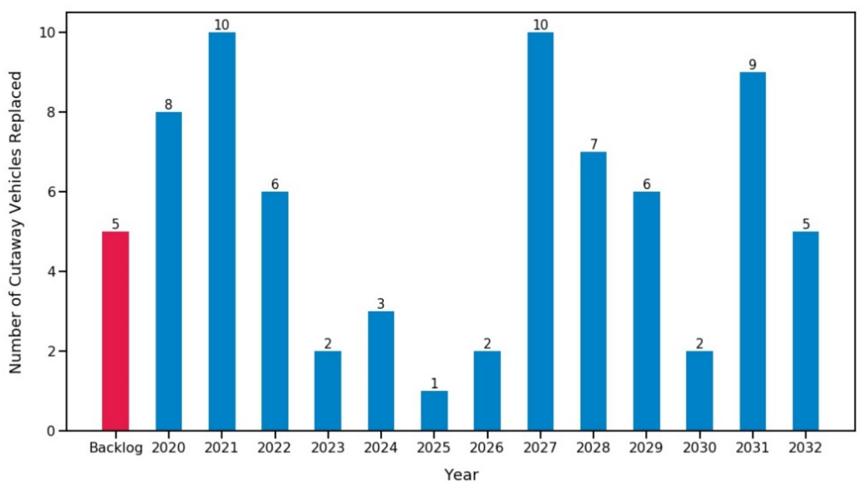
Backlog and Projected Replacement Costs for Revenue Vehicles



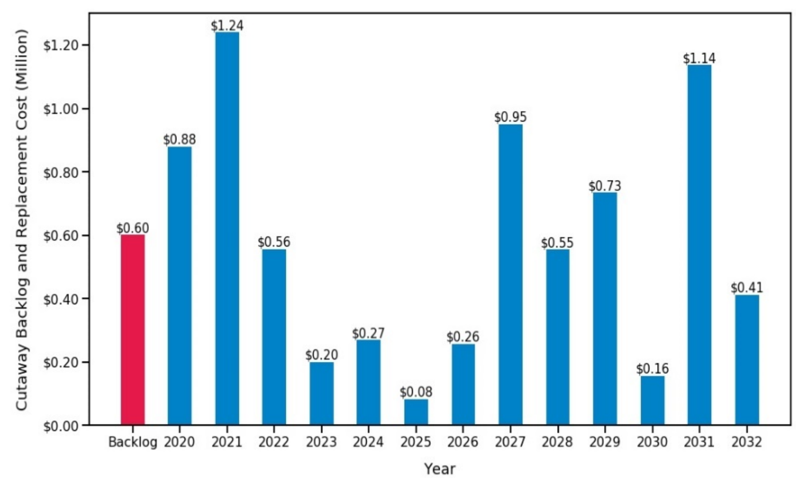
Backlog and Projected Replacement of Buses



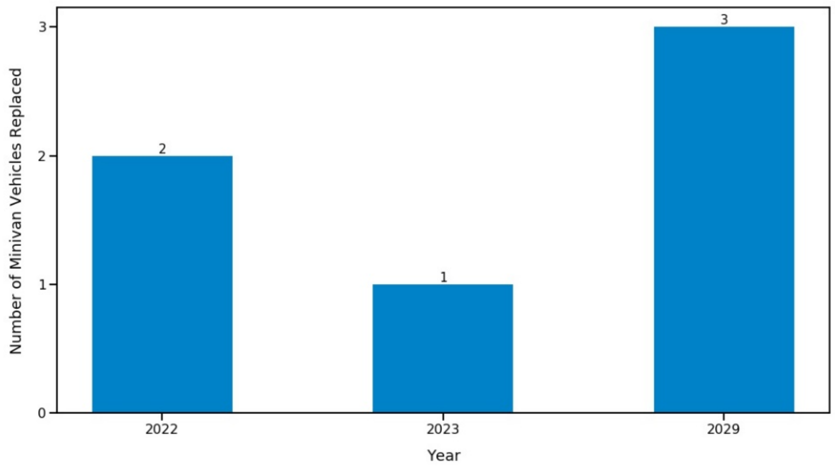
Backlog and Projected Replacement Cost for Buses



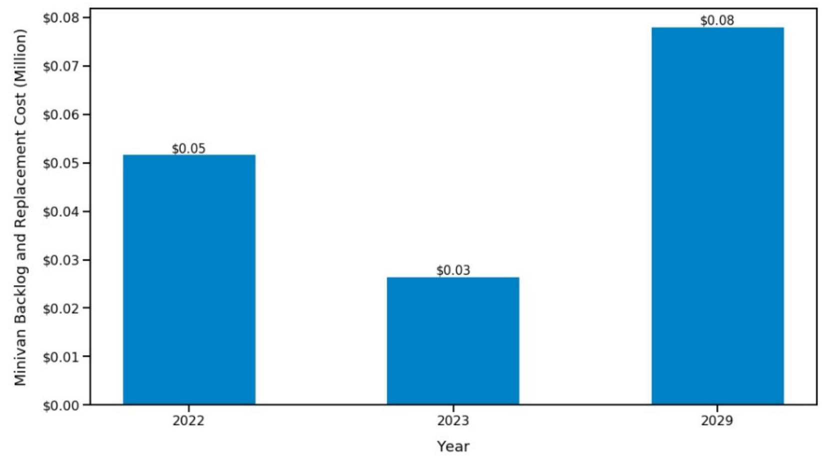
Backlog and Projected Replacement of Cutaways



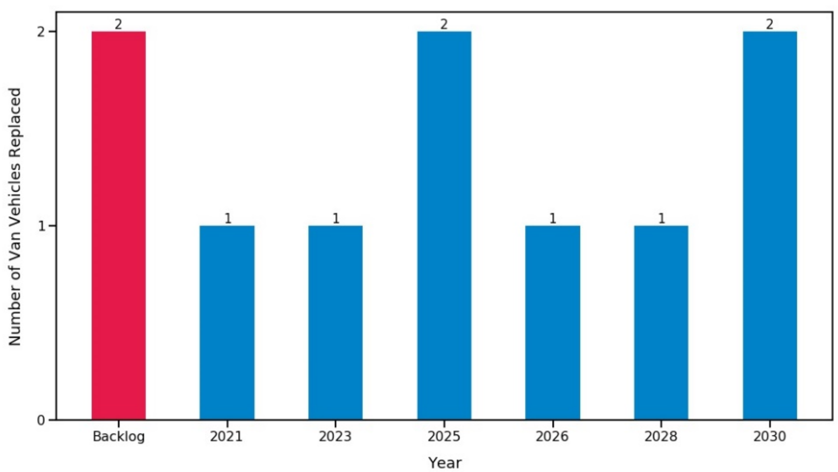
Backlog and Projected Replacement Cost for Cutaways



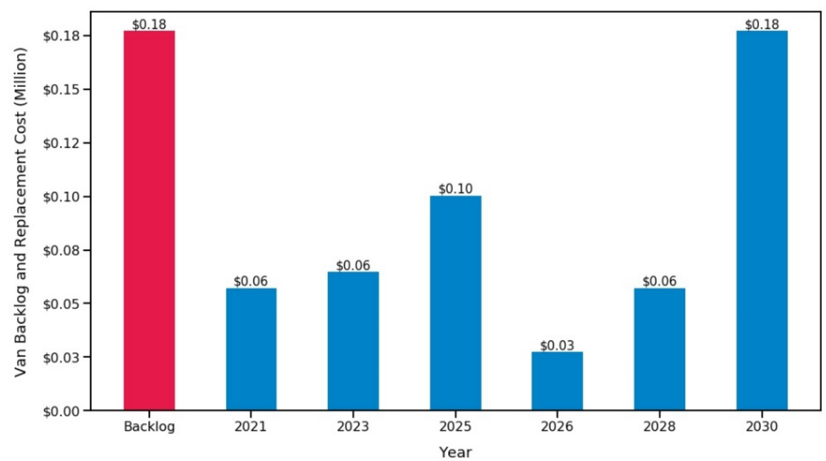
Backlog and Projected Replacement of Minivans



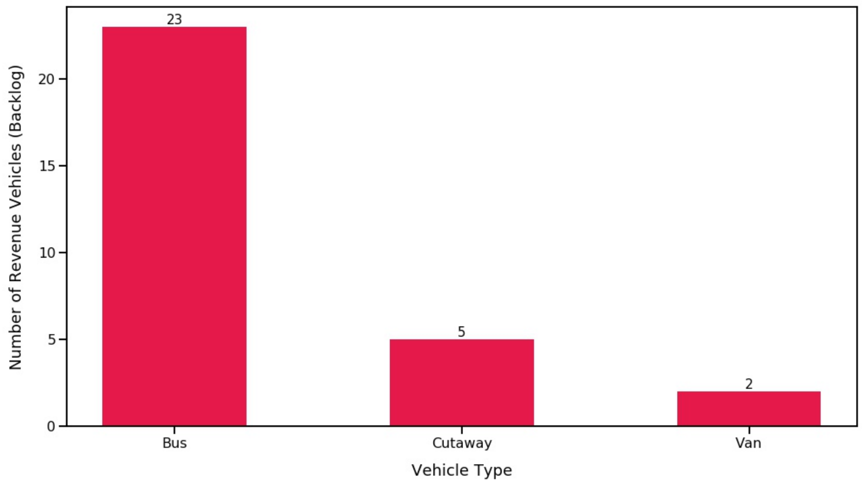
Backlog and Projected Replacement Cost for Minivans



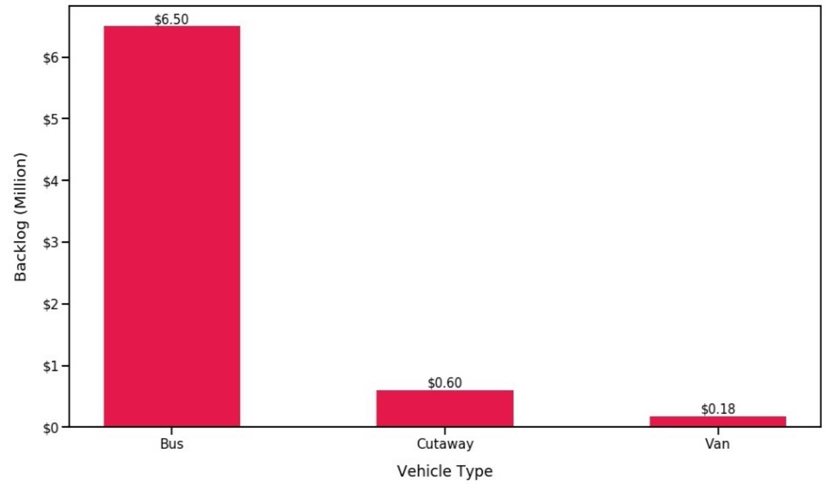
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

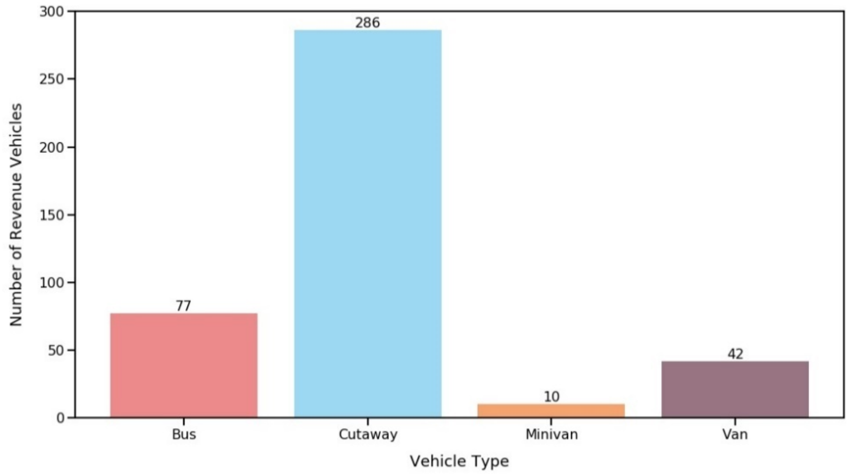


Backlog of the Revenue Vehicles by Vehicle Type

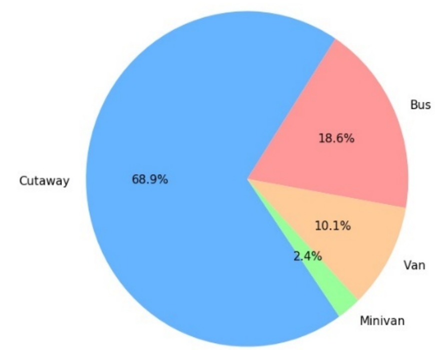


Funds Needed for Backlog by Vehicle Type

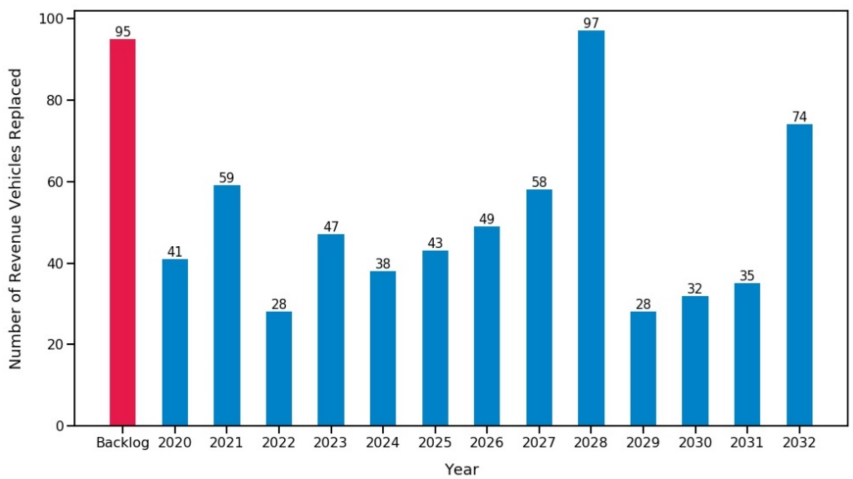
30 NJ – Revenue Vehicles Information for New Jersey's Small Urban and Rural Transit Systems (NTD 2017)



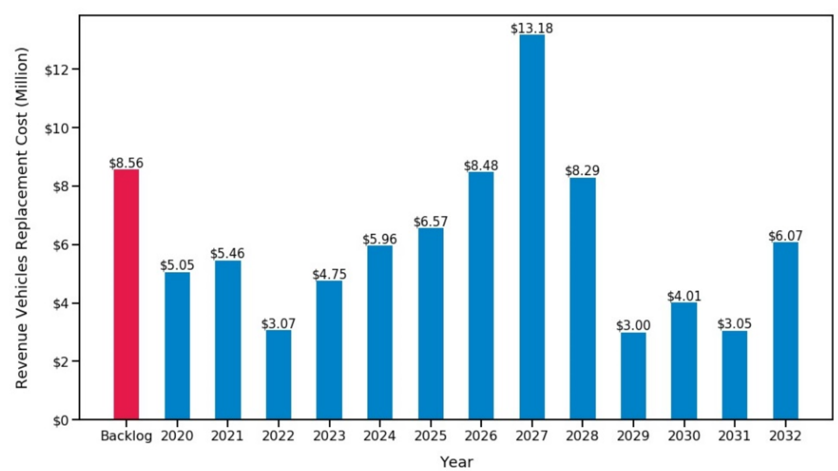
Number of Revenue Vehicles by Vehicle Type



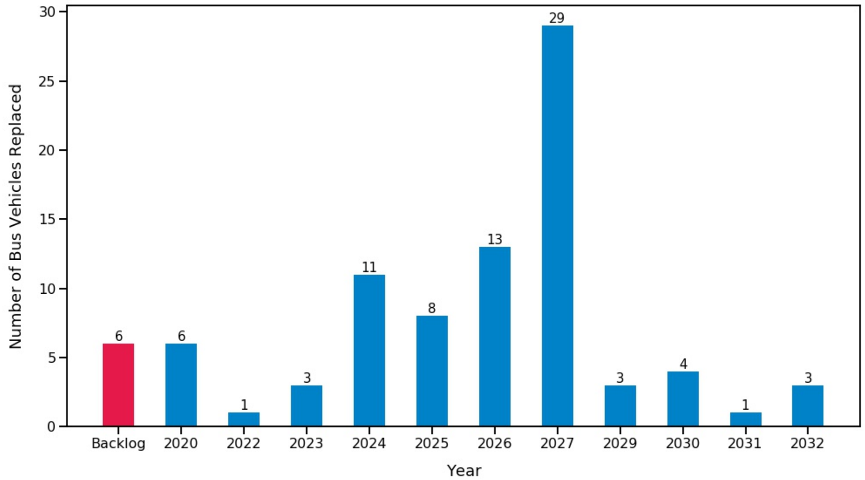
Percentage of Revenue Vehicles



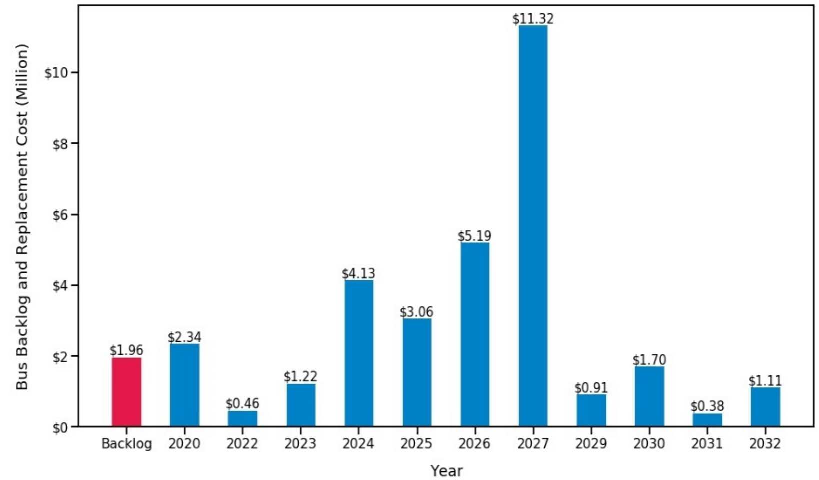
Backlog and Projected Replacement of Revenue Vehicles



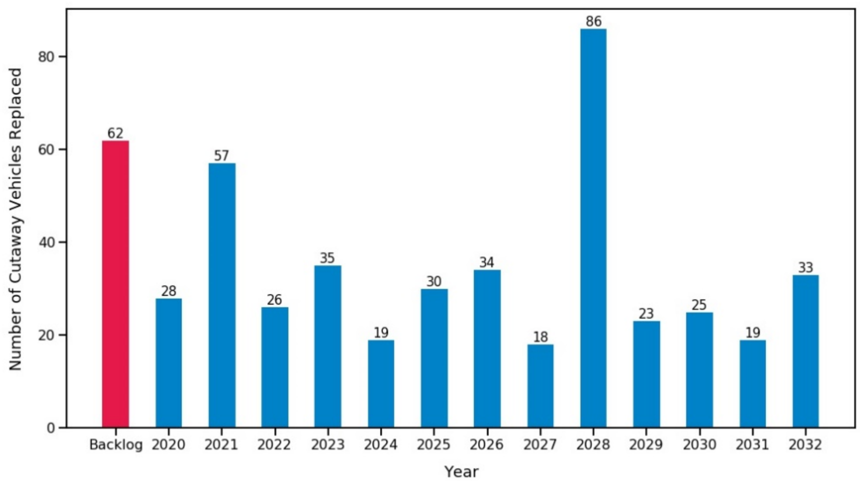
Backlog and Projected Replacement Costs for Revenue Vehicles



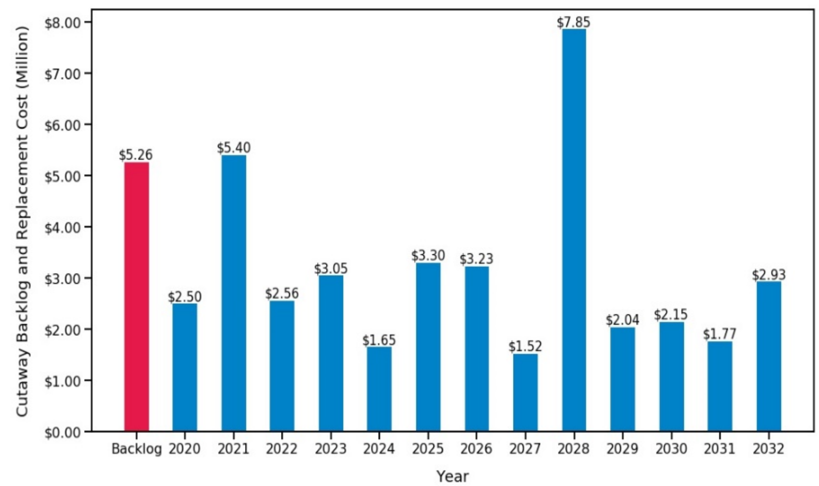
Backlog and Projected Replacement of Buses



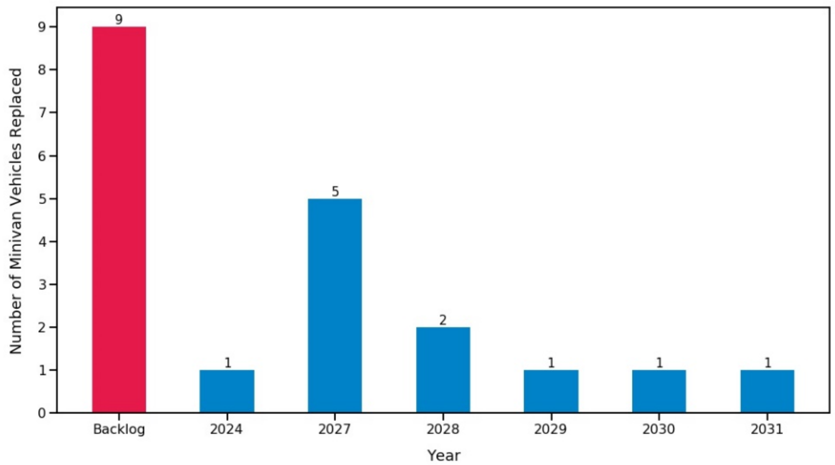
Backlog and Projected Replacement Cost for Buses

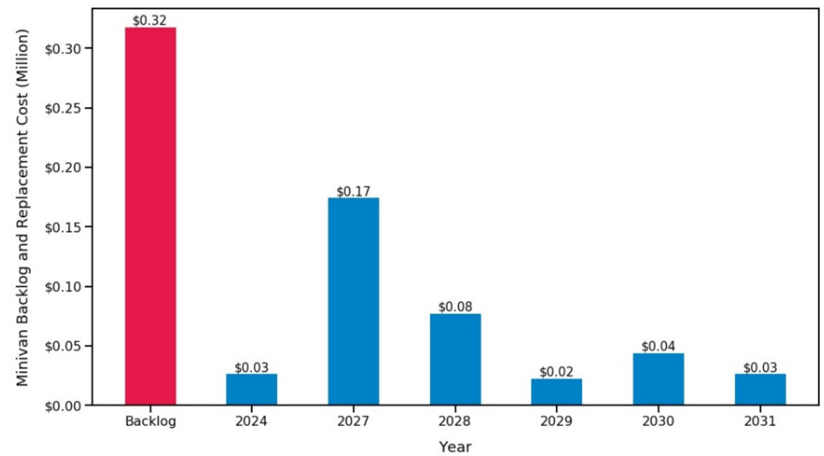


Backlog and Projected Replacement of Cutaways



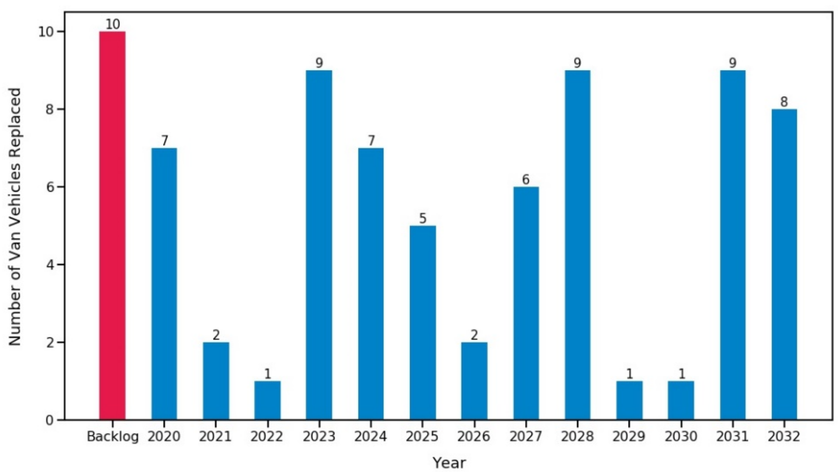
Backlog and Projected Replacement Cost for Cutaways

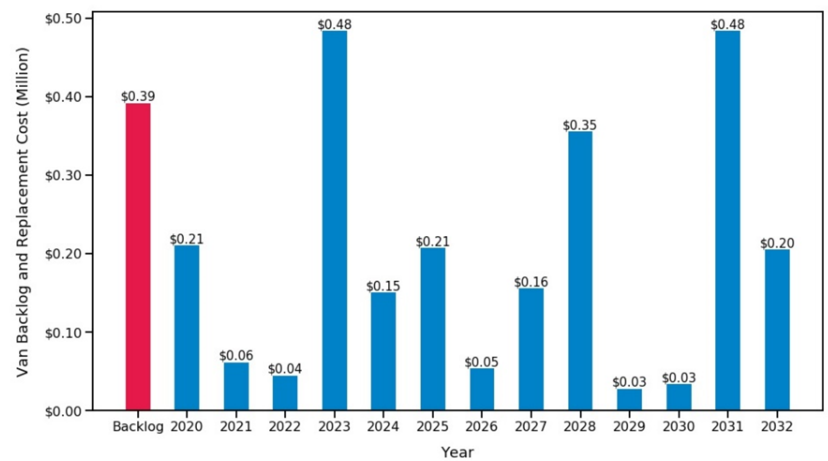




Backlog and Projected Replacement of Minivans

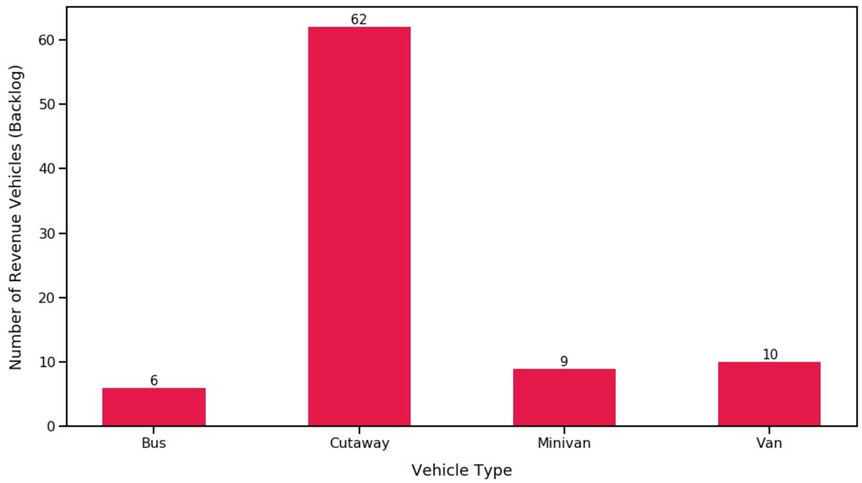
Backlog and Projected Replacement Cost for Minivans



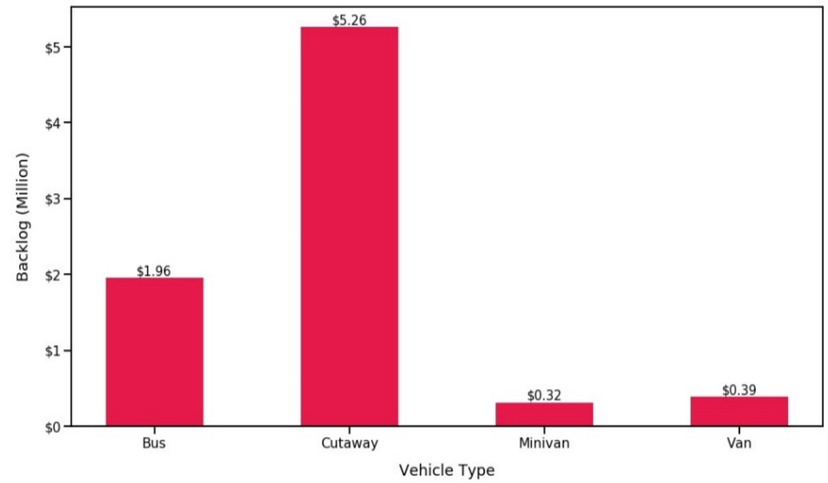


Backlog and Projected Replacement of Vans

Backlog and Projected Replacement Cost for Vans

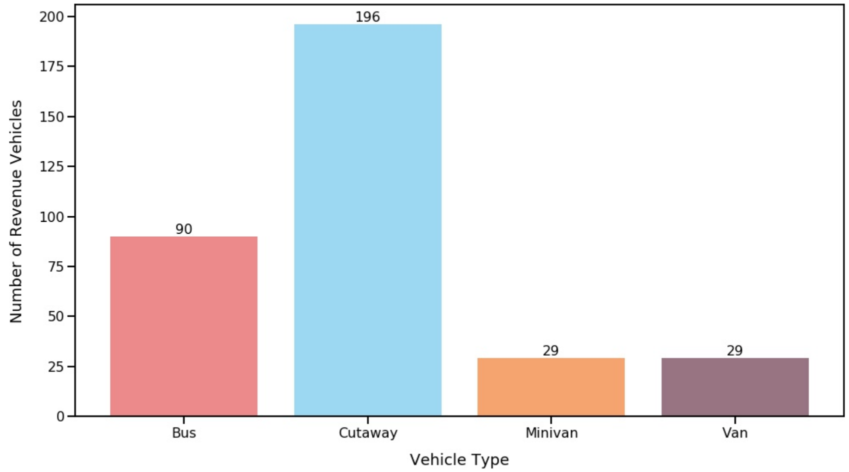


Backlog of the Revenue Vehicles by Vehicle Type

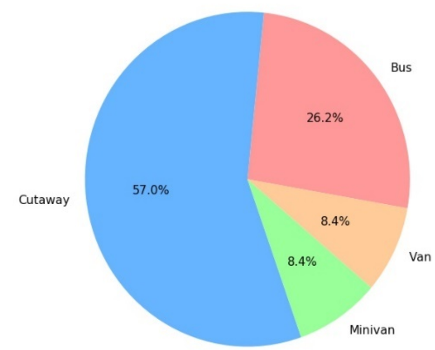


Funds Needed for Backlog by Vehicle Type

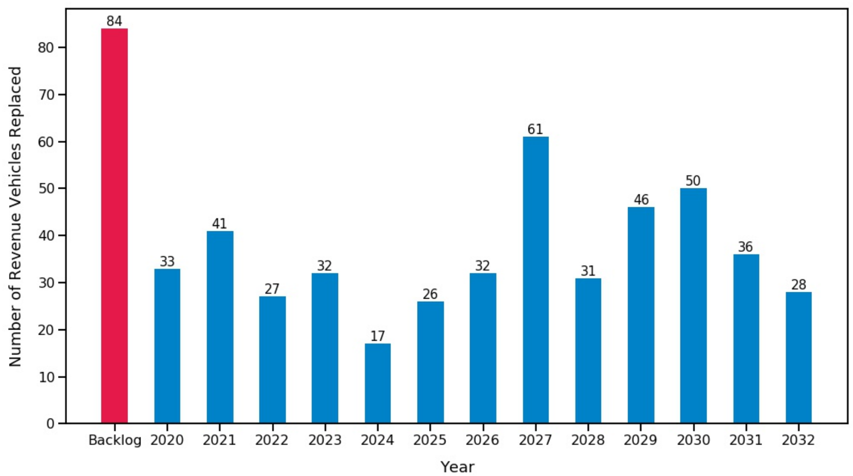
31 NM – Revenue Vehicles Information for New Mexico's Small Urban and Rural Transit Systems (NTD 2017)



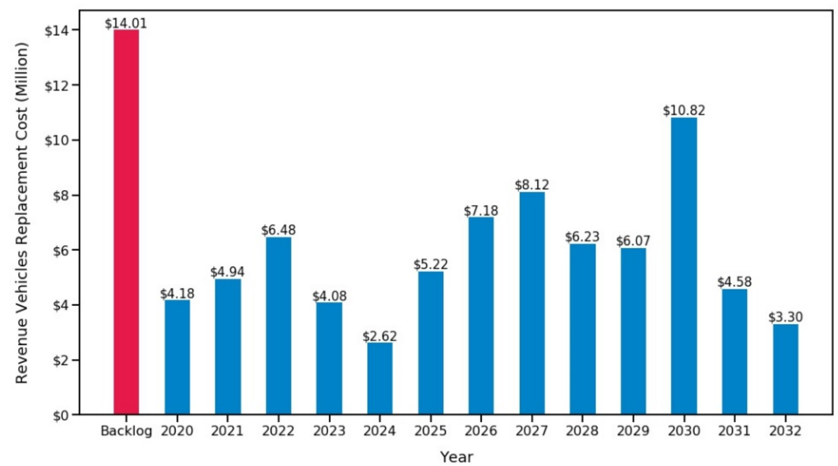
Number of Revenue Vehicles by Vehicle Type



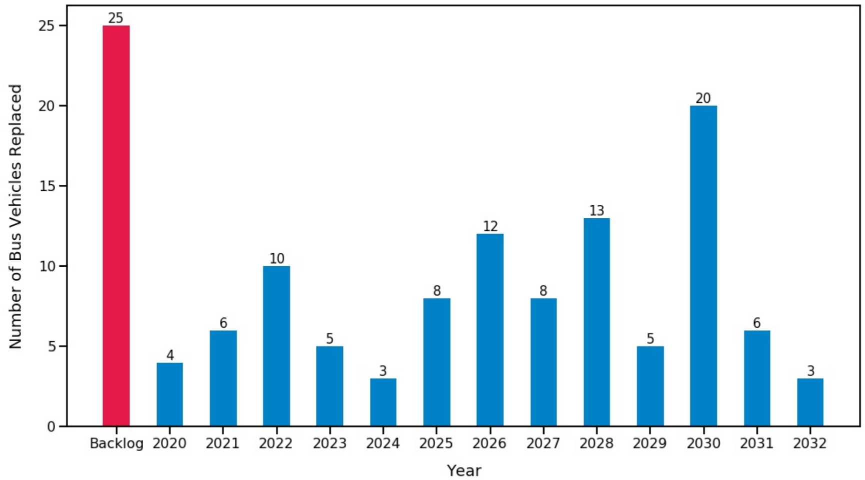
Percentage of Revenue Vehicles



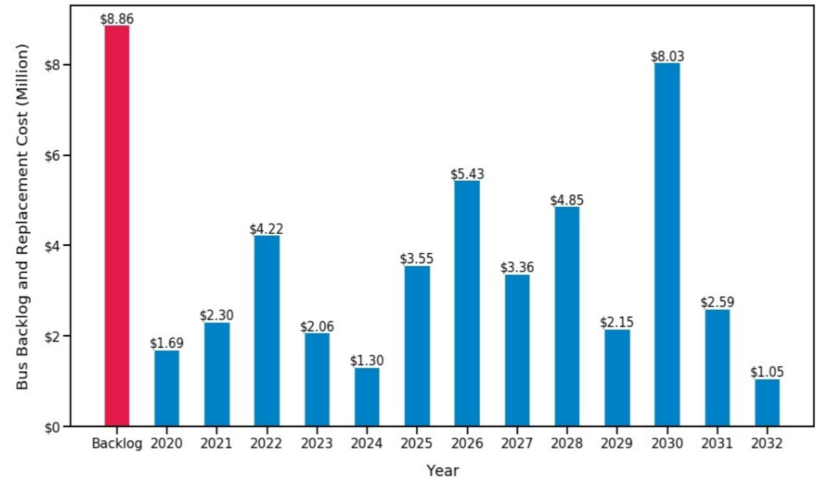
Backlog and Projected Replacement of Revenue Vehicles



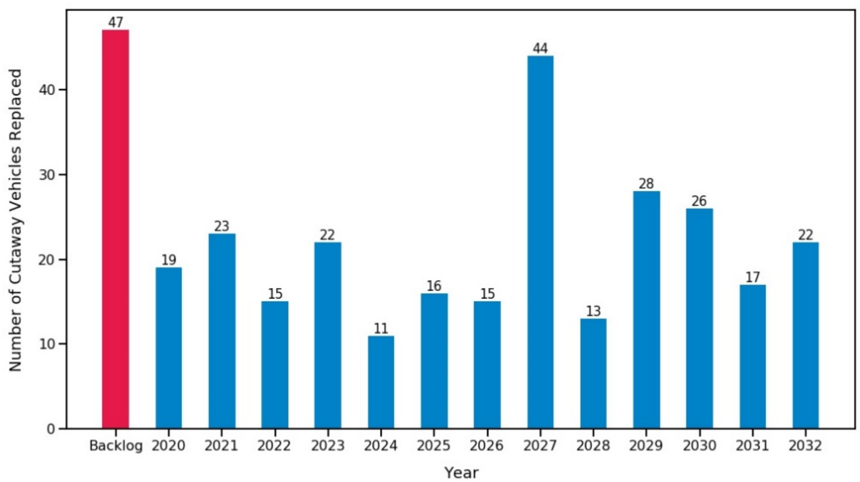
Backlog and Projected Replacement Costs for Revenue Vehicles



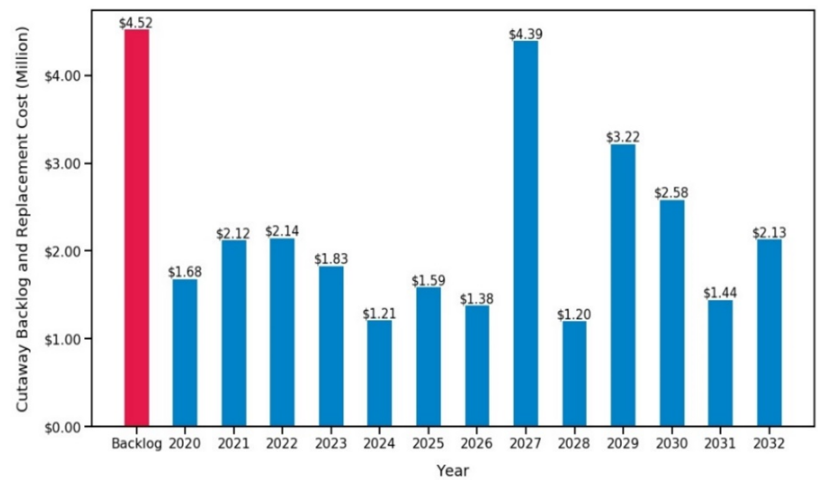
Backlog and Projected Replacement of Buses



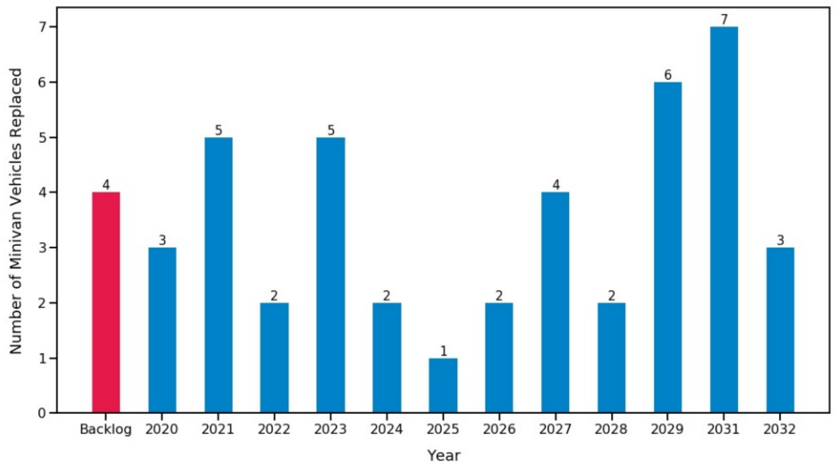
Backlog and Projected Replacement Cost for Buses



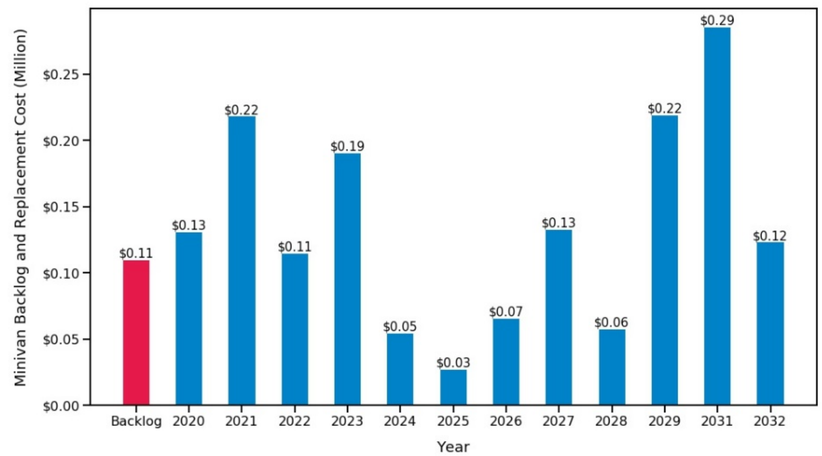
Backlog and Projected Replacement of Cutaways



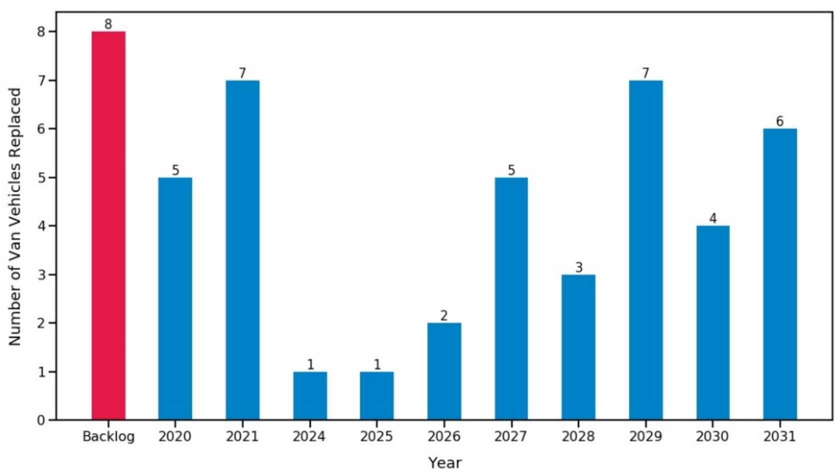
Backlog and Projected Replacement Cost for Cutaways



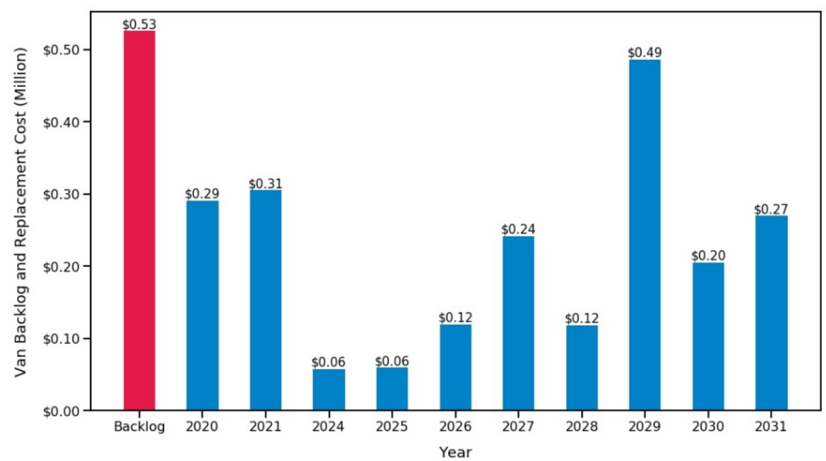
Backlog and Projected Replacement of Minivans



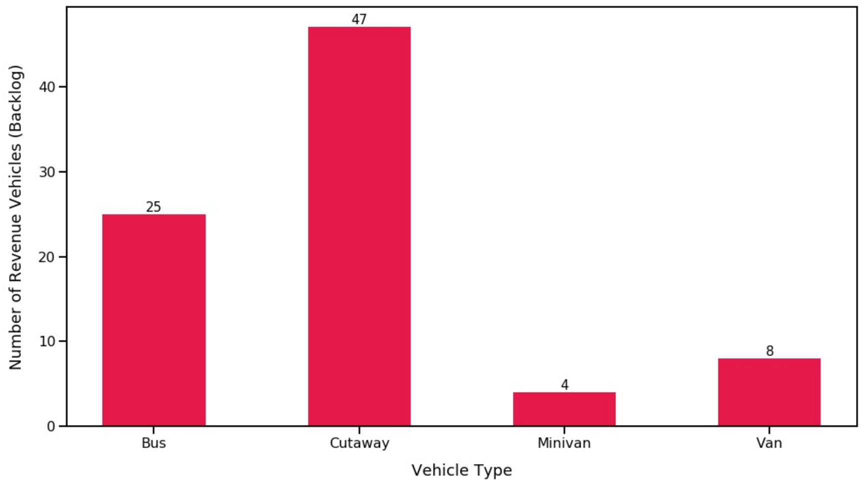
Backlog and Projected Replacement Cost for Minivans



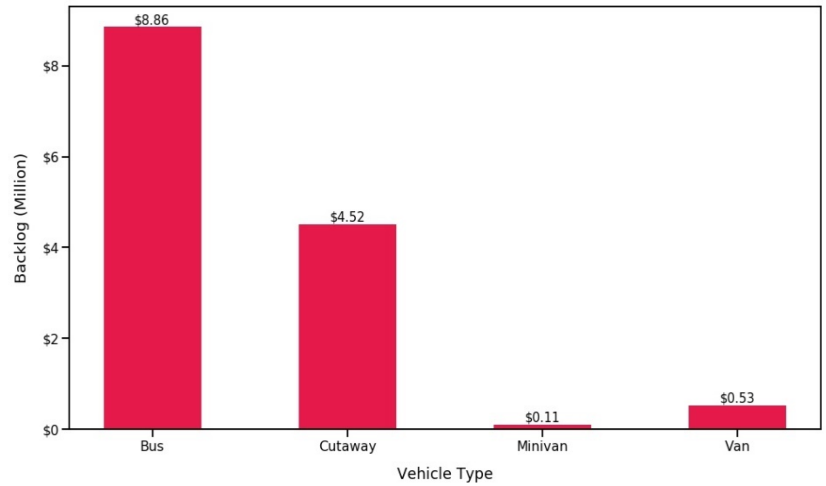
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

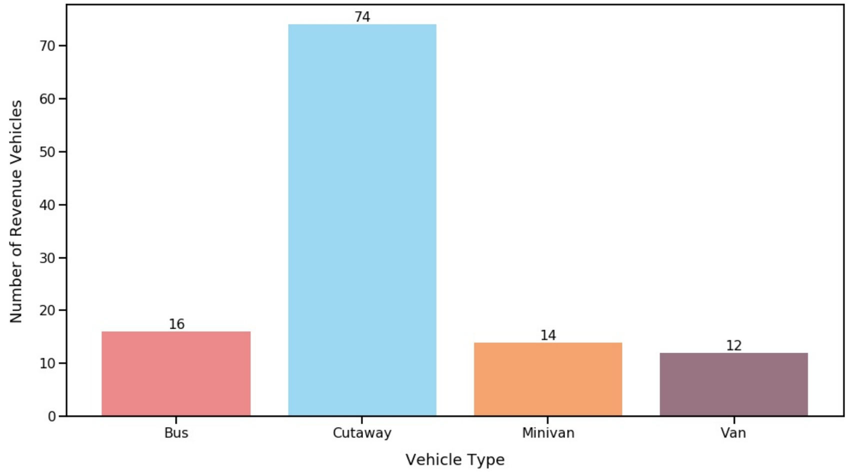


Backlog of the Revenue Vehicles by Vehicle Type

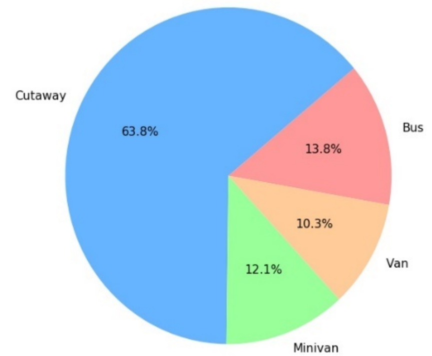


Funds Needed for Backlog by Vehicle Type

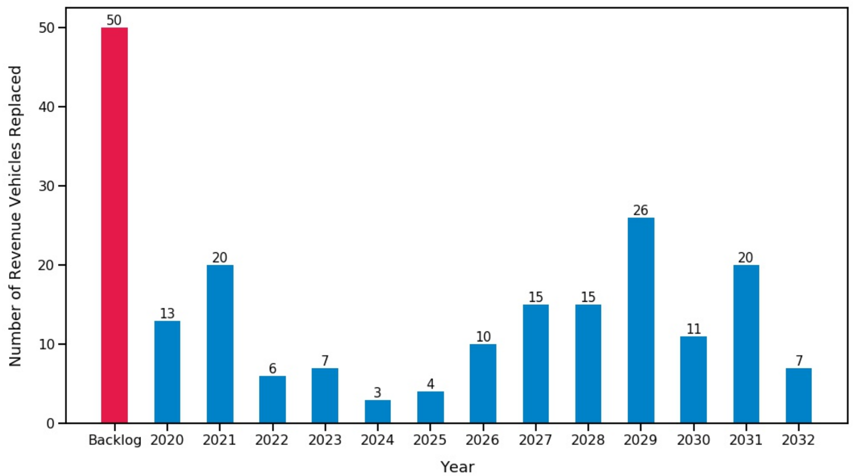
32 NV – Revenue Vehicles Information for Nevada's Small Urban and Rural Transit Systems (NTD 2017)



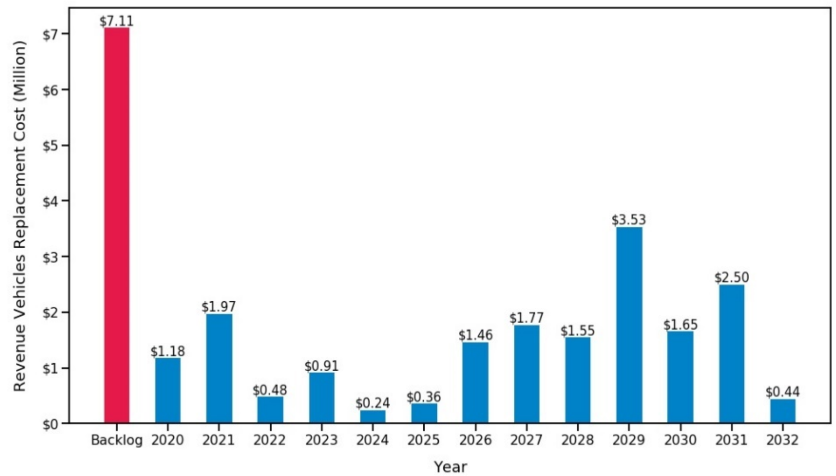
Number of Revenue Vehicles by Vehicle Type



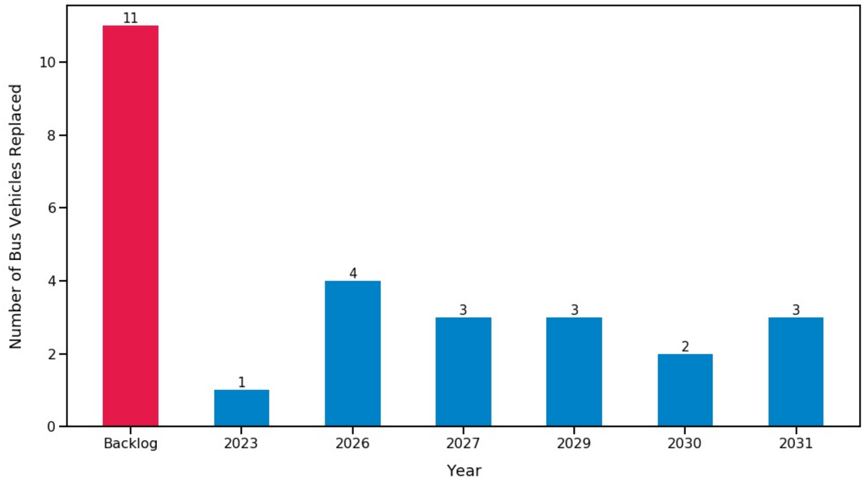
Percentage of Revenue Vehicles



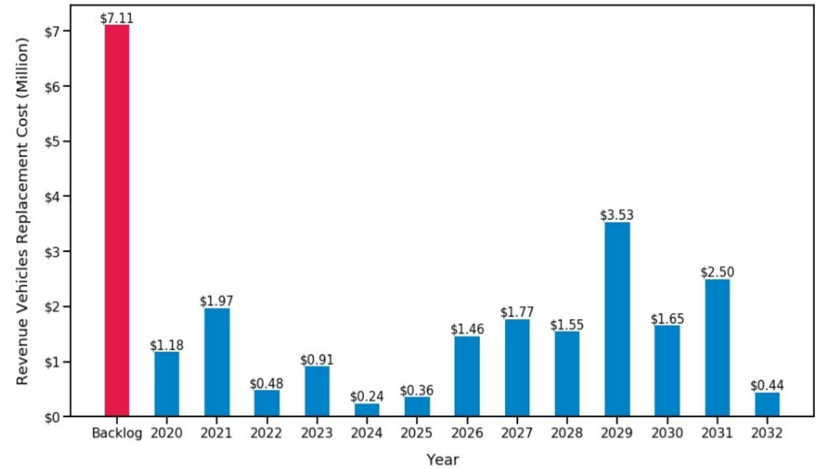
Backlog and Projected Replacement of Revenue Vehicles



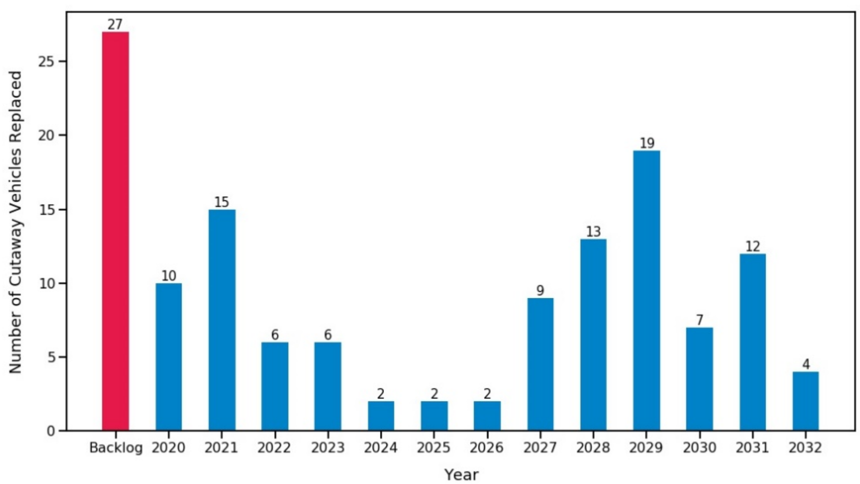
Backlog and Projected Replacement Costs for Revenue Vehicles



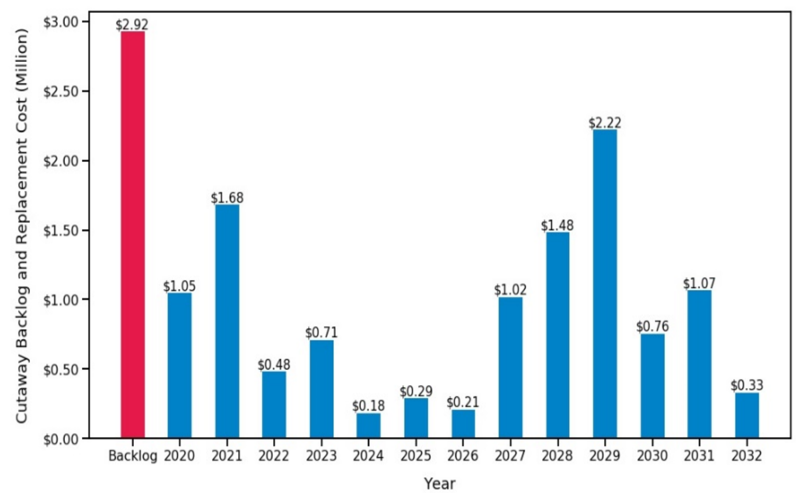
Backlog and Projected Replacement of Buses



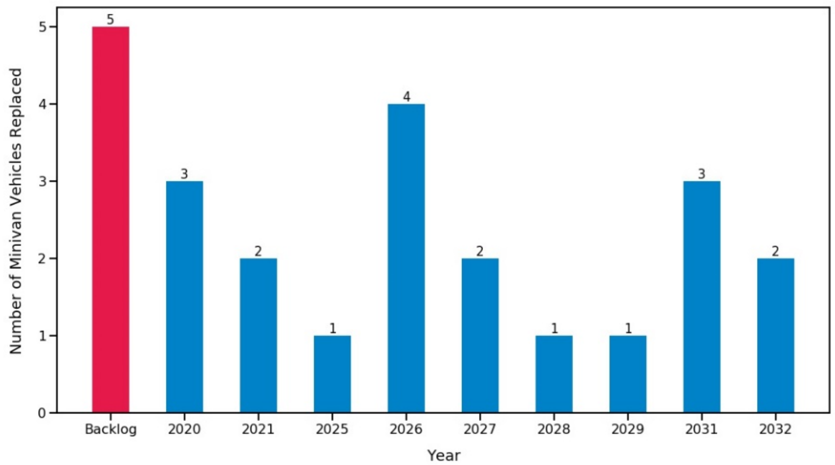
Backlog and Projected Replacement Cost for Buses



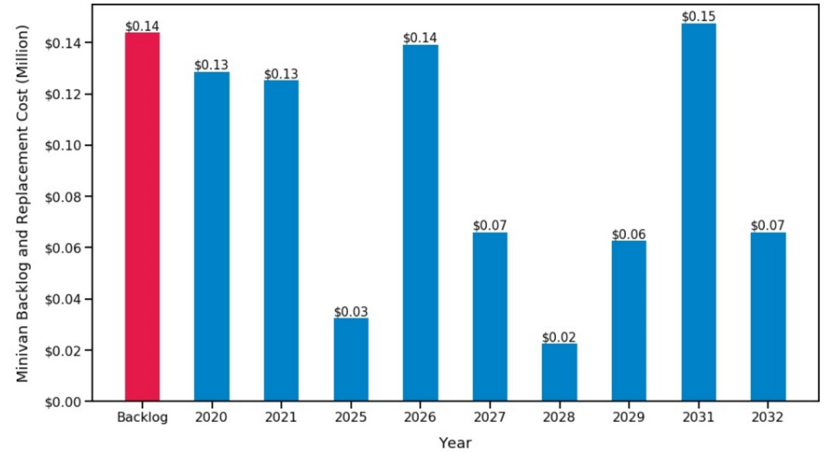
Backlog and Projected Replacement of Cutaways



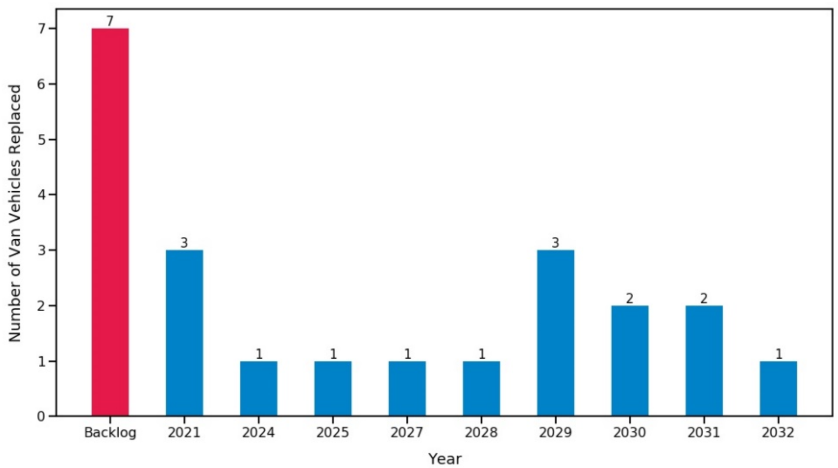
Backlog and Projected Replacement Cost for Cutaways



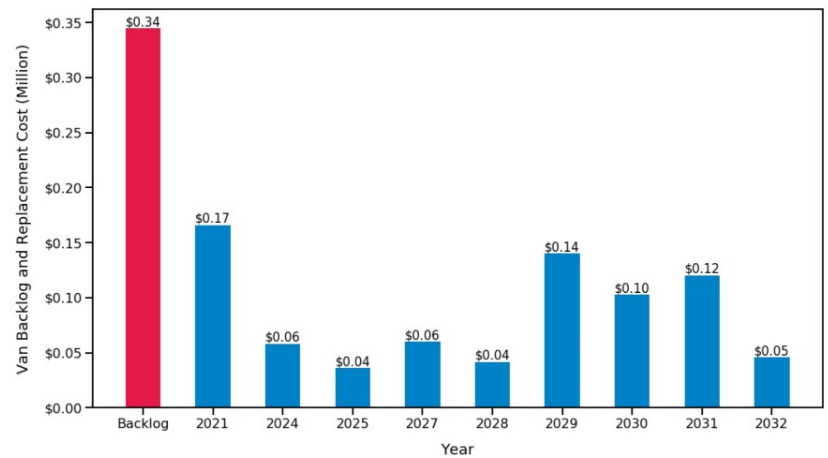
Backlog and Projected Replacement of Minivans



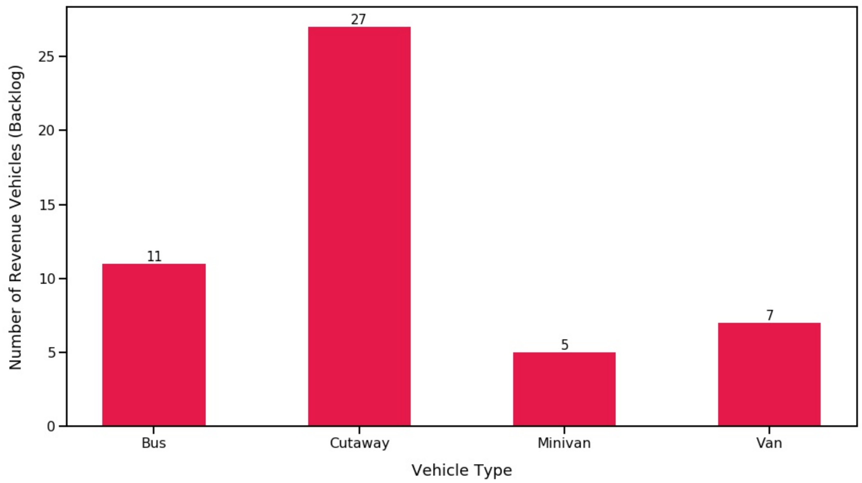
Backlog and Projected Replacement Cost for Minivans



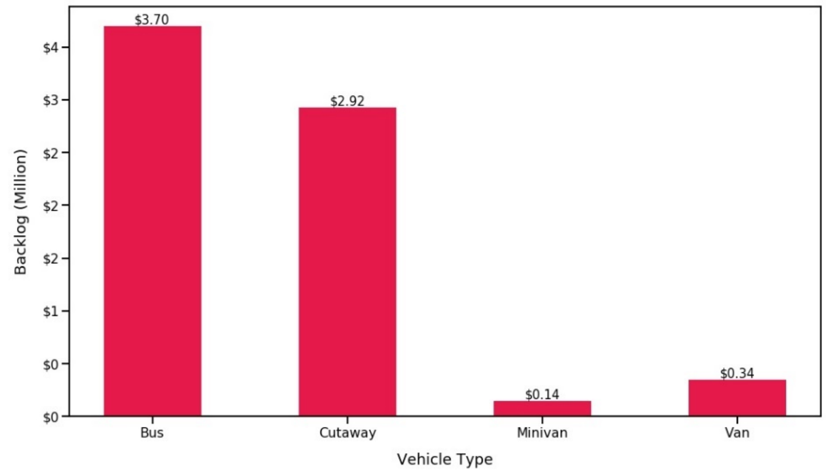
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

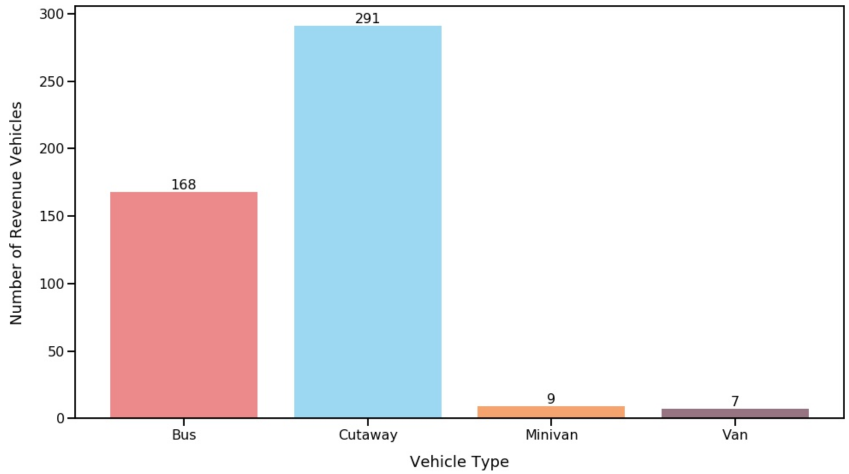


Backlog of the Revenue Vehicles by Vehicle Type

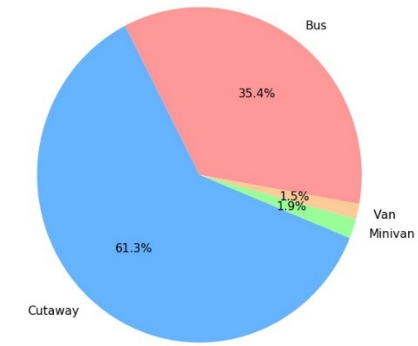


Funds Needed for Backlog by Vehicle Type

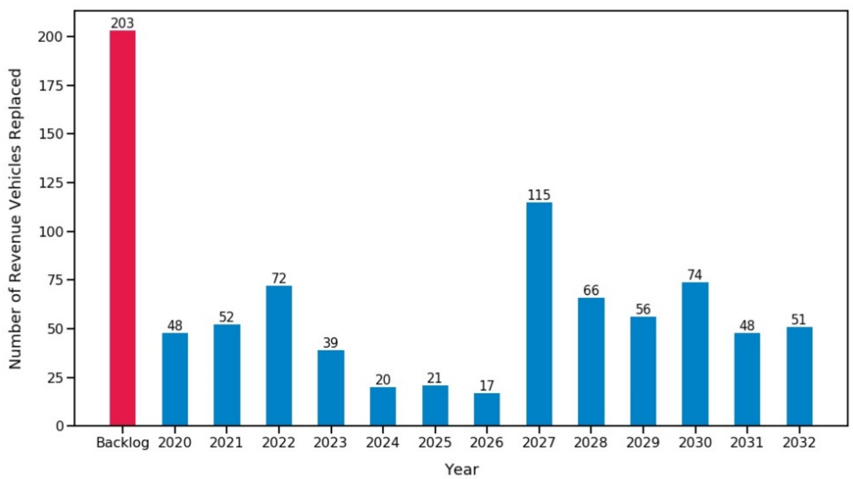
33 NY – Revenue Vehicles Information for New York's Small Urban and Rural Transit Systems (NTD 2017)



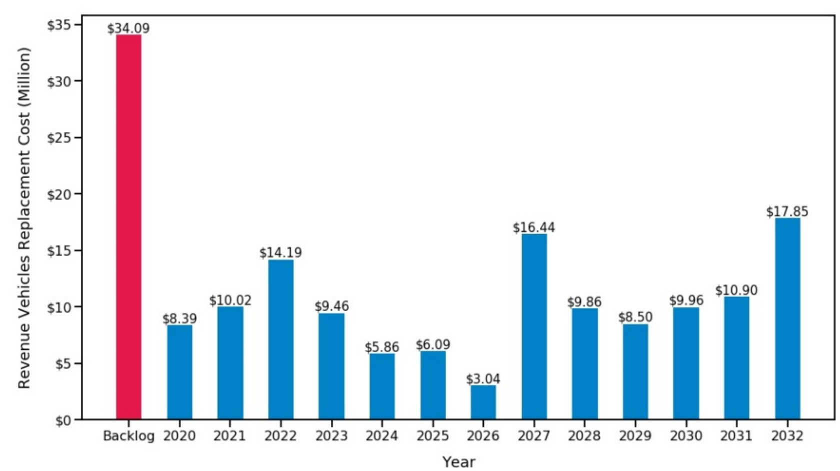
Number of Revenue Vehicles by Vehicle Type



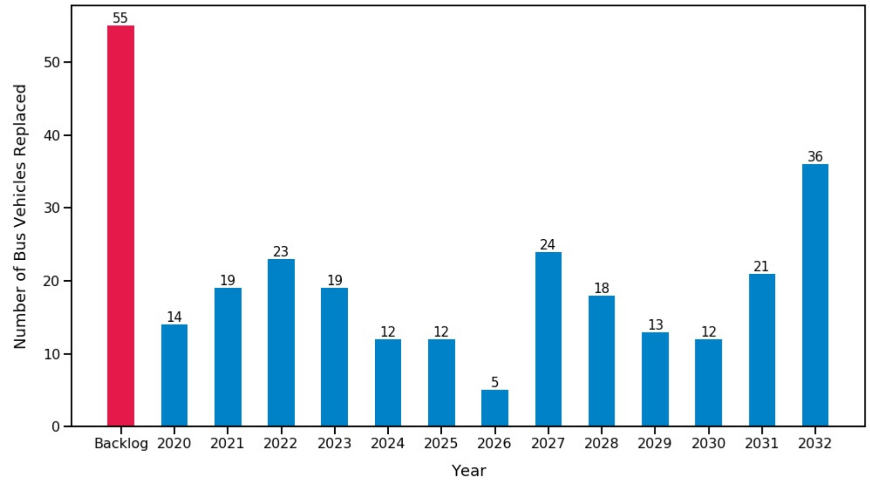
Percentage of Revenue Vehicles



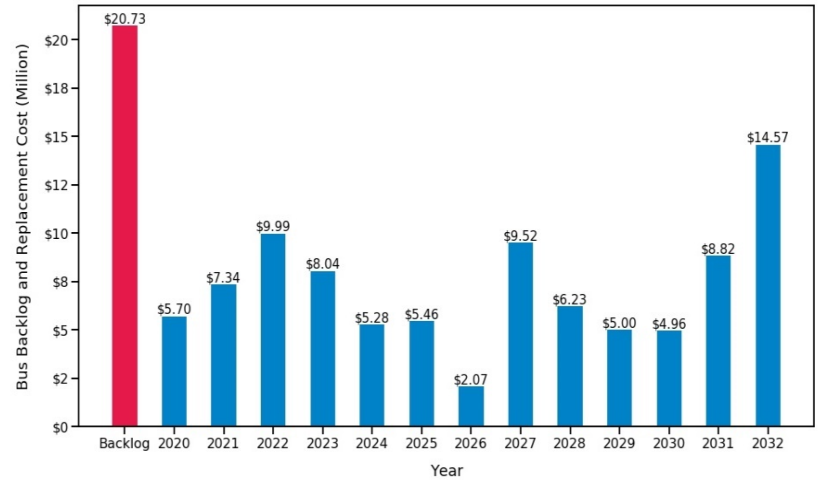
Backlog and Projected Replacement of Revenue Vehicles



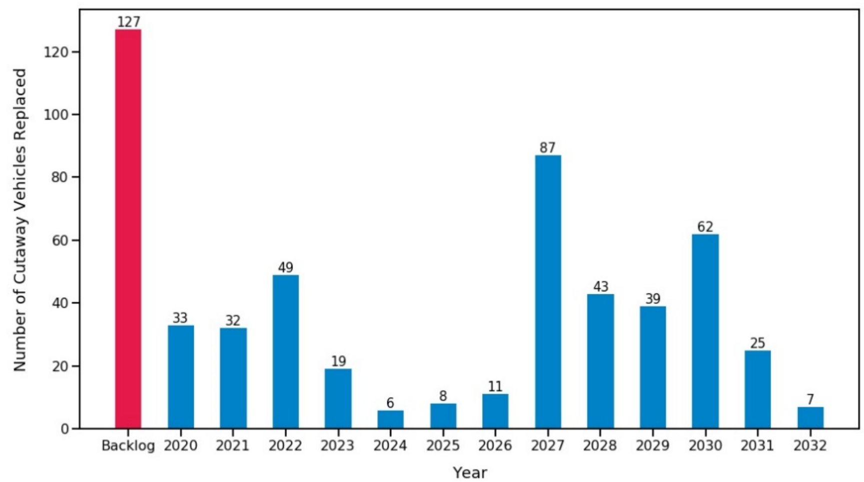
Backlog and Projected Replacement Costs for Revenue Vehicles



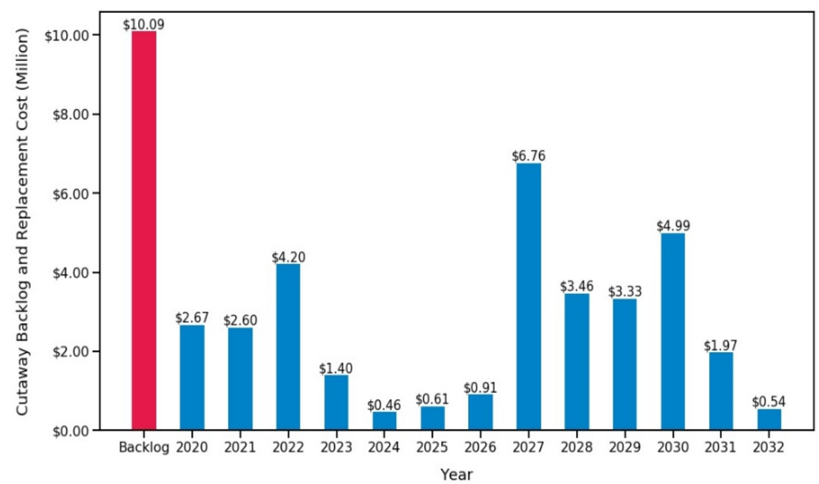
Backlog and Projected Replacement of Buses



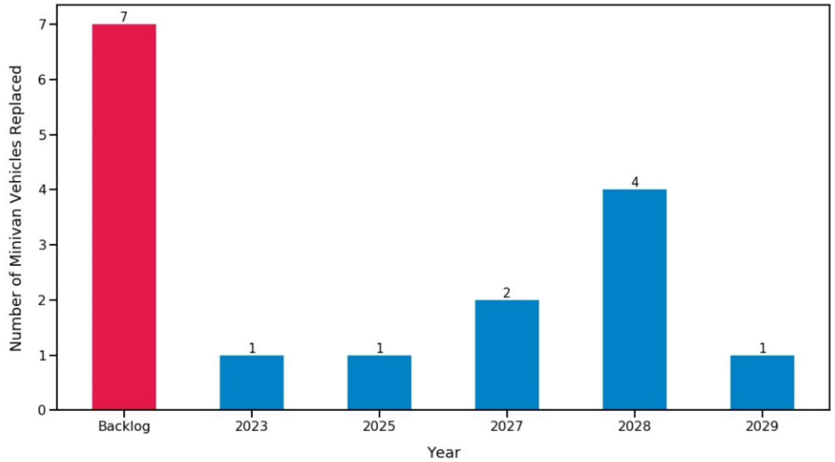
Backlog and Projected Replacement Cost for Buses



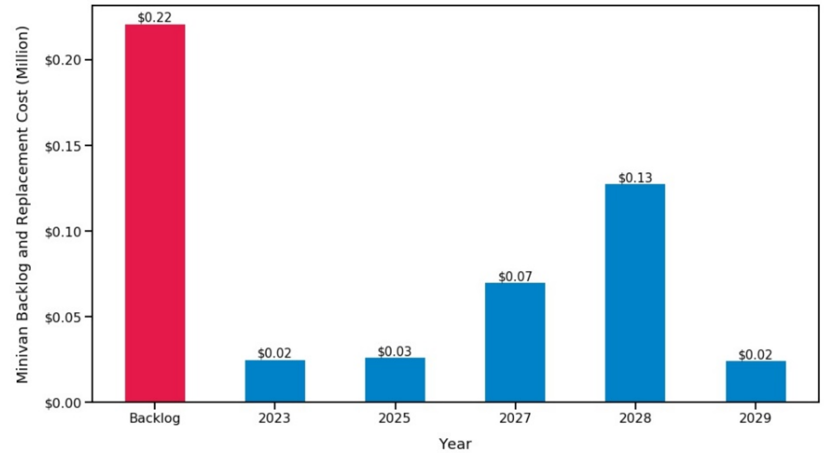
Backlog and Projected Replacement of Cutaways



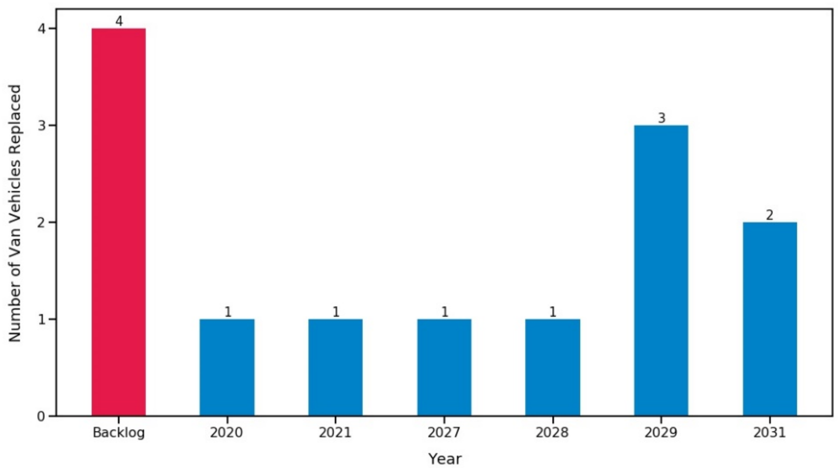
Backlog and Projected Replacement Cost for Cutaways



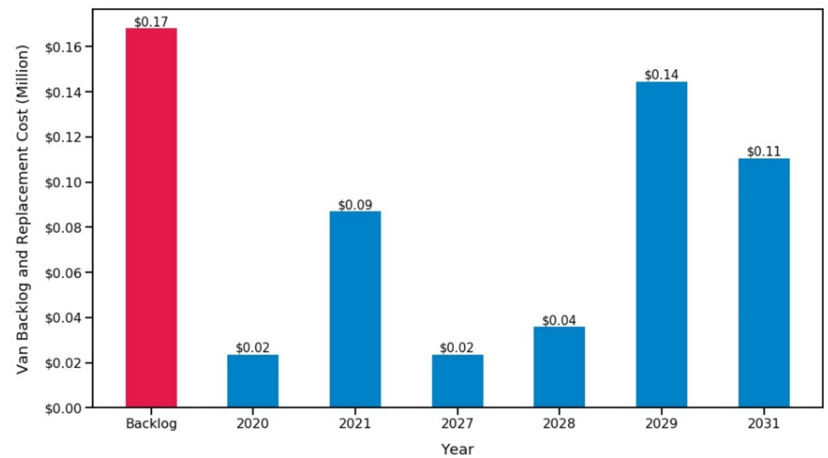
Backlog and Projected Replacement of Minivans



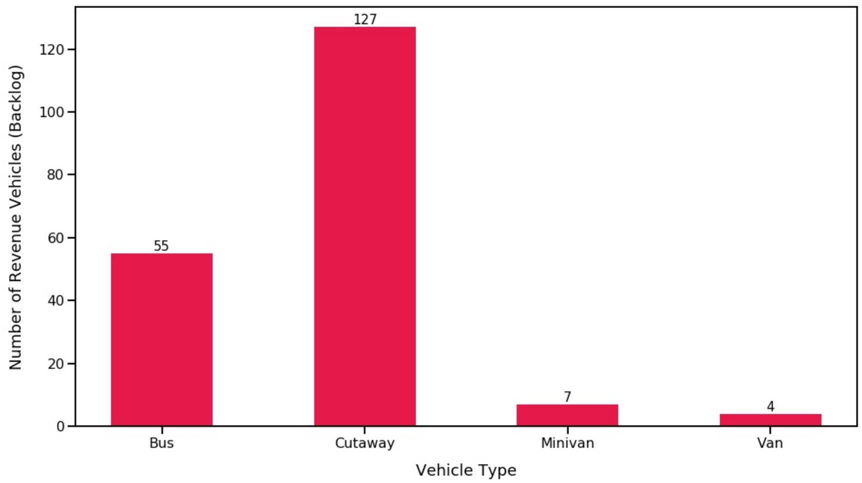
Backlog and Projected Replacement Cost for Minivans



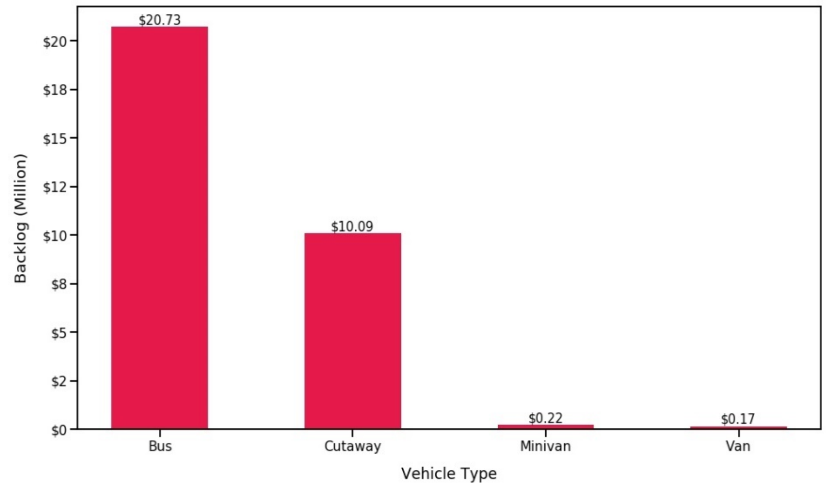
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

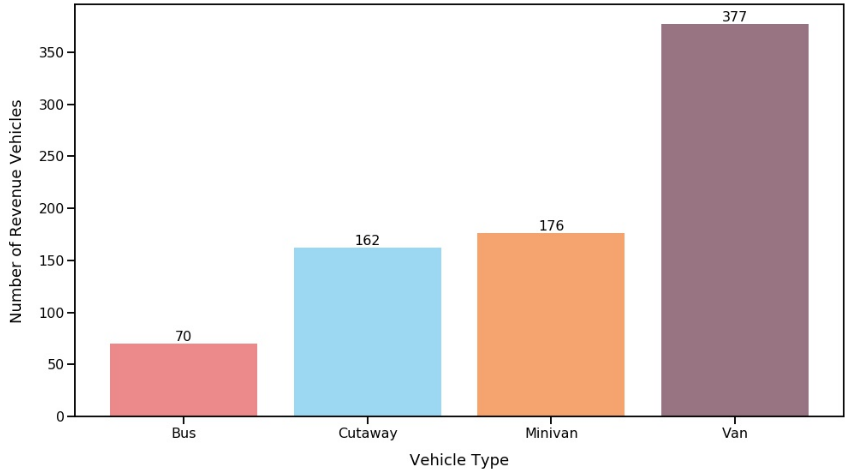


Backlog of the Revenue Vehicles by Vehicle Type

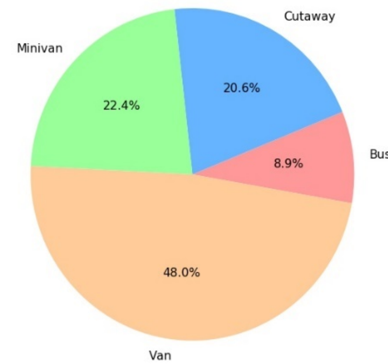


Funds Needed for Backlog by Vehicle Type

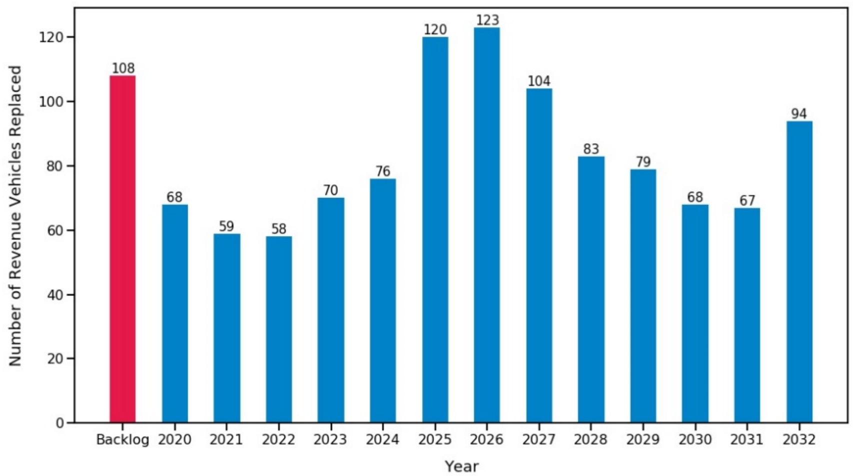
34 OH – Revenue Vehicles Information for Ohio's Small Urban and Rural Transit Systems (NTD 2017)



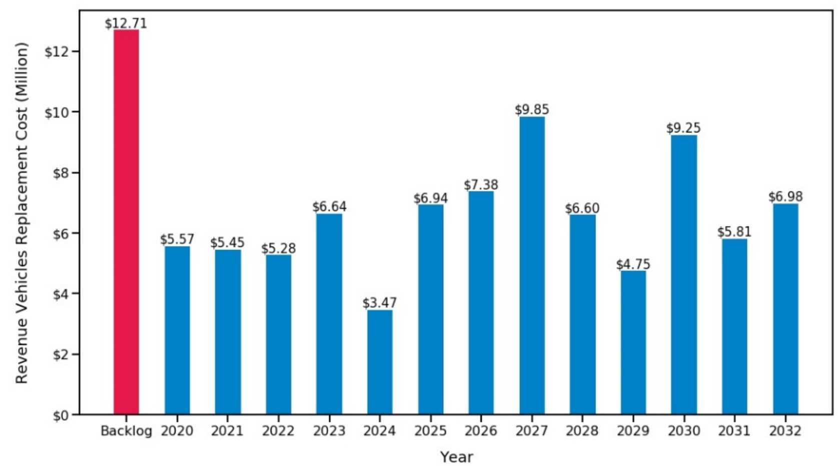
Number of Revenue Vehicles by Vehicle Type



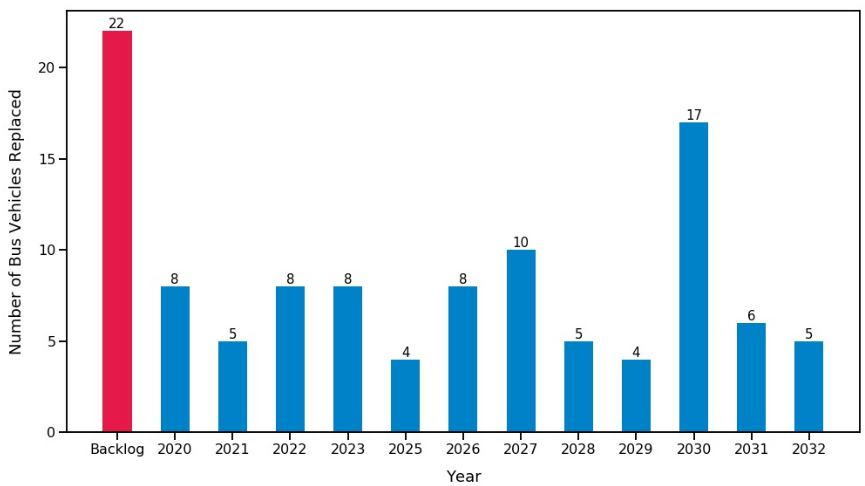
Percentage of Revenue Vehicles



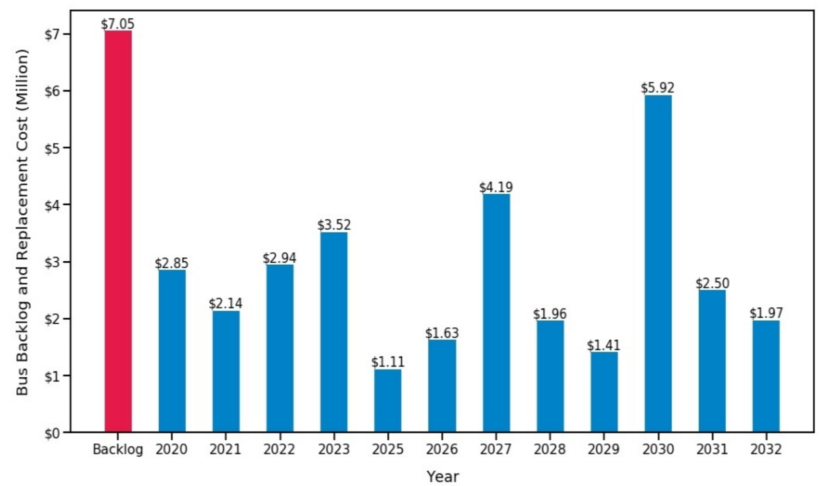
Backlog and Projected Replacement of Revenue Vehicles



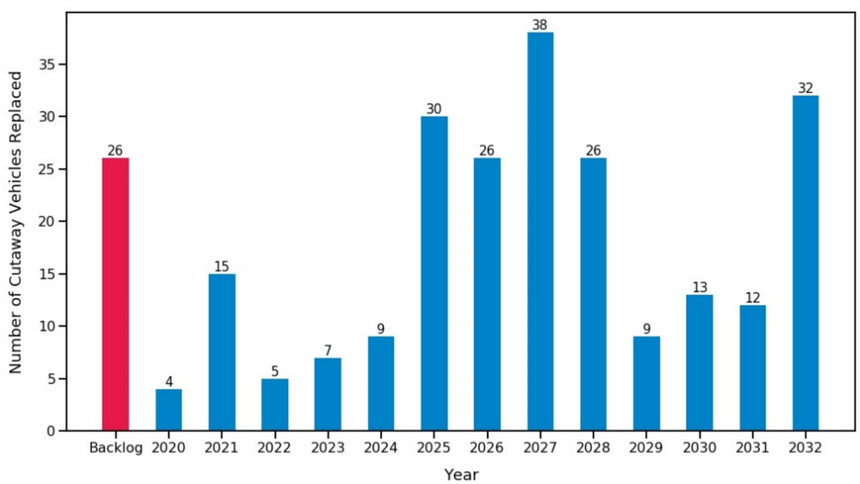
Backlog and Projected Replacement Costs for Revenue Vehicles



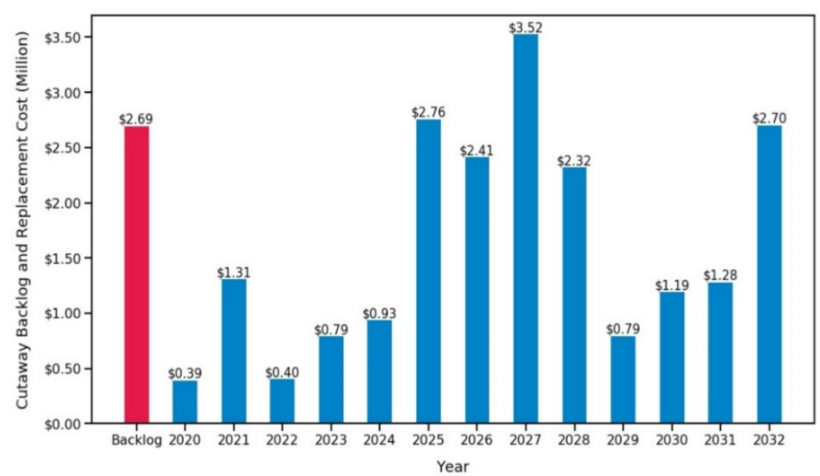
Backlog and Projected Replacement of Buses



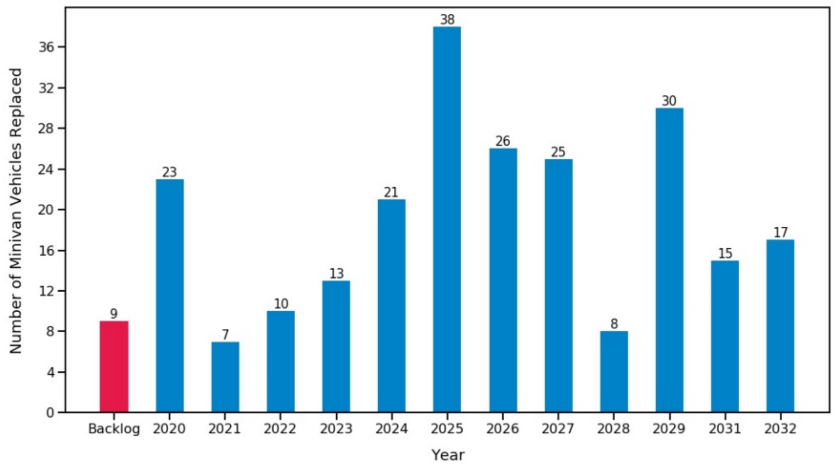
Backlog and Projected Replacement Cost for Buses



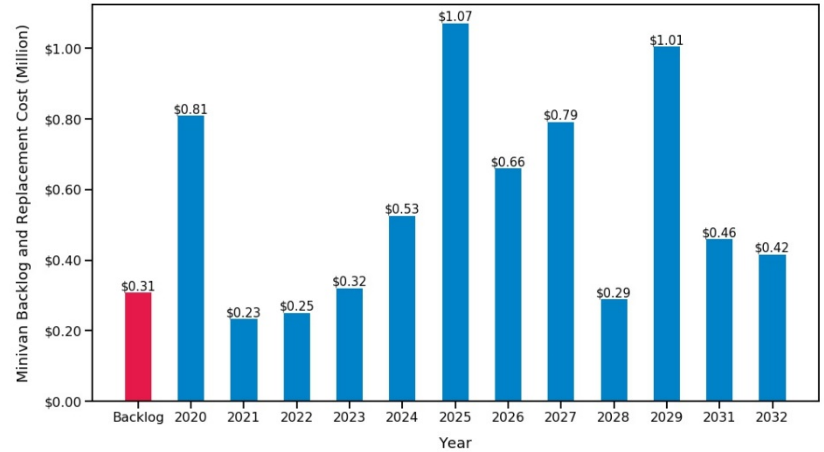
Backlog and Projected Replacement of Cutaways



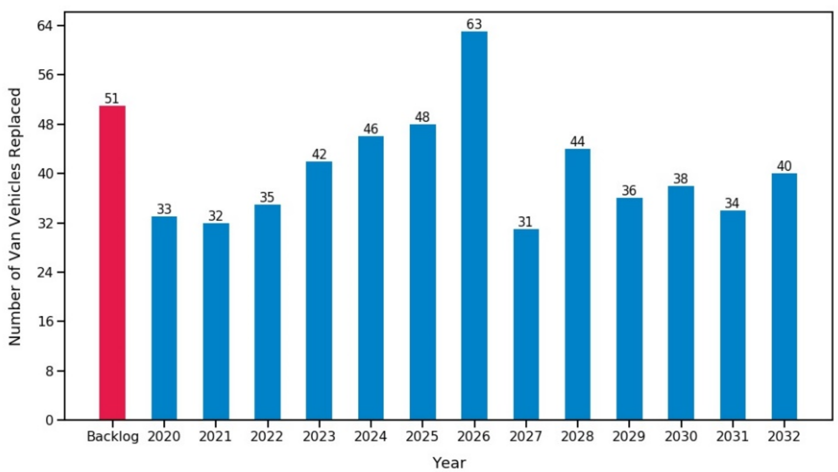
Backlog and Projected Replacement Cost for Cutaways



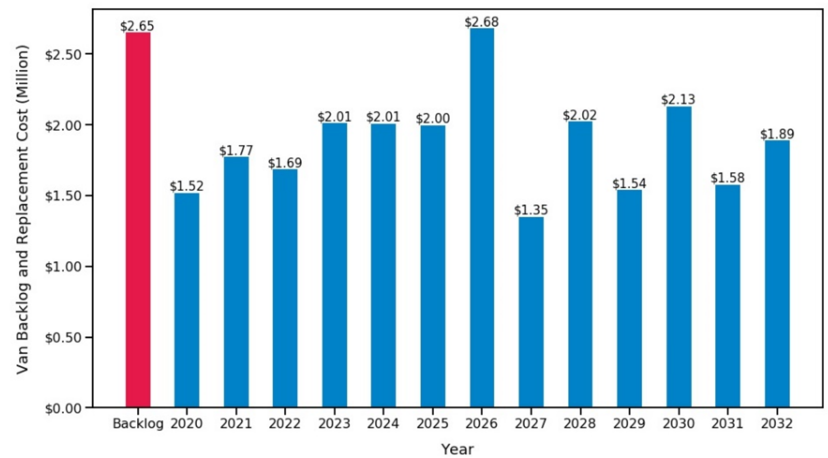
Backlog and Projected Replacement of Minivans



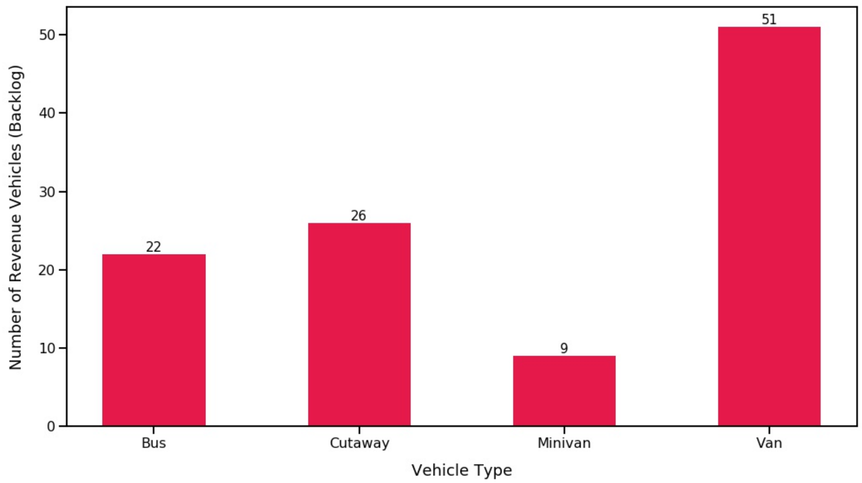
Backlog and Projected Replacement Cost for Minivans



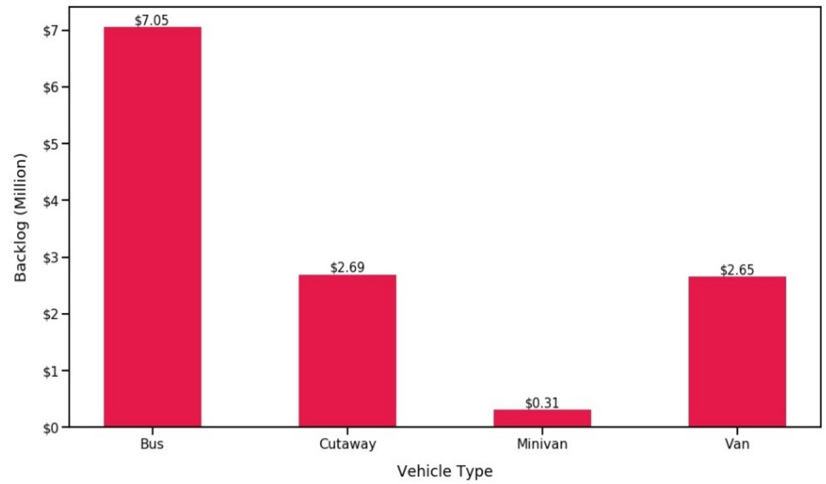
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

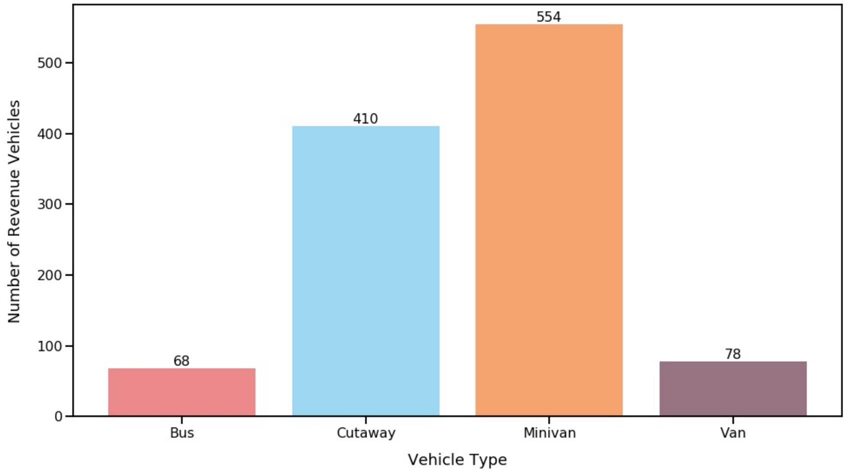


Backlog of the Revenue Vehicles by Vehicle Type

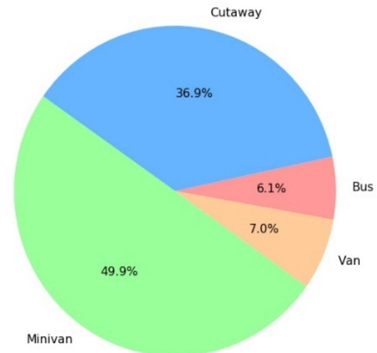


Funds Needed for Backlog by Vehicle Type

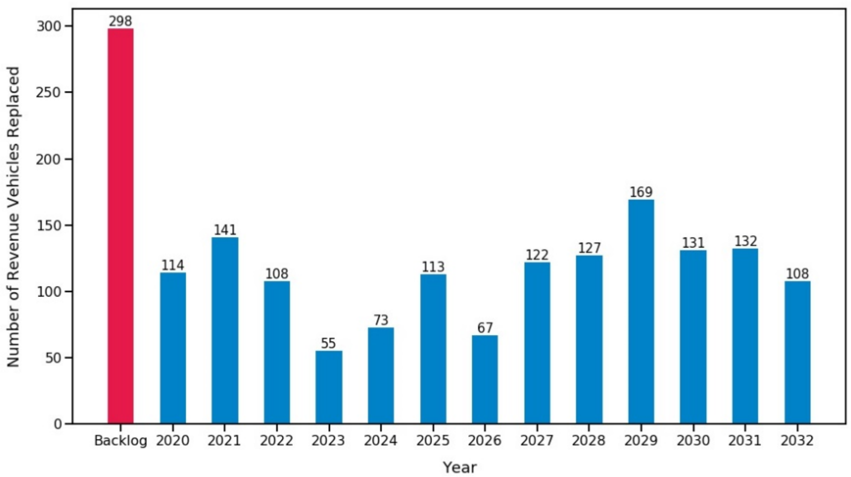
35 OK – Revenue Vehicles Information for Oklahoma's Small Urban and Rural Transit Systems (NTD 2017)



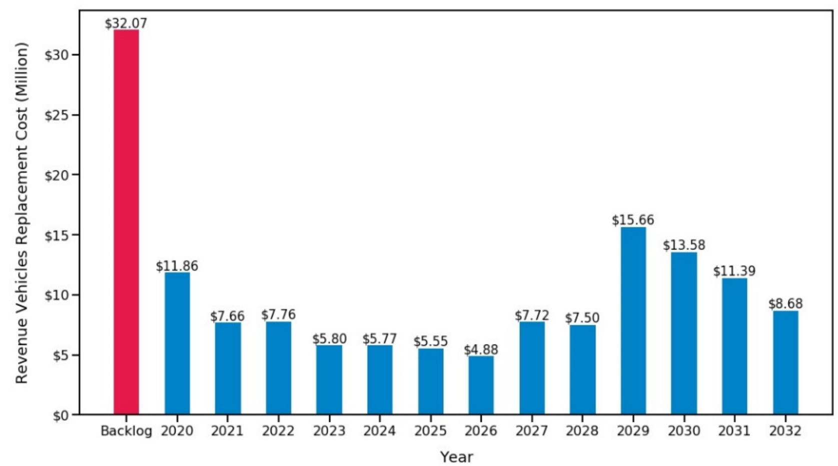
Number of Revenue Vehicles by Vehicle Type



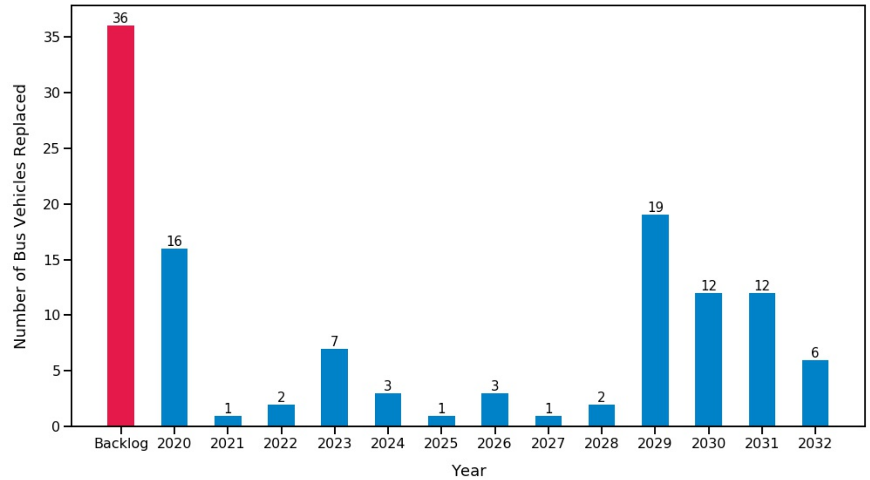
Percentage of Revenue Vehicles



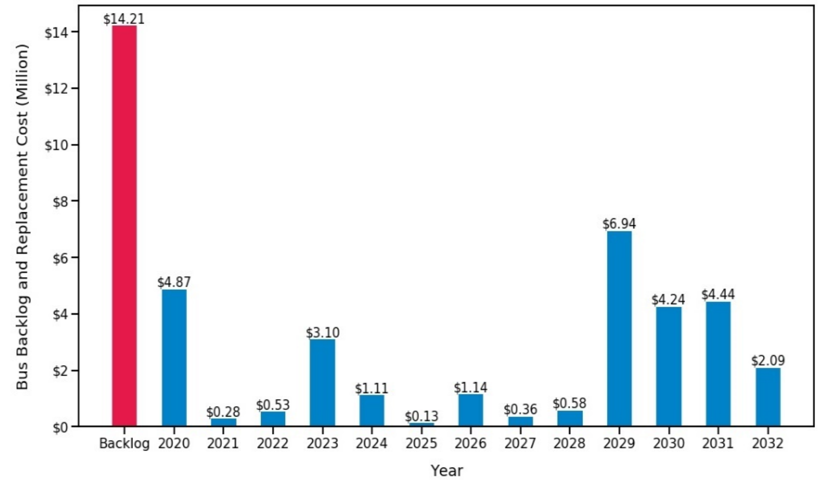
Backlog and Projected Replacement of Revenue Vehicles



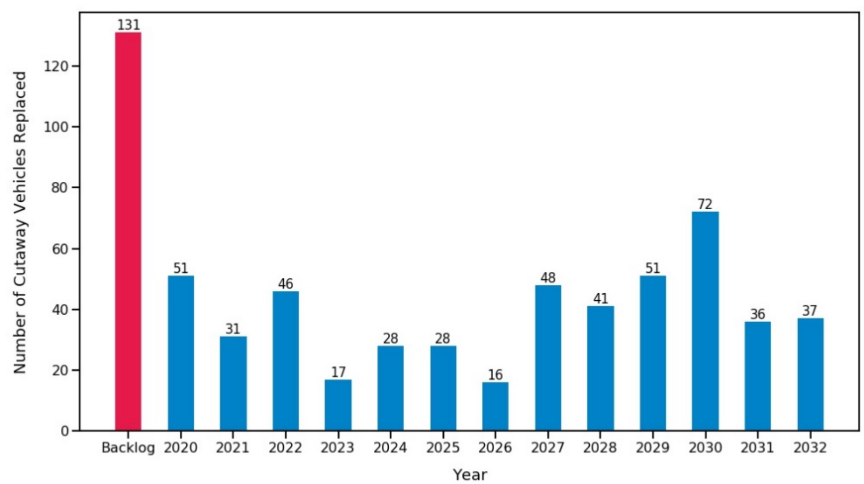
Backlog and Projected Replacement Costs for Revenue Vehicles



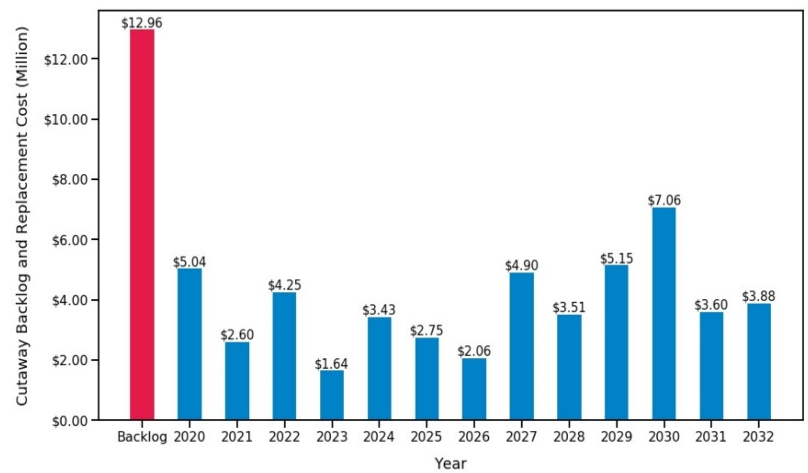
Backlog and Projected Replacement of Buses



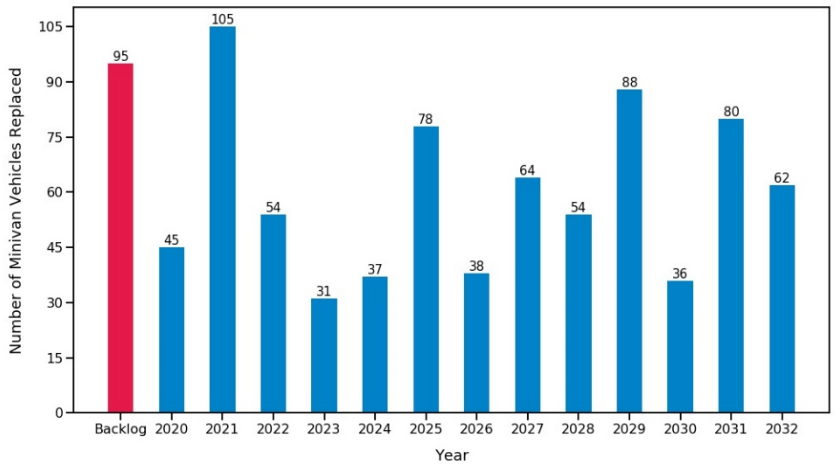
Backlog and Projected Replacement Cost for Buses



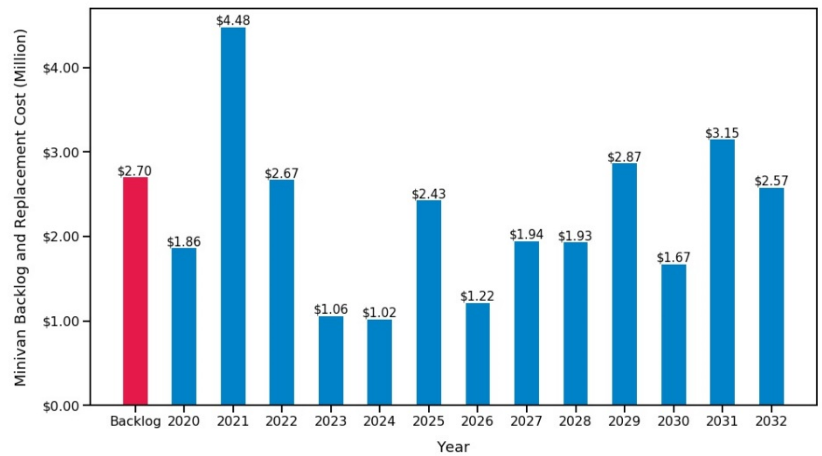
Backlog and Projected Replacement of Cutaways



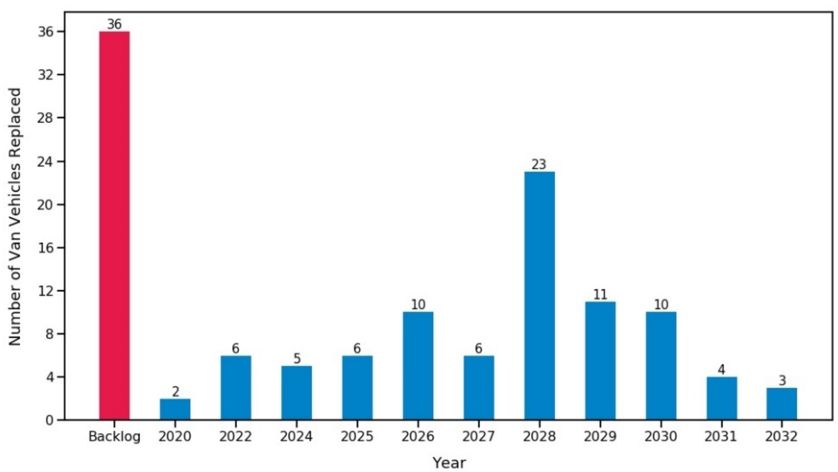
Backlog and Projected Replacement Cost for Cutaways



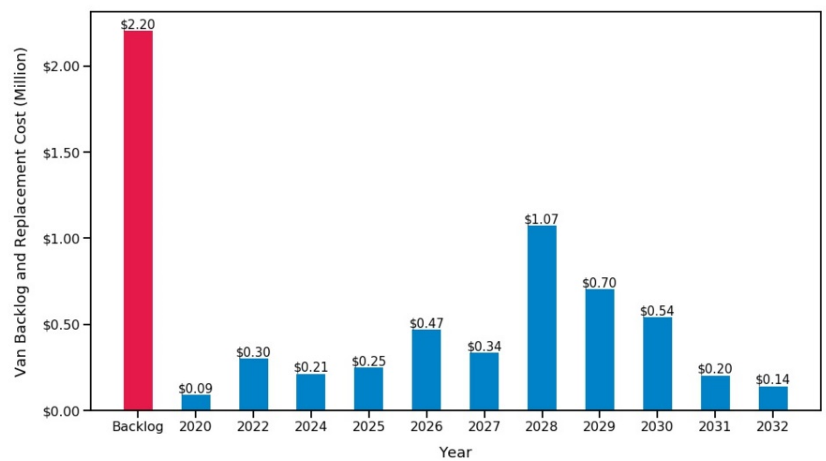
Backlog and Projected Replacement of Minivans



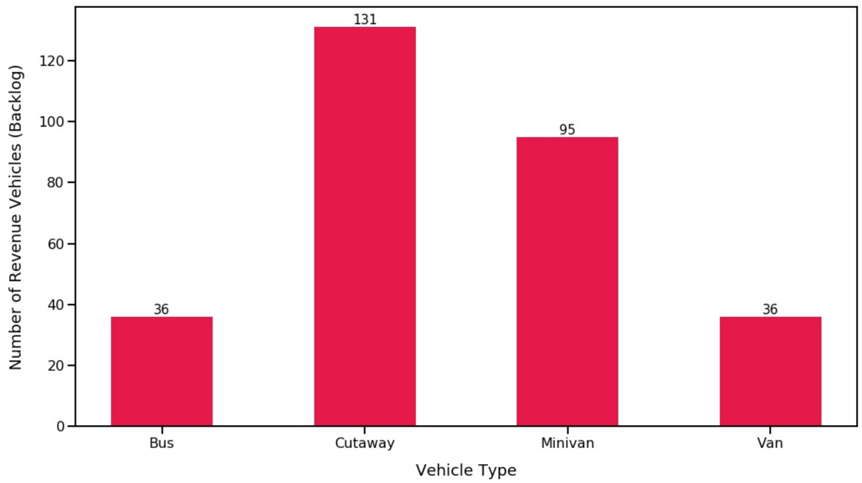
Backlog and Projected Replacement Cost for Minivans



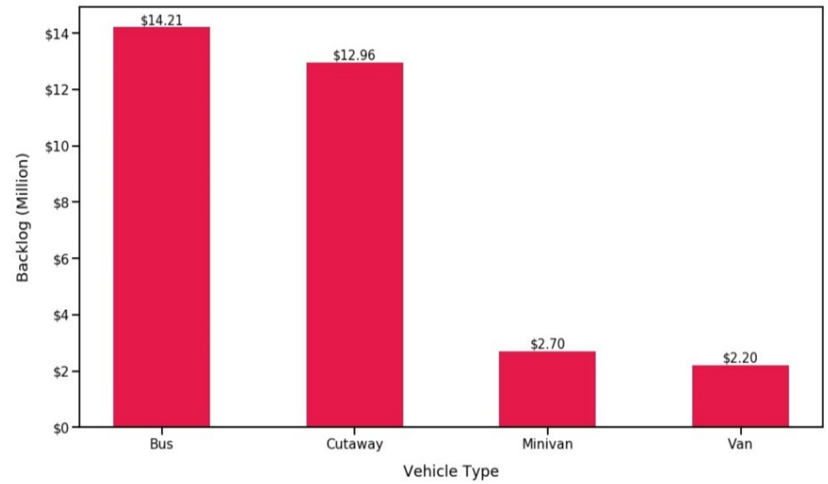
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

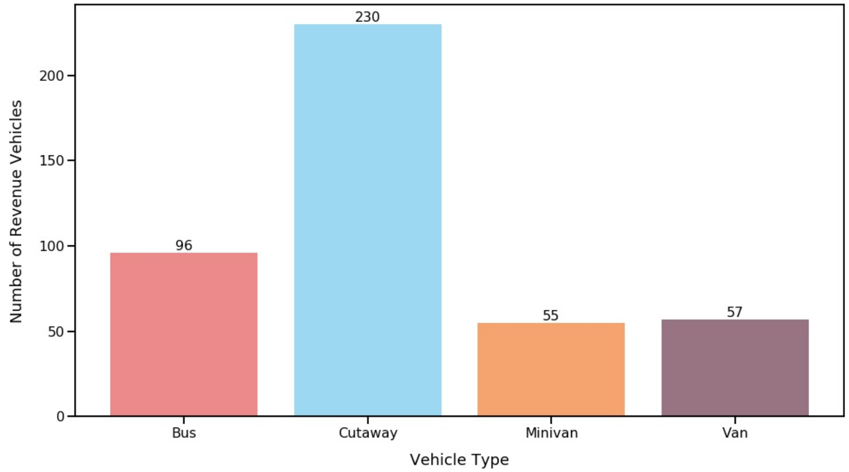


Backlog of the Revenue Vehicles by Vehicle Type

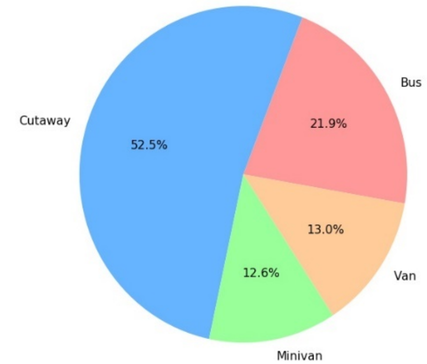


Funds Needed for Backlog by Vehicle Type

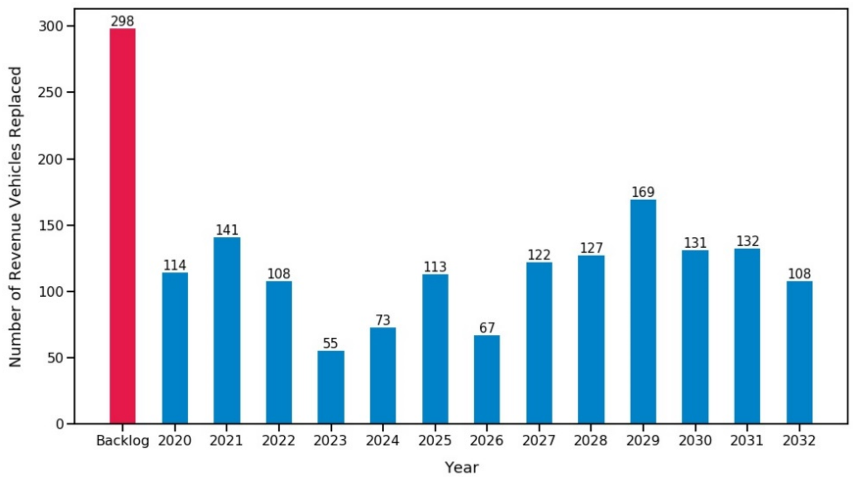
36 OR – Revenue Vehicles Information for Oregon's Small Urban and Rural Transit Systems (NTD 2017)



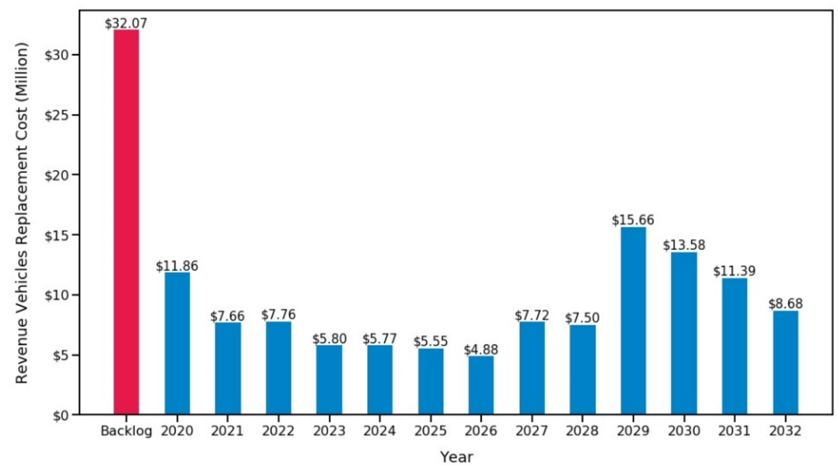
Number of Revenue Vehicles by Vehicle Type



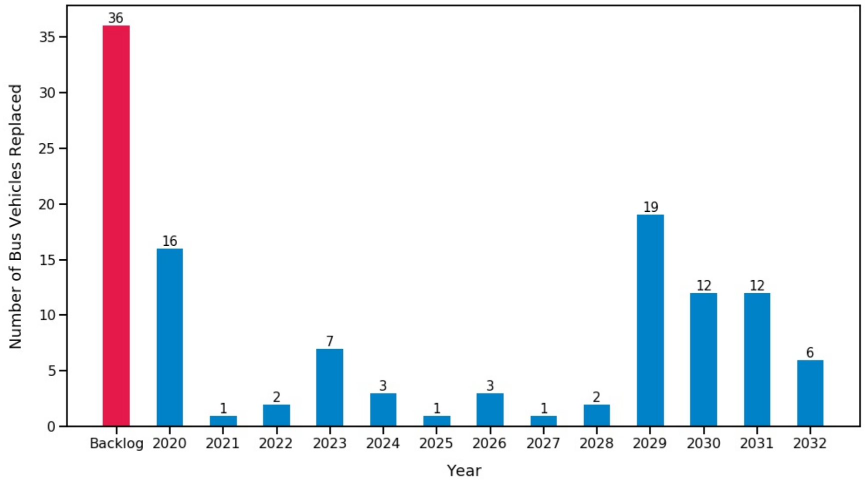
Percentage of Revenue Vehicles



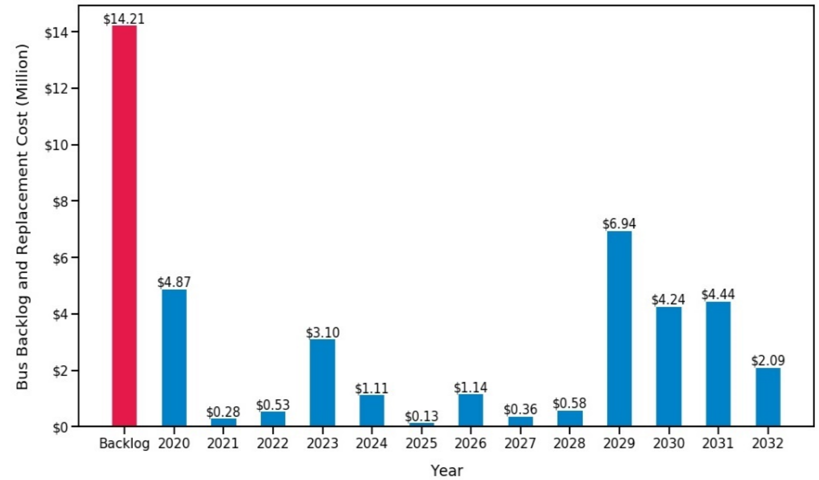
Backlog and Projected Replacement of Revenue Vehicles



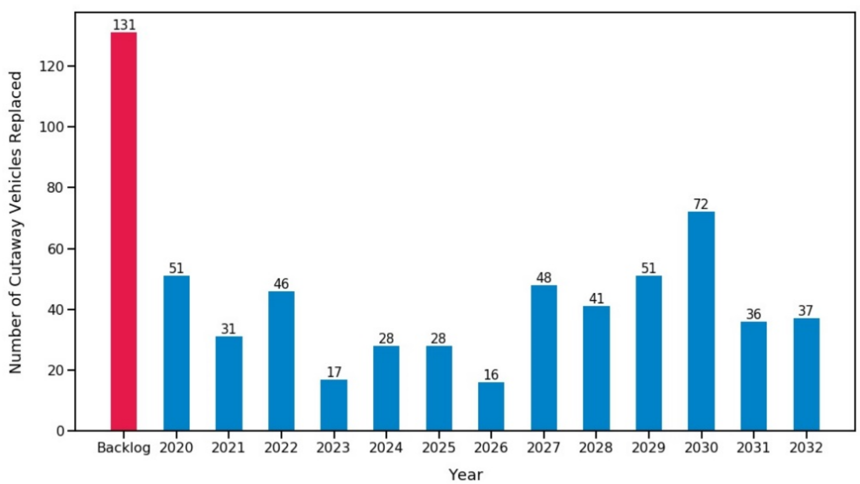
Backlog and Projected Replacement Costs for Revenue Vehicles



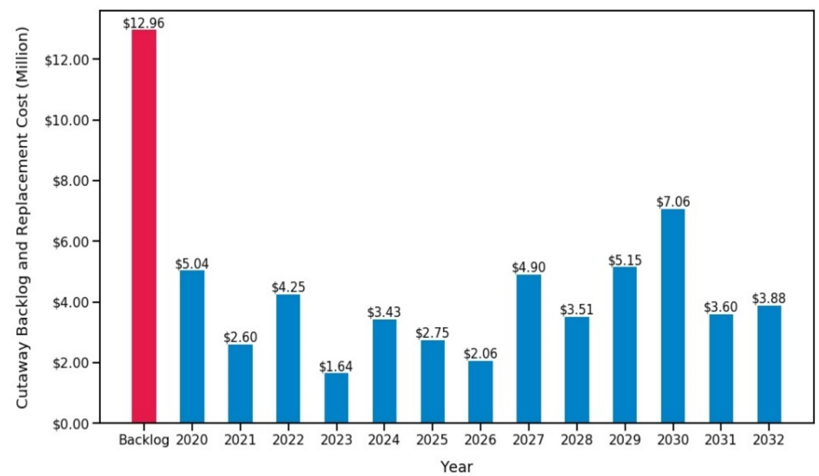
Backlog and Projected Replacement of Buses



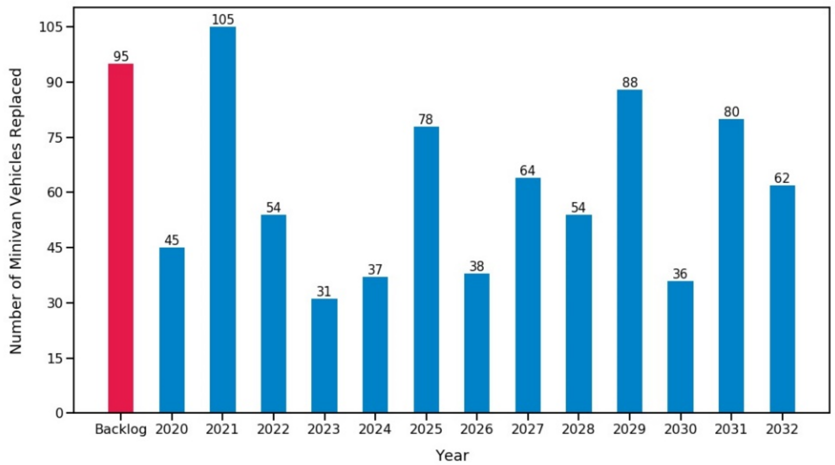
Backlog and Projected Replacement Cost for Buses



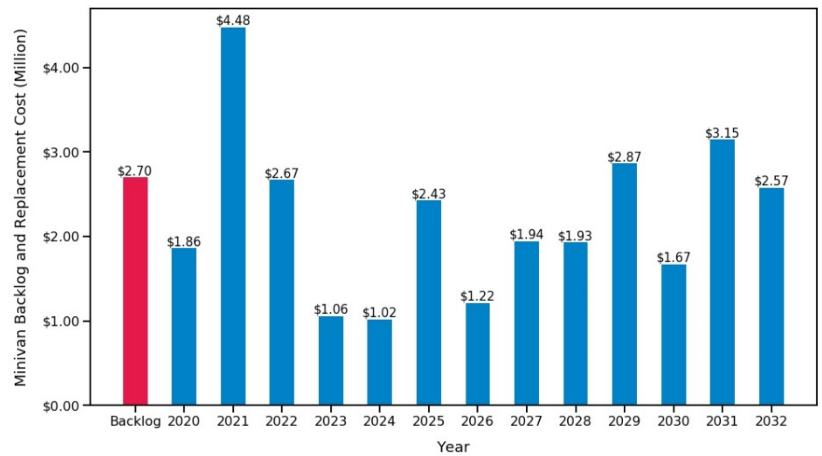
Backlog and Projected Replacement of Cutaways



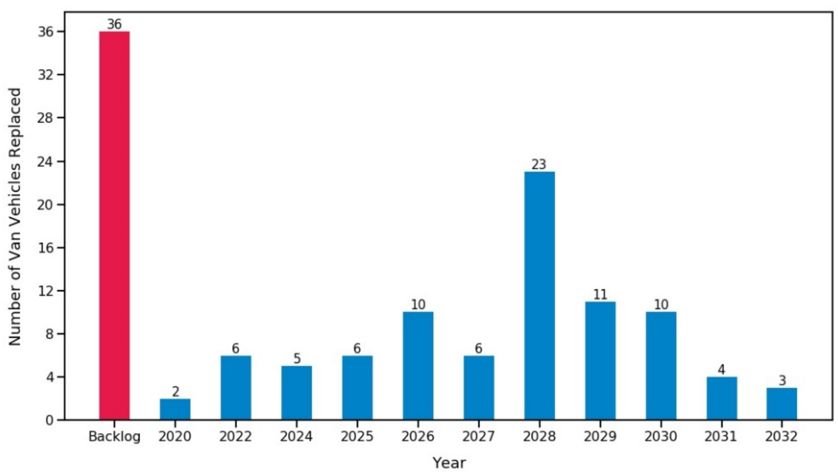
Backlog and Projected Replacement Cost for Cutaways



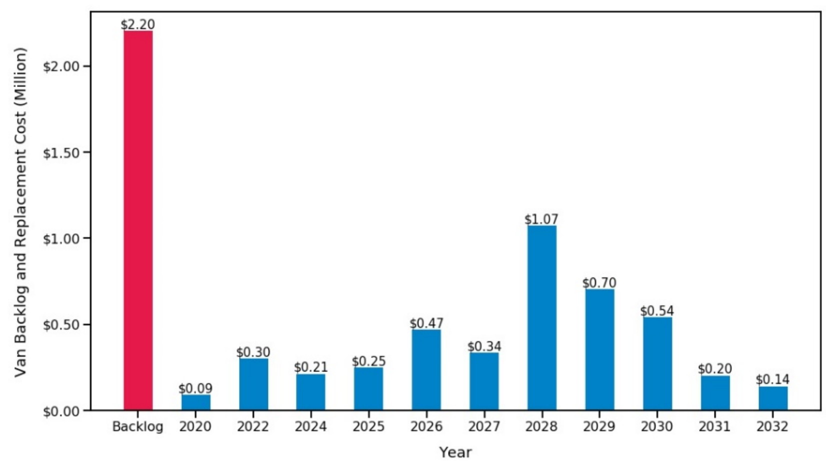
Backlog and Projected Replacement of Minivans



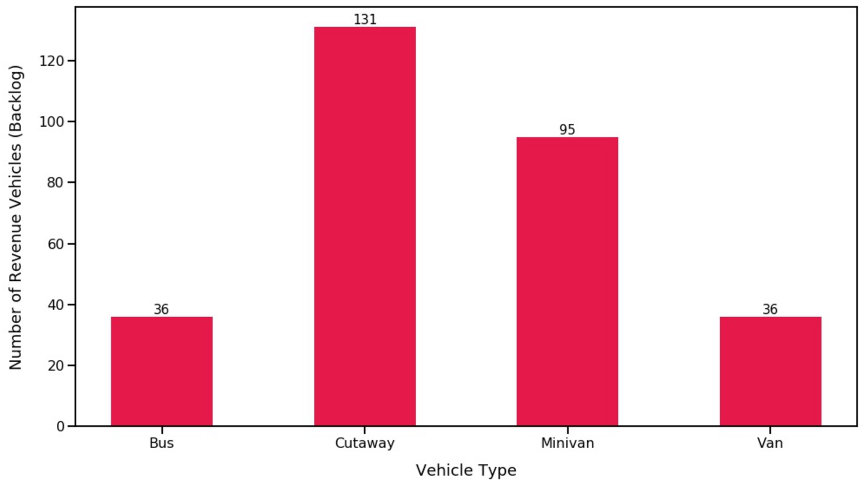
Backlog and Projected Replacement Cost for Minivans



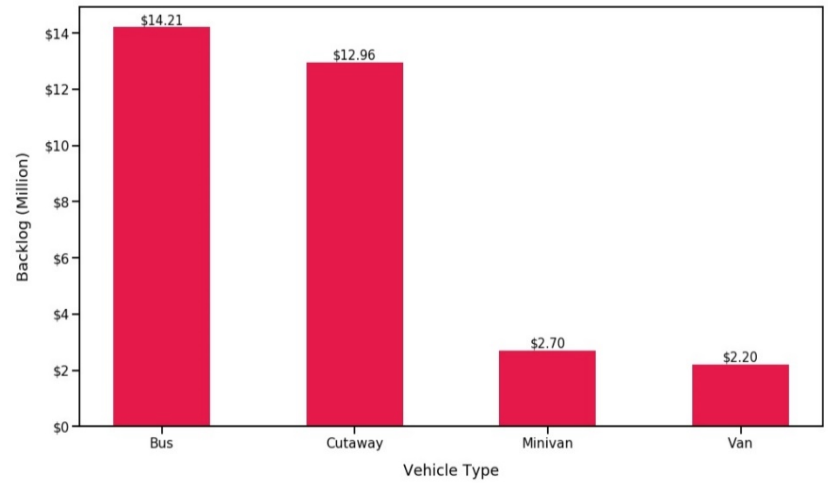
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

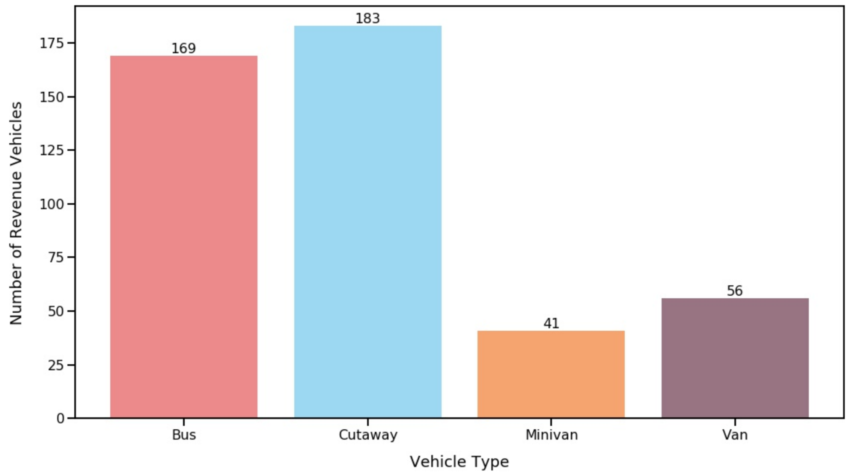


Backlog of the Revenue Vehicles by Vehicle Type

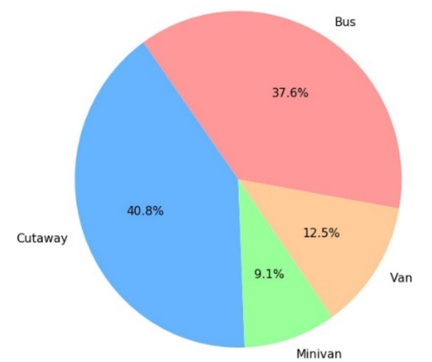


Funds Needed for Backlog by Vehicle Type

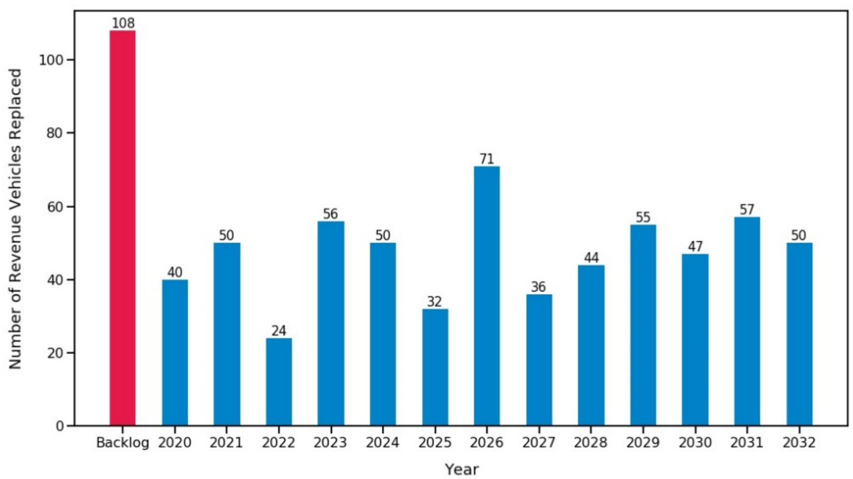
37 PA – Revenue Vehicles Information for Pennsylvania's Small Urban and Rural Transit Systems (NTD 2017)



Number of Revenue Vehicles by Vehicle Type

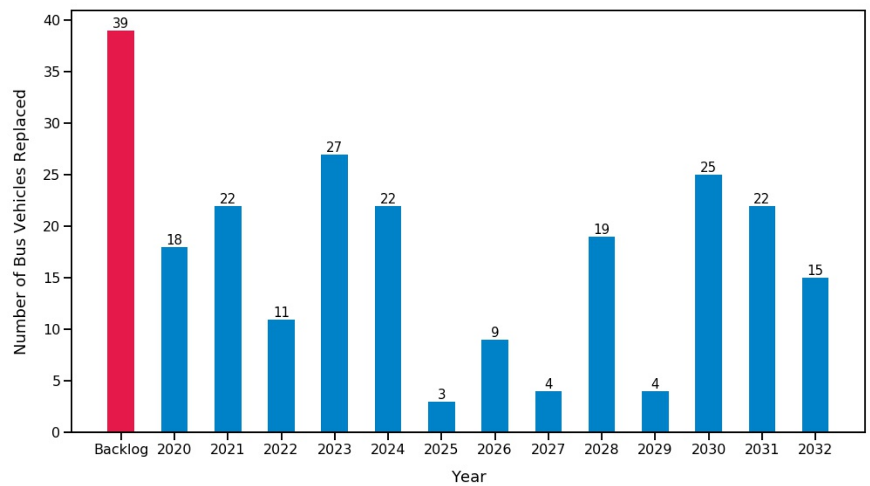


Percentage of Revenue Vehicles

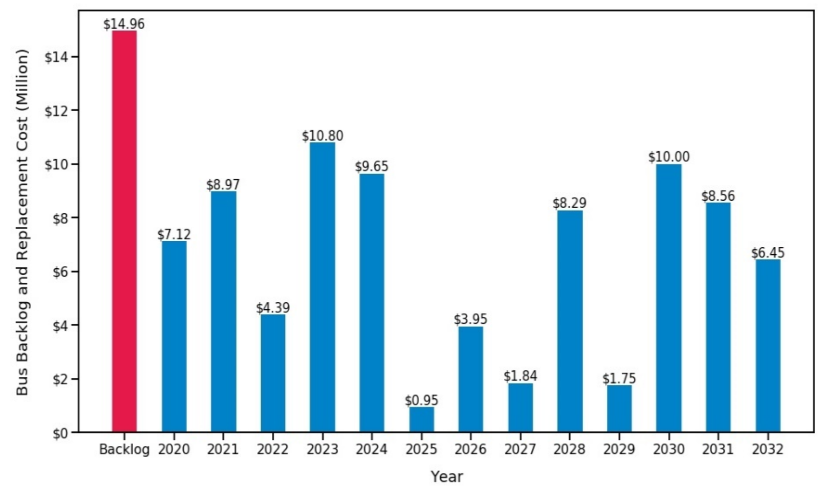


Backlog and Projected Replacement of Revenue Vehicles

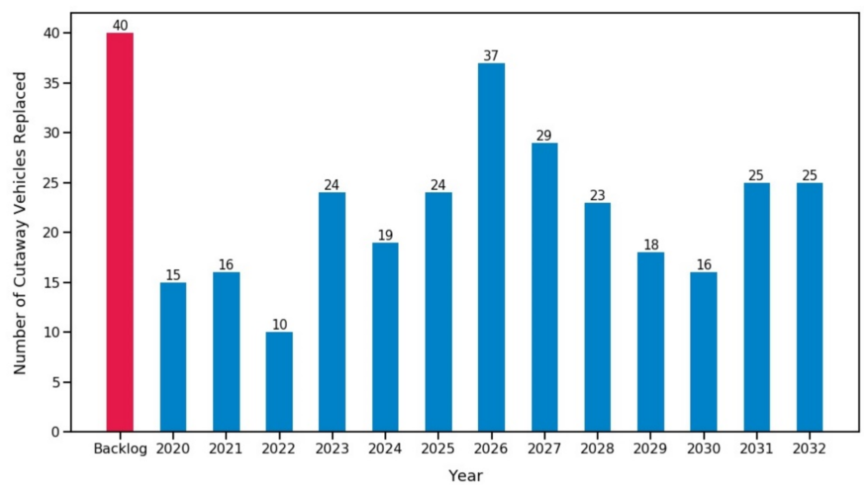
Backlog and Projected Replacement Costs for Revenue Vehicles



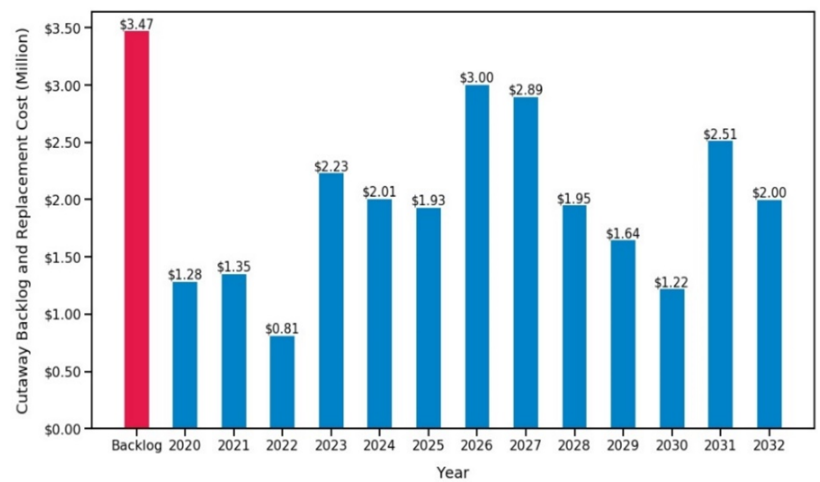
Backlog and Projected Replacement of Buses



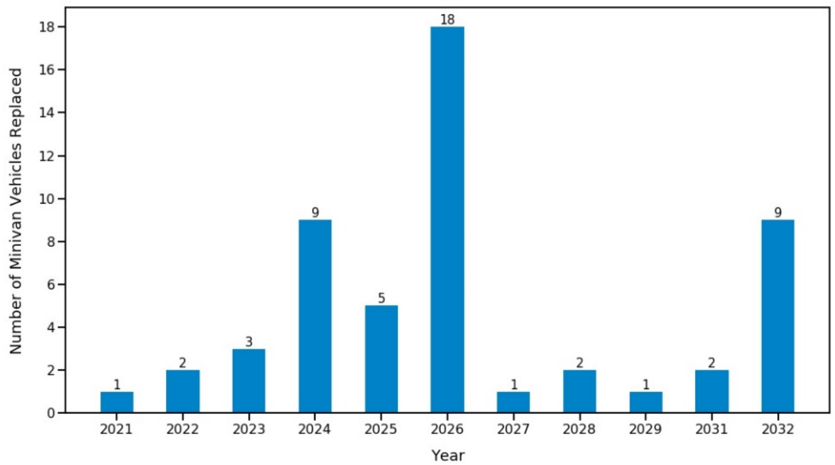
Backlog and Projected Replacement Cost for Buses



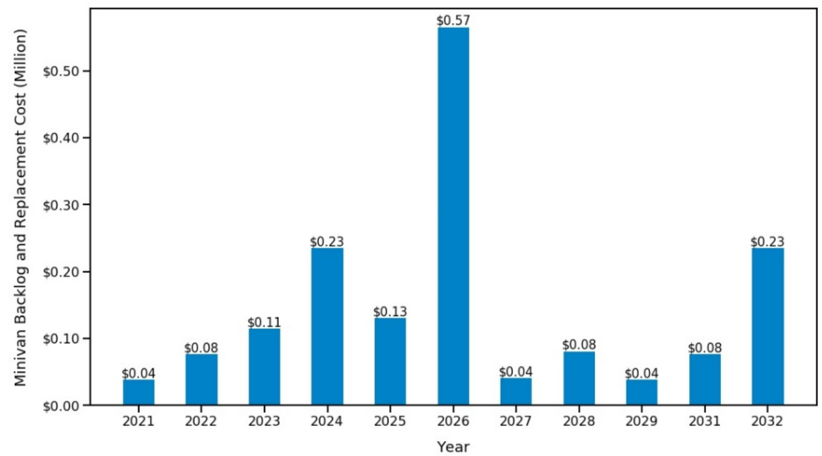
Backlog and Projected Replacement of Cutaways



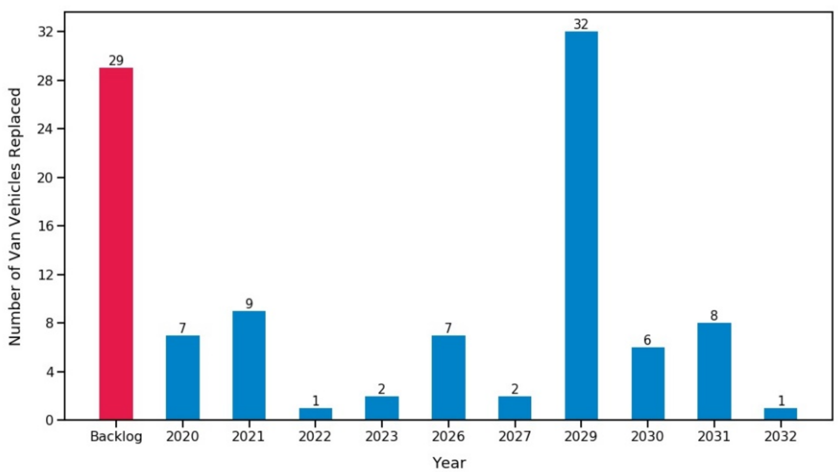
Backlog and Projected Replacement Cost for Cutaways



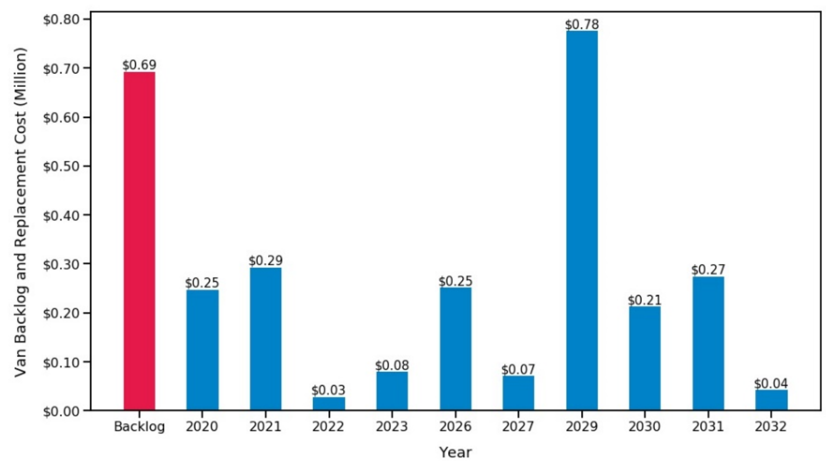
Backlog and Projected Replacement of Minivans



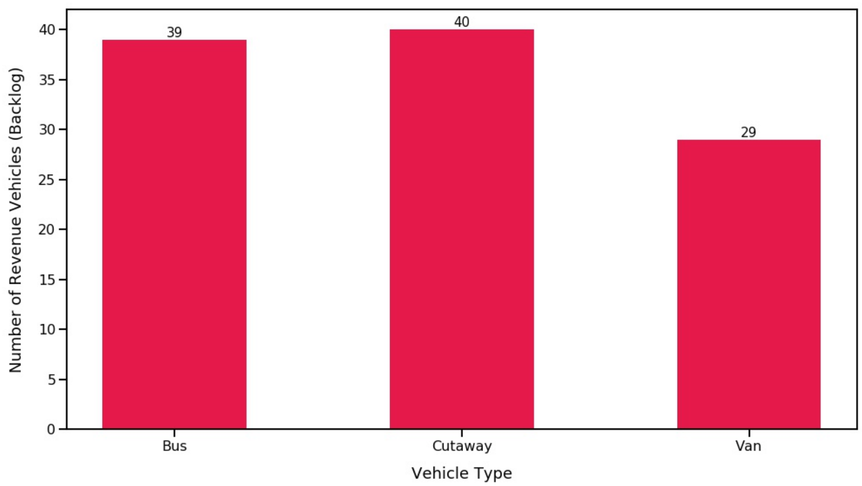
Backlog and Projected Replacement Cost for Minivans

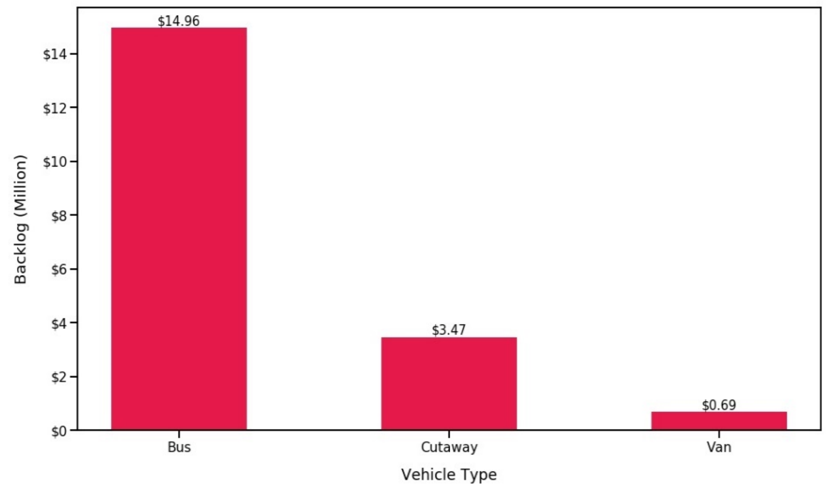


Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

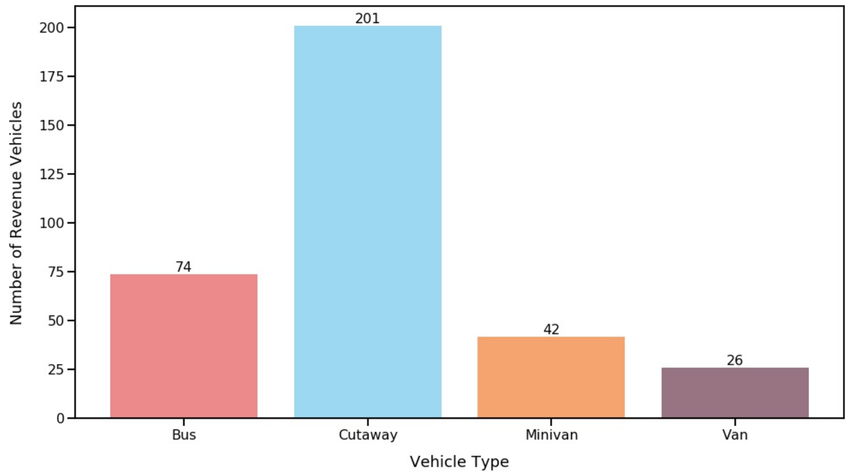




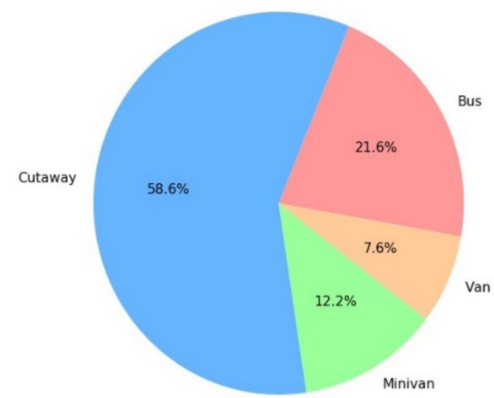
Backlog of the Revenue Vehicles by Vehicle Type

Funds Needed for Backlog by Vehicle Type

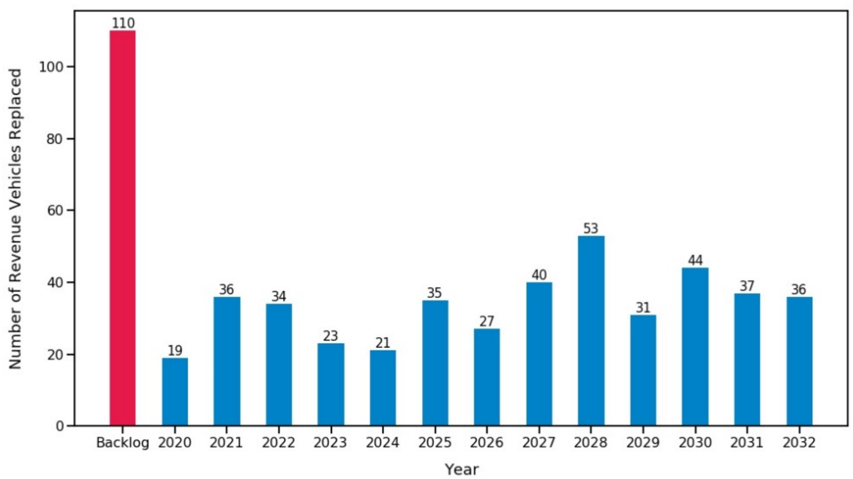
38 SC – Revenue Vehicles Information for South Carolina's Small Urban and Rural Transit Systems (NTD 2017)



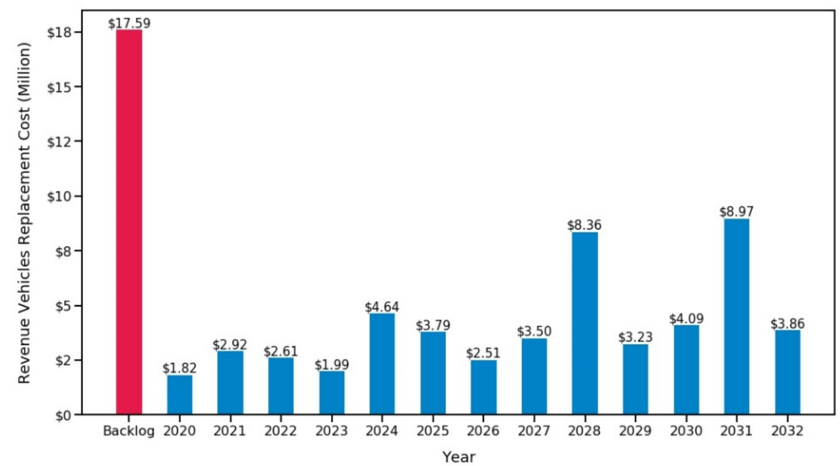
Number of Revenue Vehicles by Vehicle Type



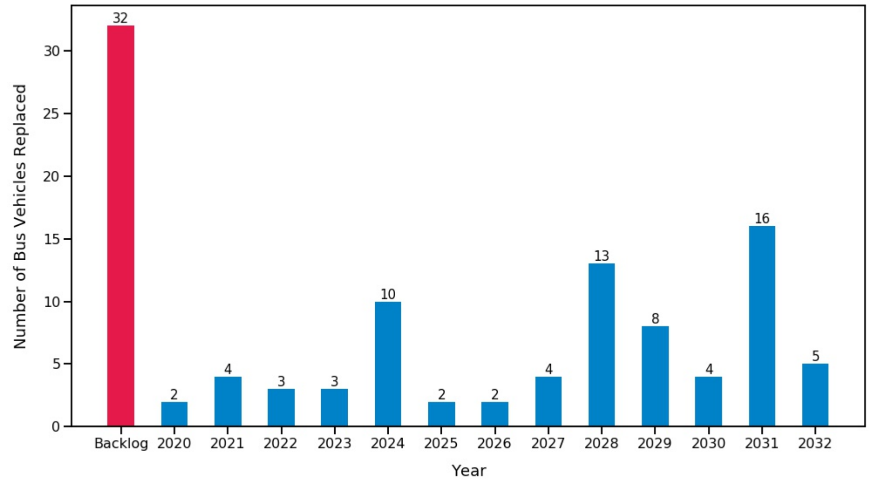
Percentage of Revenue Vehicles



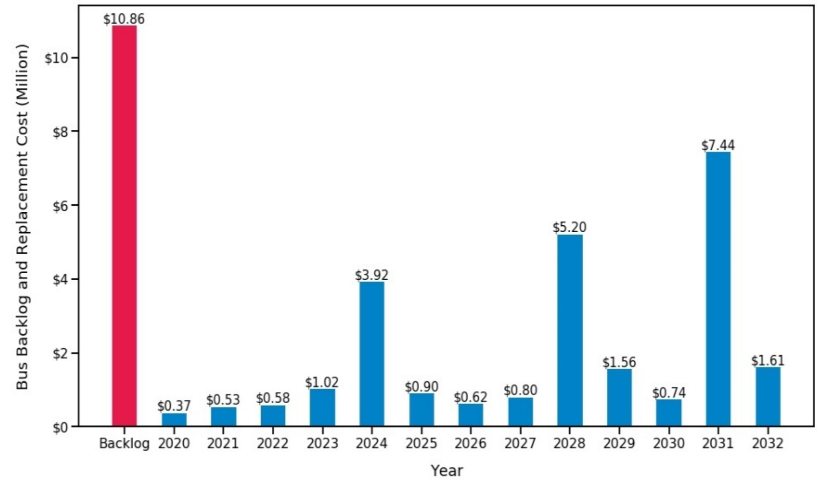
Backlog and Projected Replacement of Revenue Vehicles



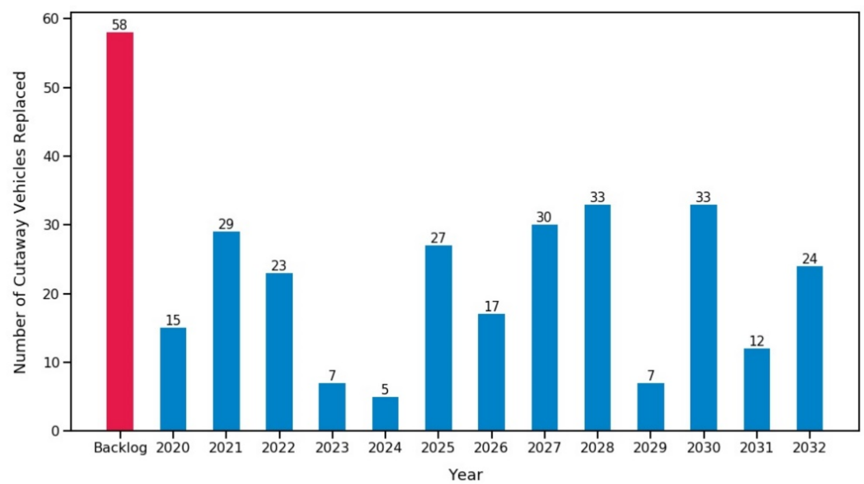
Backlog and Projected Replacement Costs for Revenue Vehicles



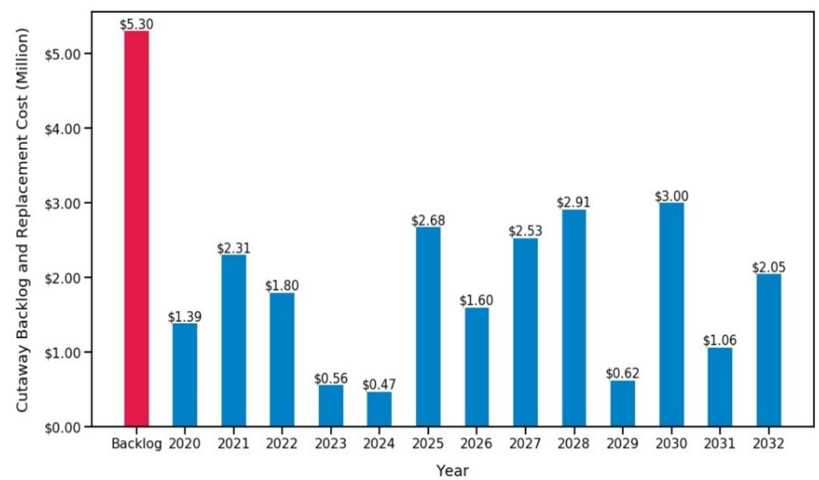
Backlog and Projected Replacement of Buses



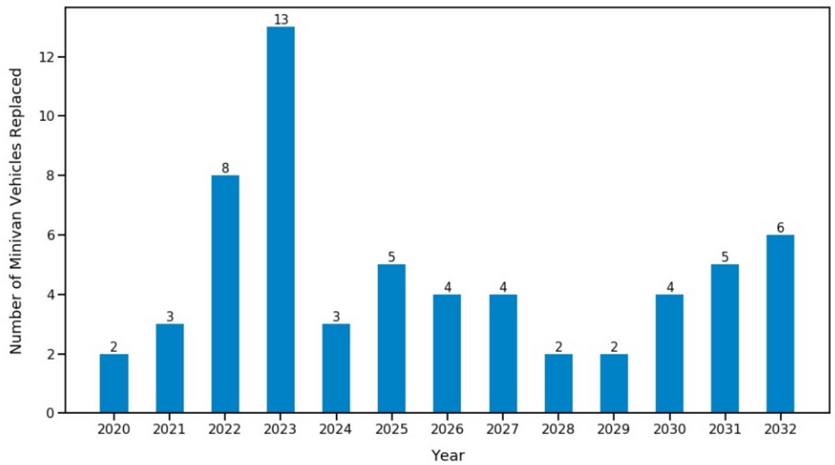
Backlog and Projected Replacement Cost for Buses



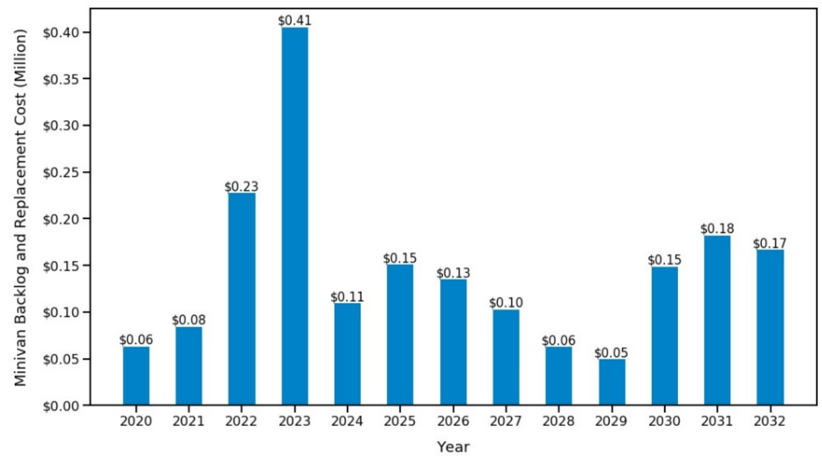
Backlog and Projected Replacement of Cutaways



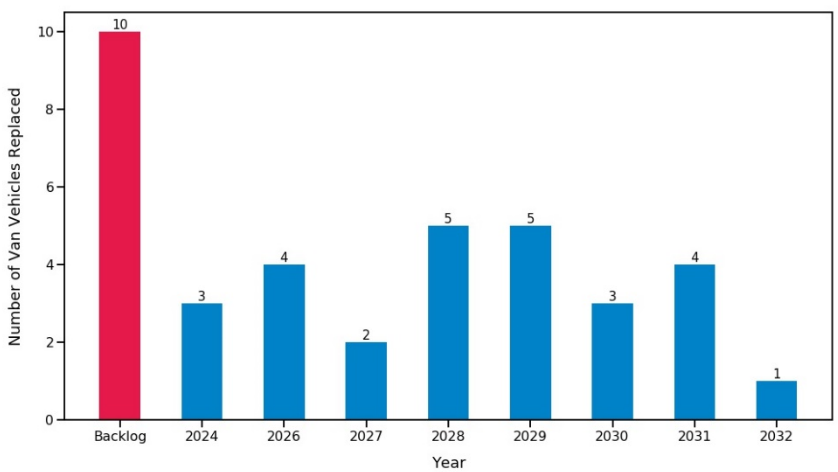
Backlog and Projected Replacement Cost for Cutaways



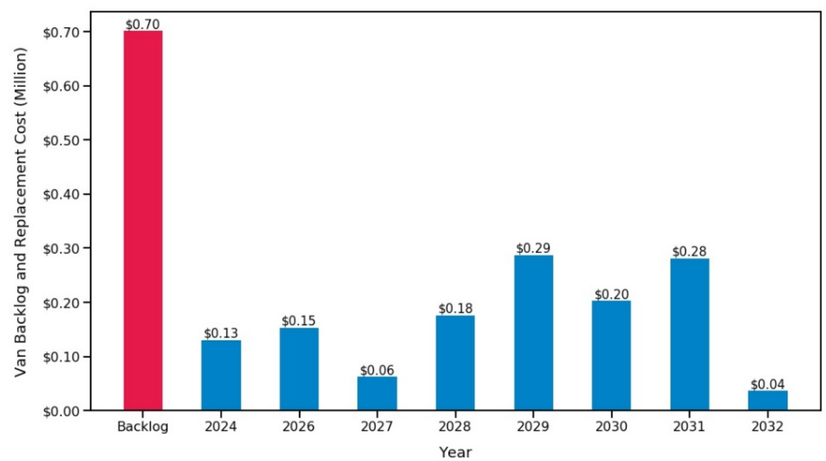
Backlog and Projected Replacement of Minivans



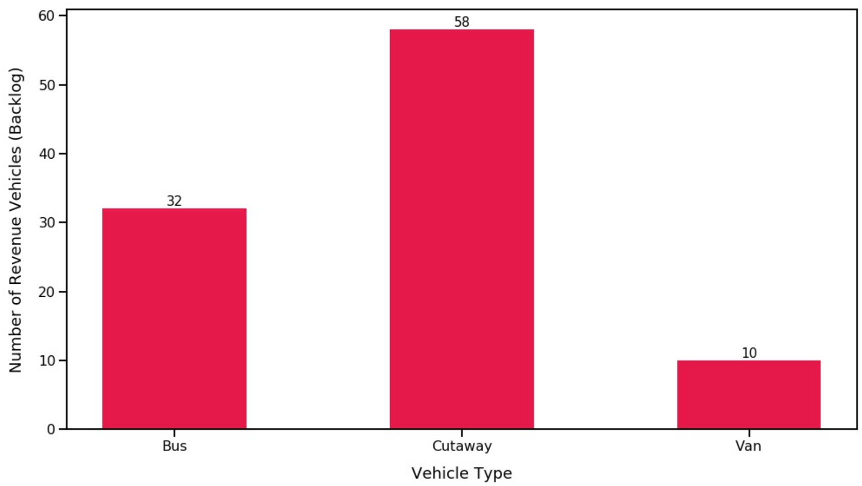
Backlog and Projected Replacement Cost for Minivans



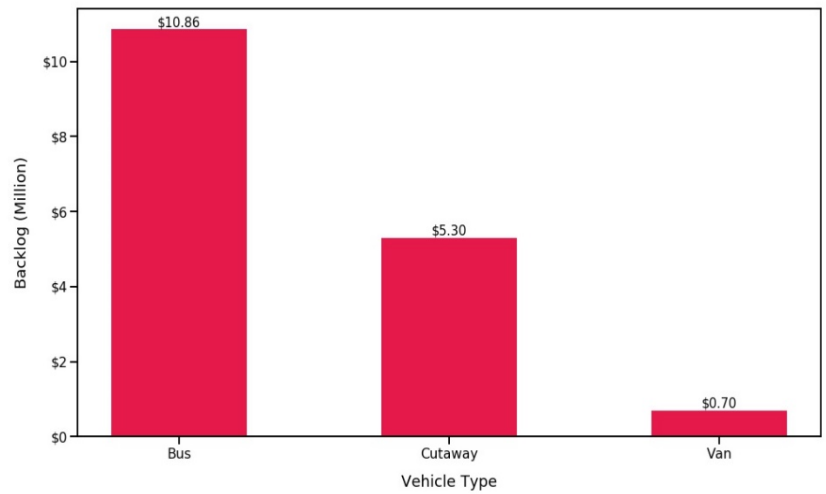
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

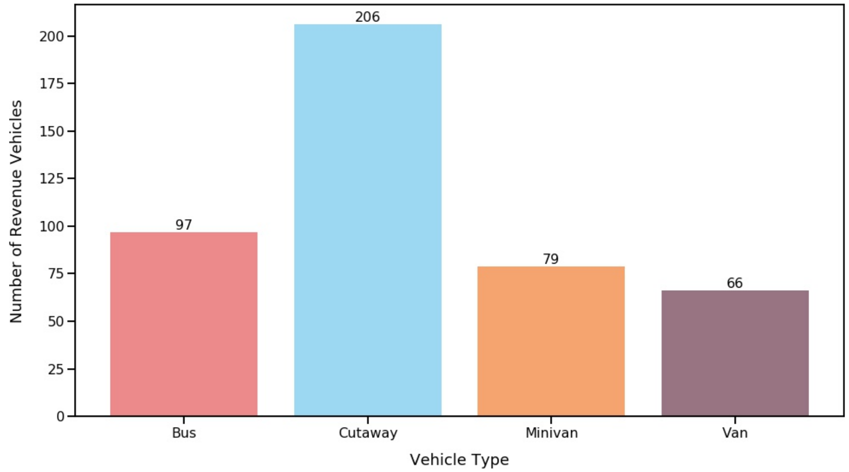


Backlog of the Revenue Vehicles by Vehicle Type

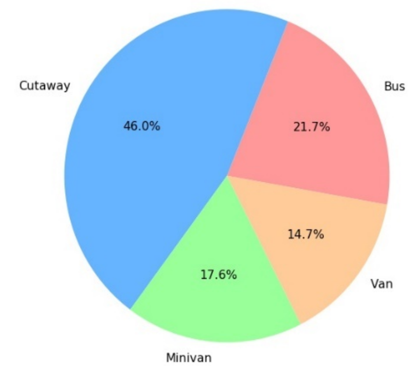


Funds Needed for Backlog by Vehicle Type

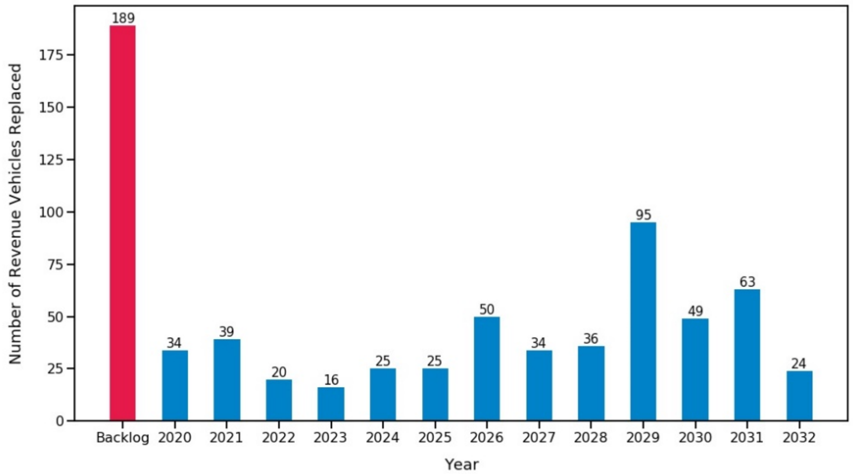
39 SD – Revenue Vehicles Information for South Dakota's Small Urban and Rural Transit Systems (NTD 2017)



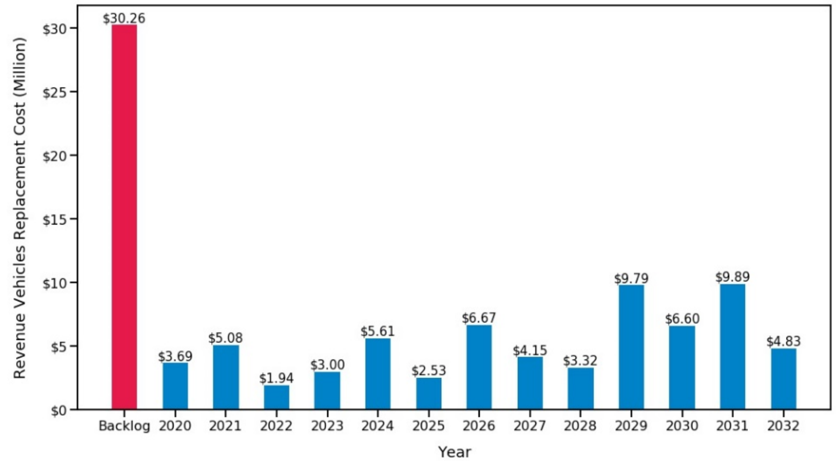
Number of Revenue Vehicles by Vehicle Type



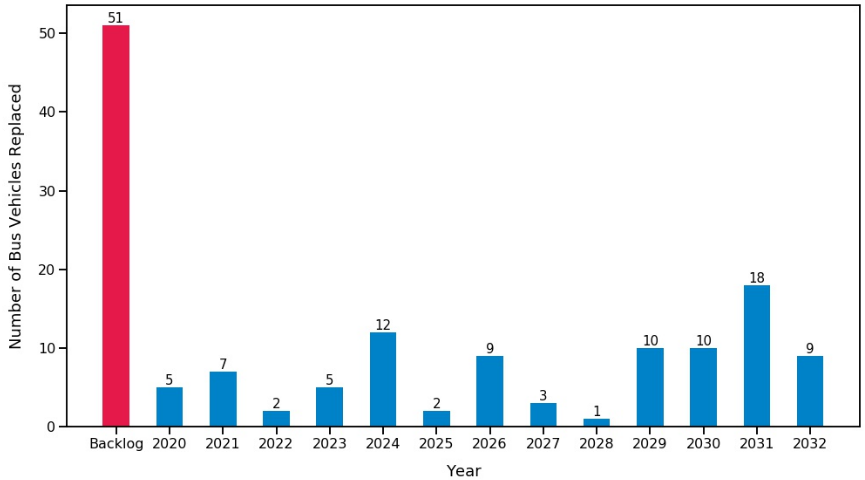
Percentage of Revenue Vehicles



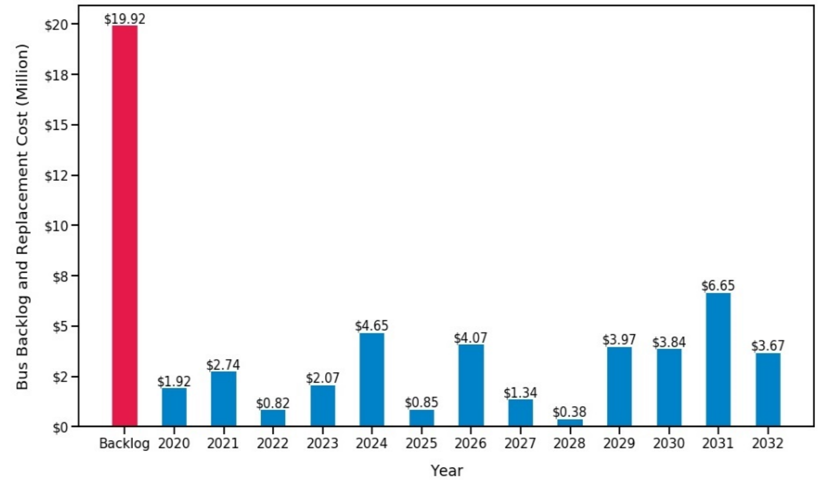
Backlog and Projected Replacement of Revenue Vehicles



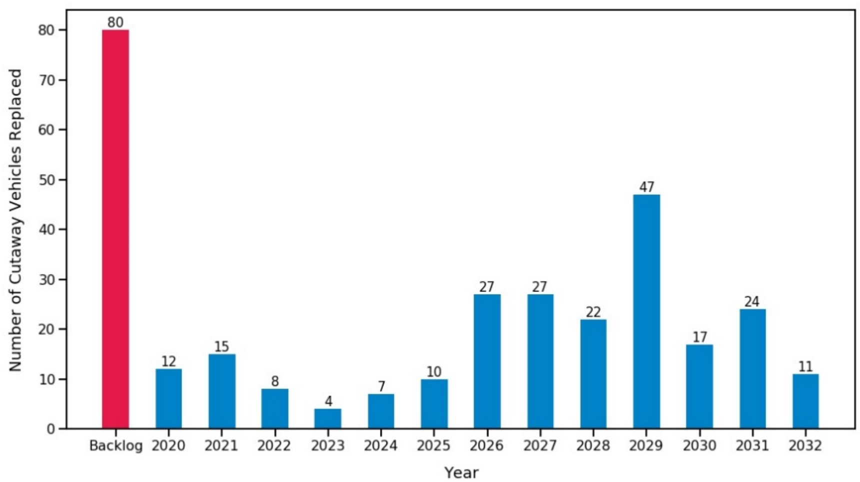
Backlog and Projected Replacement Costs for Revenue Vehicles



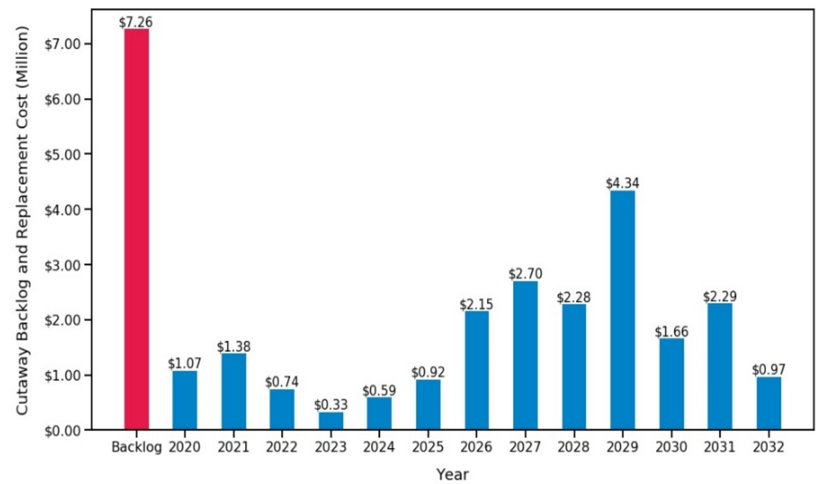
Backlog and Projected Replacement of Buses



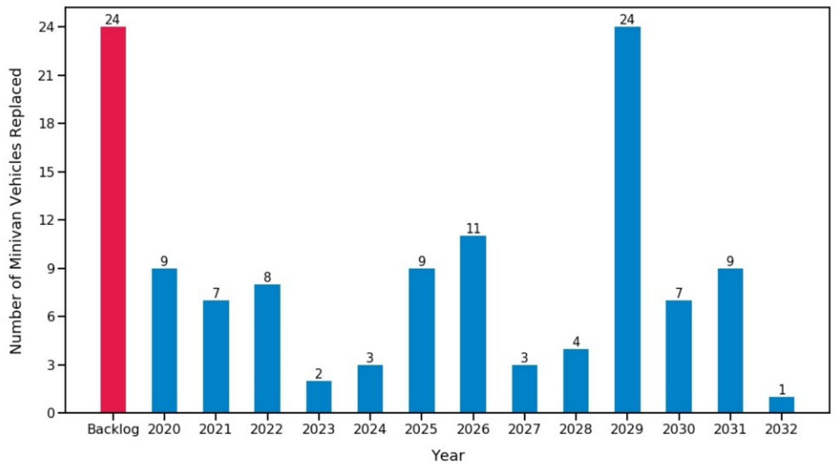
Backlog and Projected Replacement Cost for Buses



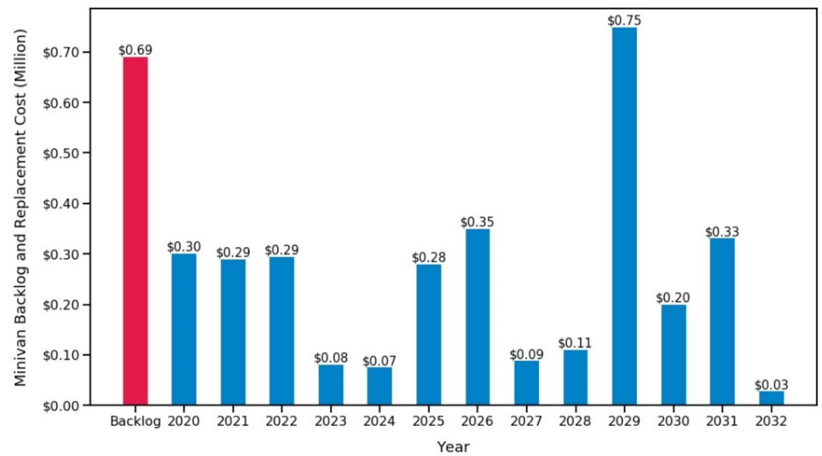
Backlog and Projected Replacement of Cutaways



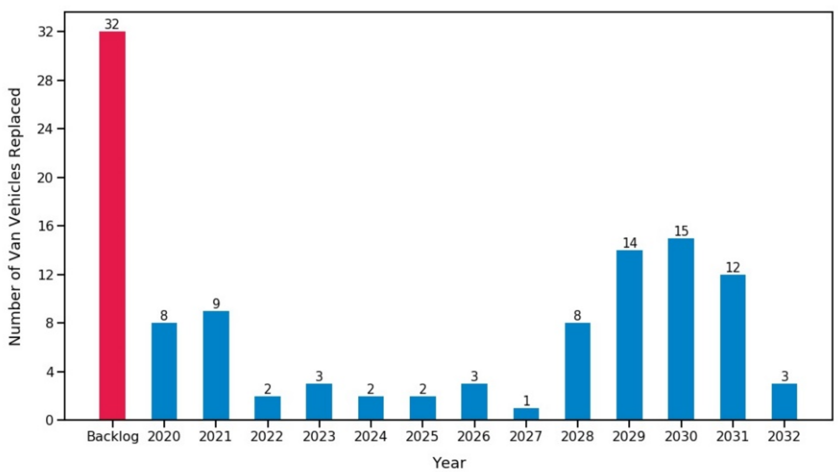
Backlog and Projected Replacement Cost for Cutaways



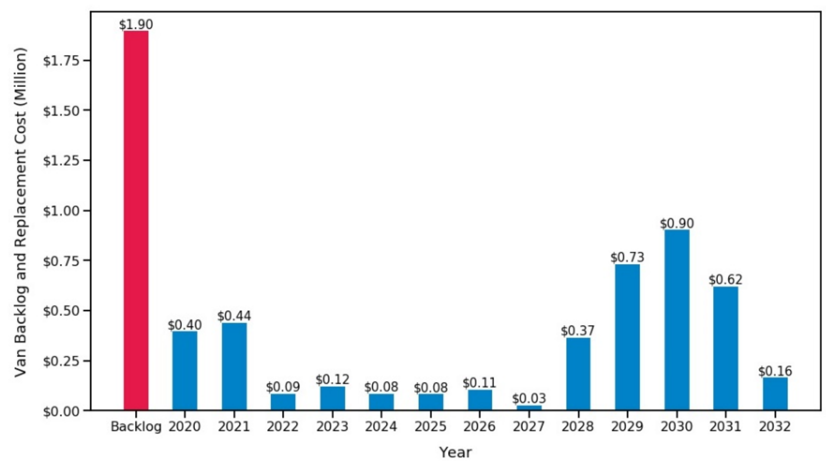
Backlog and Projected Replacement of Minivans



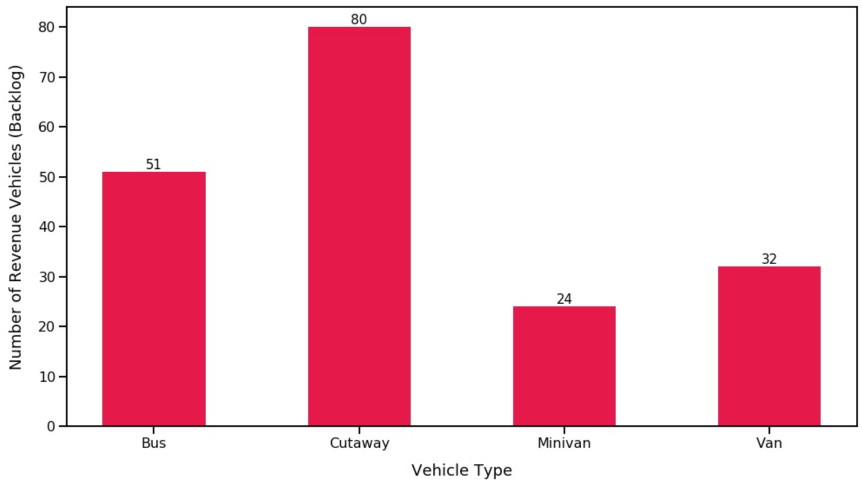
Backlog and Projected Replacement Cost for Minivans



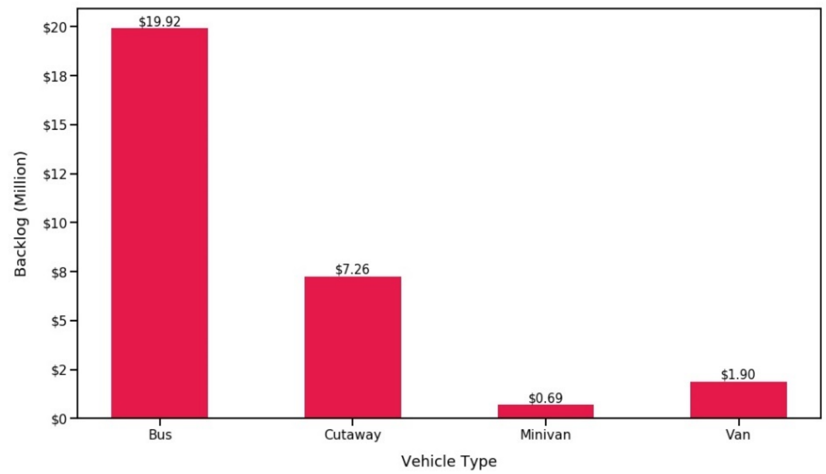
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

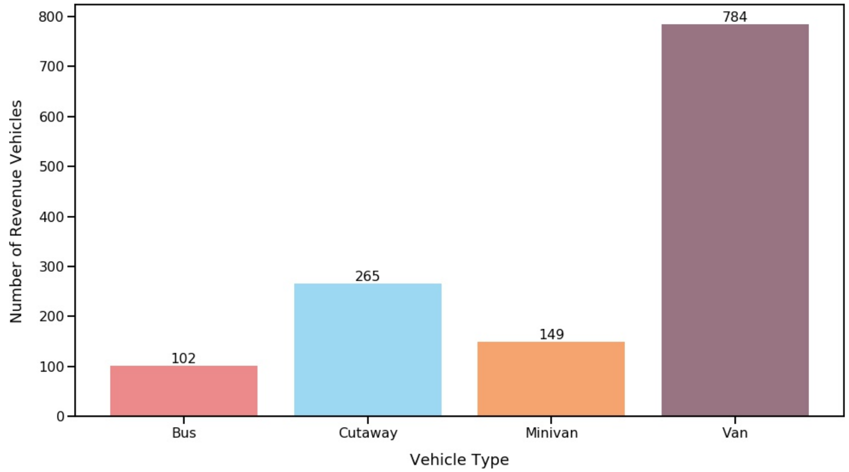


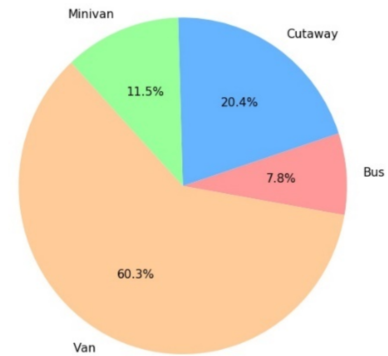
Backlog of the Revenue Vehicles by Vehicle Type



Funds Needed for Backlog by Vehicle Type

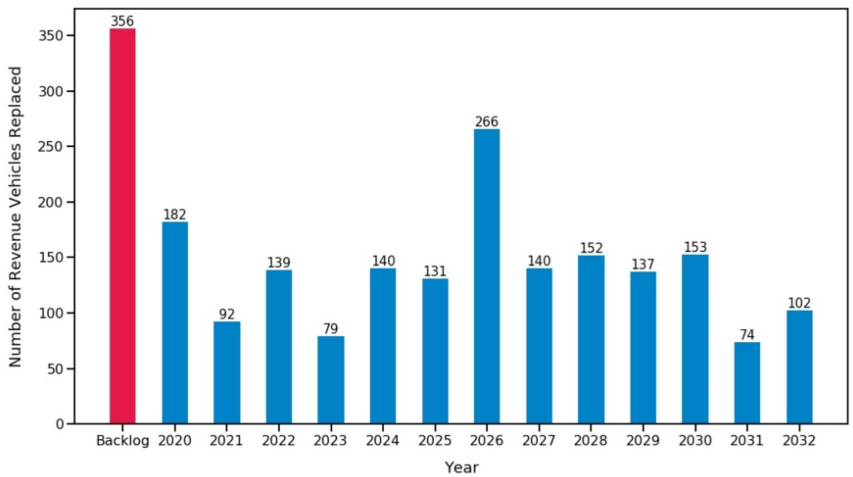
40 TN – Revenue Vehicles Information for Tennessee's Small Urban and Rural Transit Systems (NTD 2017)



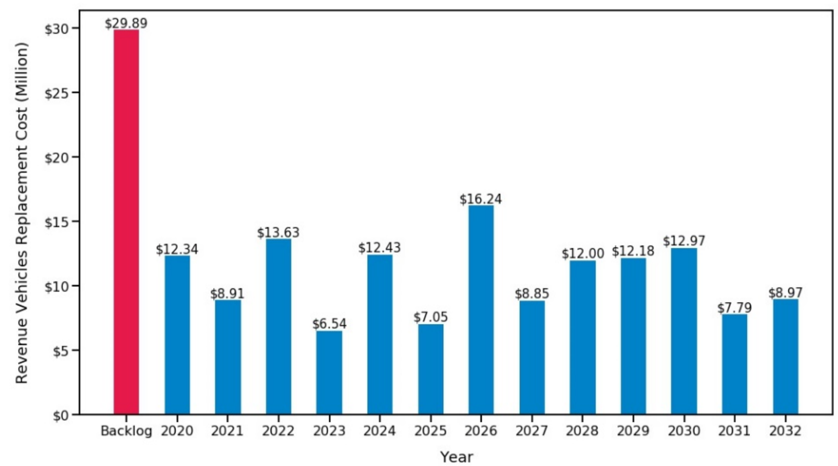


Number of Revenue Vehicles by Vehicle Type

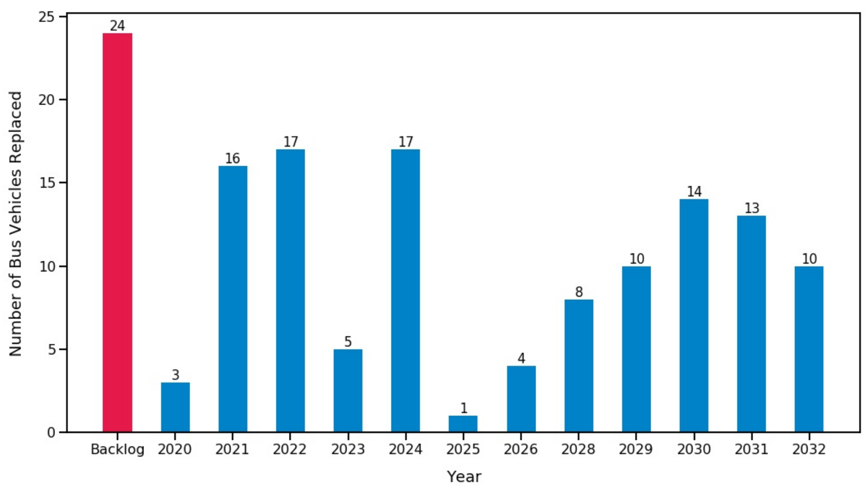
Percentage of Revenue Vehicles



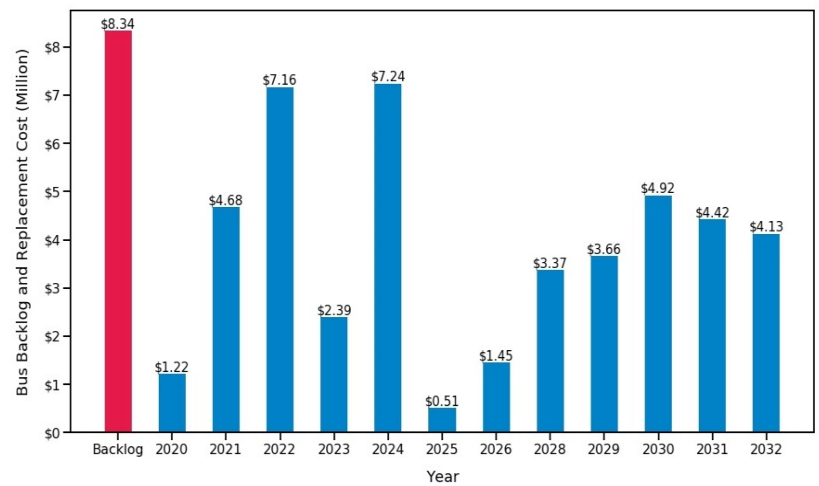
Backlog and Projected Replacement of Revenue Vehicles



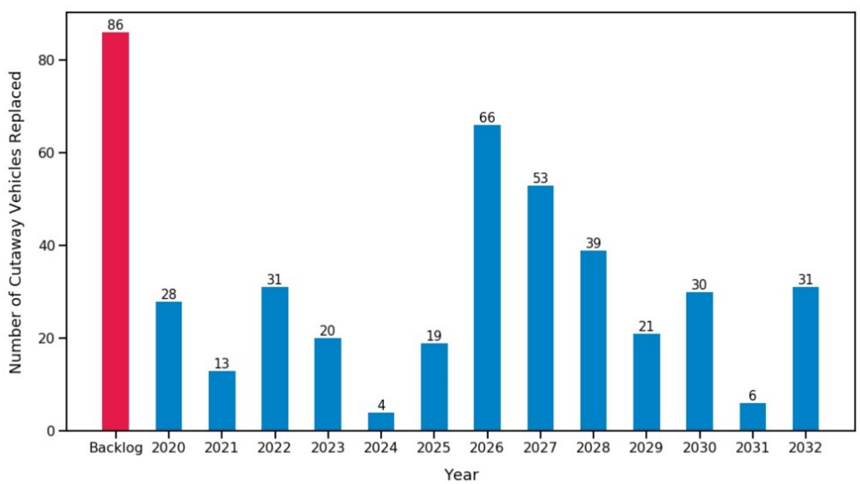
Backlog and Projected Replacement Costs for Revenue Vehicles



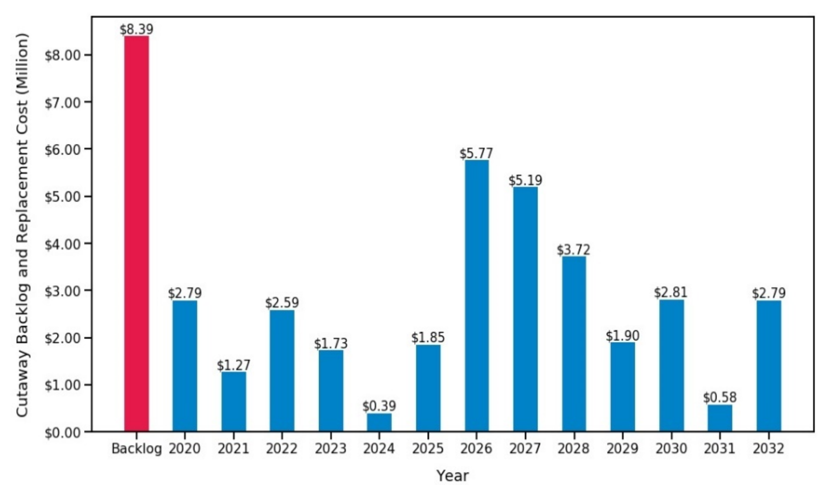
Backlog and Projected Replacement of Buses



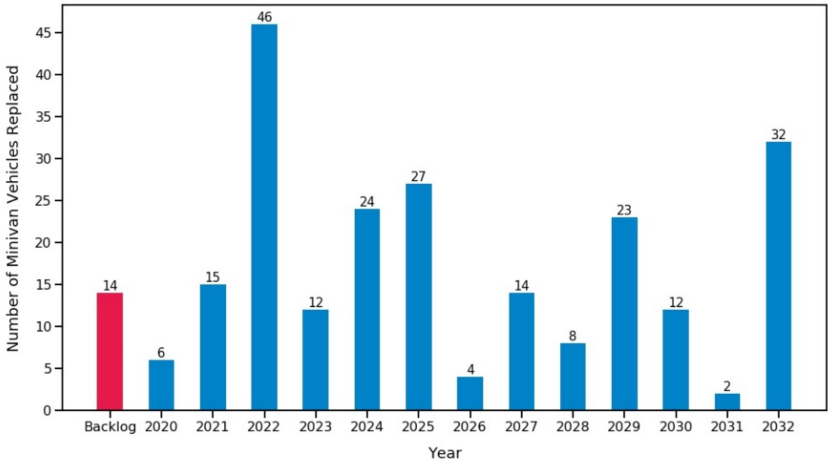
Backlog and Projected Replacement Cost for Buses



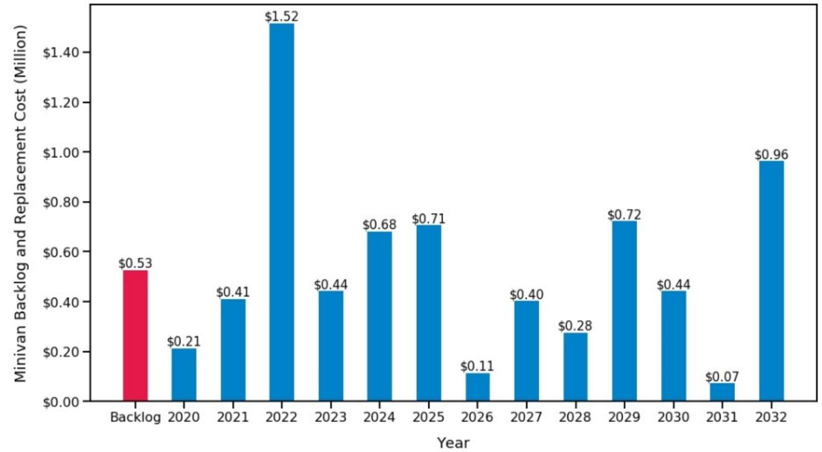
Backlog and Projected Replacement of Cutaways



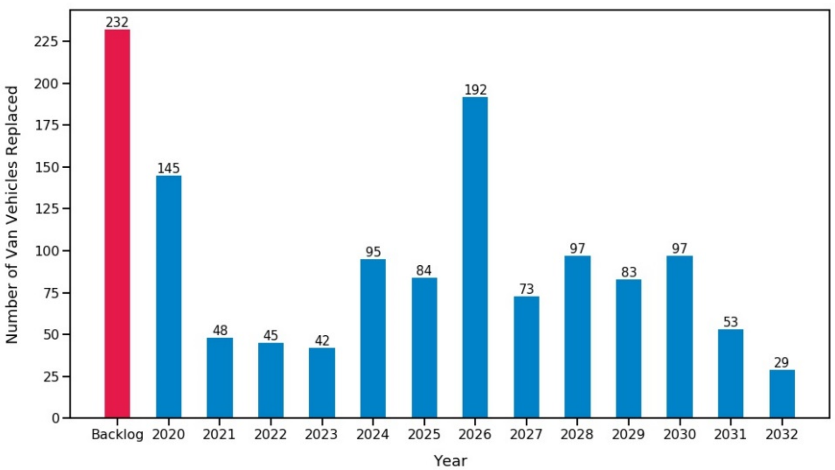
Backlog and Projected Replacement Cost for Cutaways



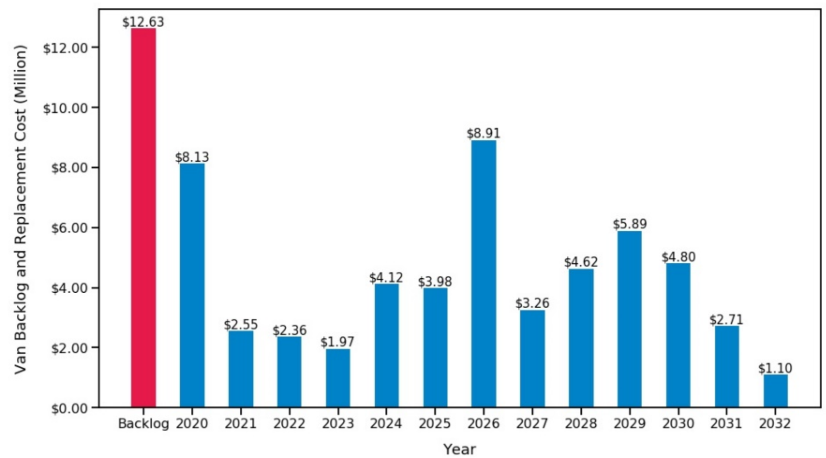
Backlog and Projected Replacement of Minivans



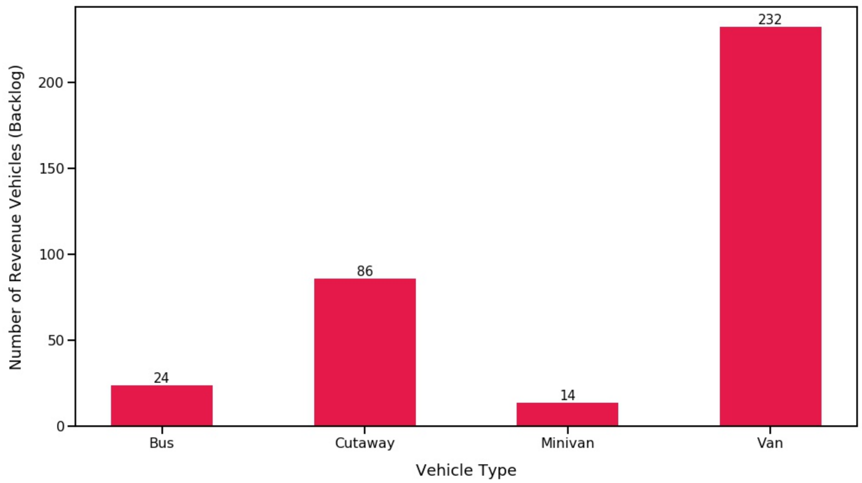
Backlog and Projected Replacement Cost for Minivans



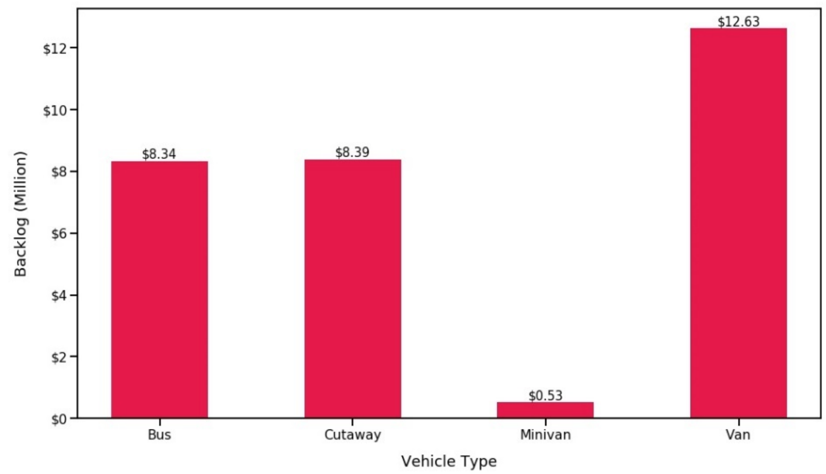
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

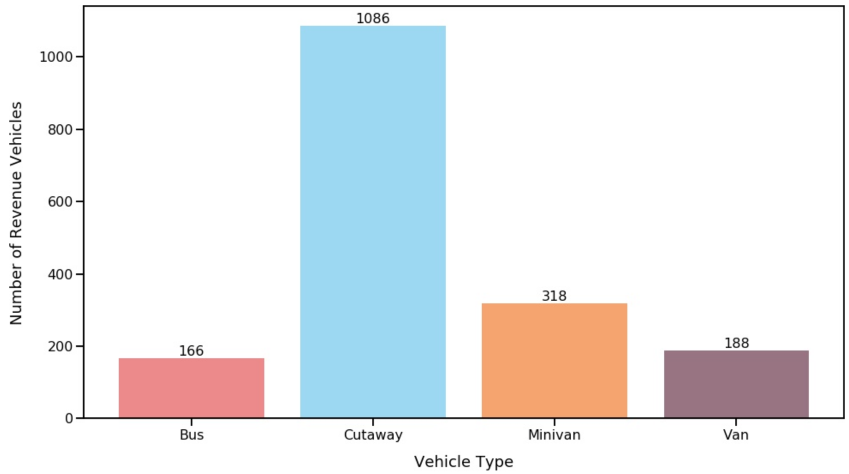


Backlog of the Revenue Vehicles by Vehicle Type

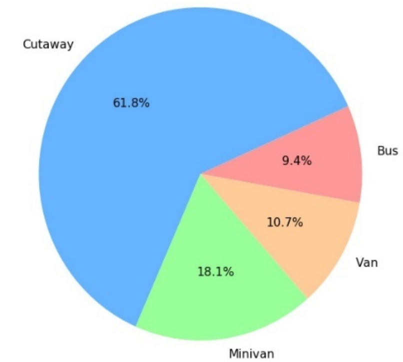


Funds Needed for Backlog by Vehicle Type

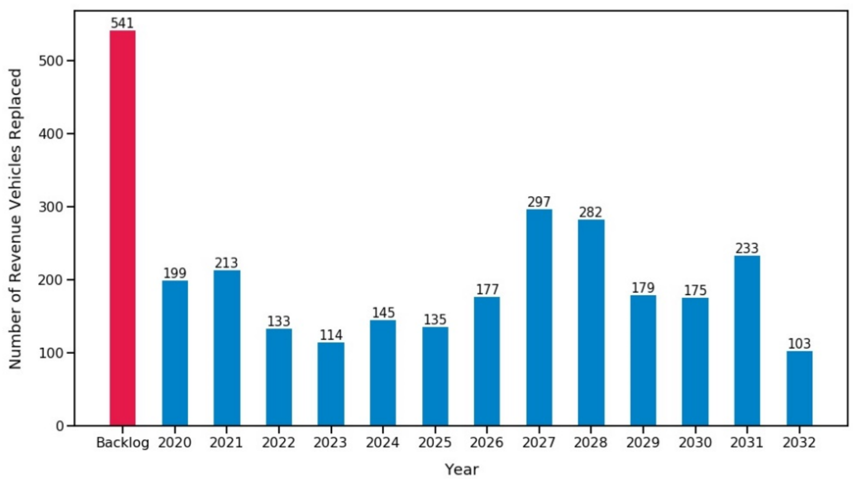
41 TX – Revenue Vehicles Information for Texas's Small Urban and Rural Transit Systems (NTD 2017)



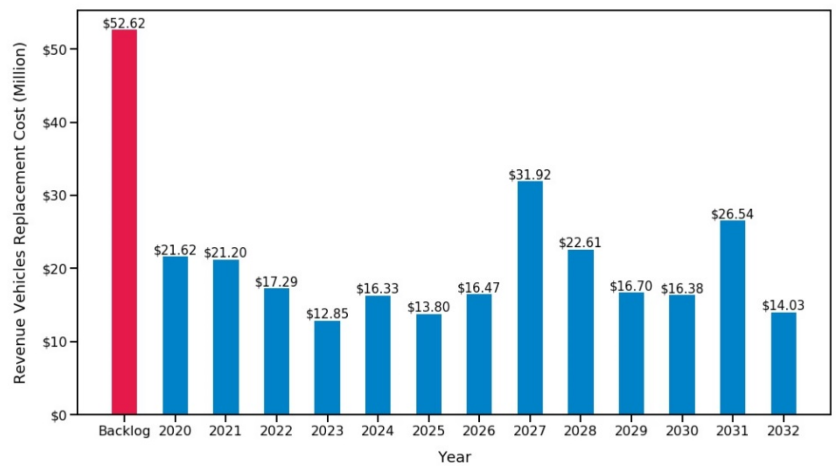
Number of Revenue Vehicles by Vehicle Type



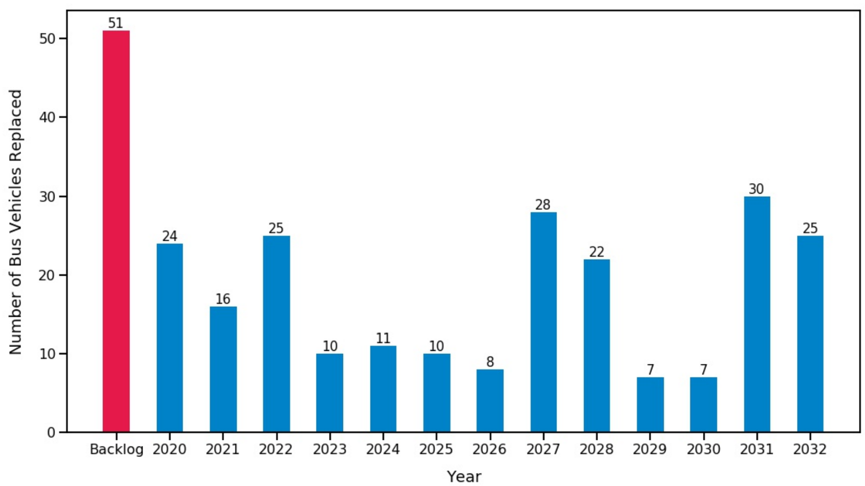
Percentage of Revenue Vehicles



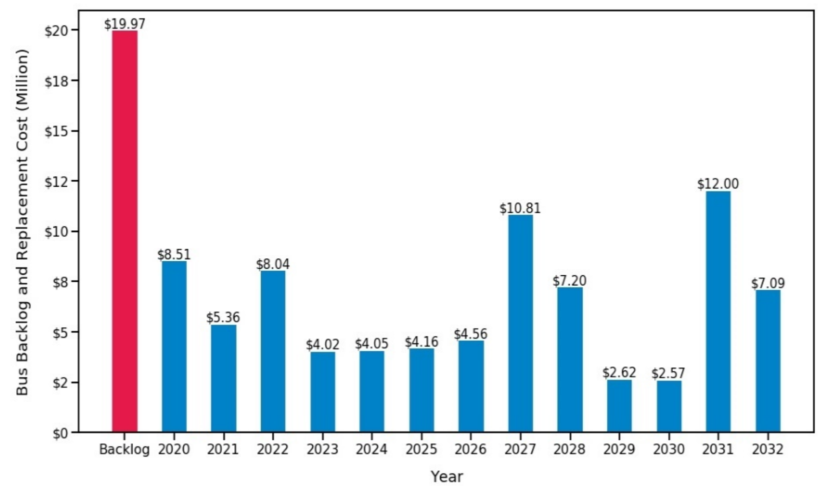
Backlog and Projected Replacement of Revenue Vehicles



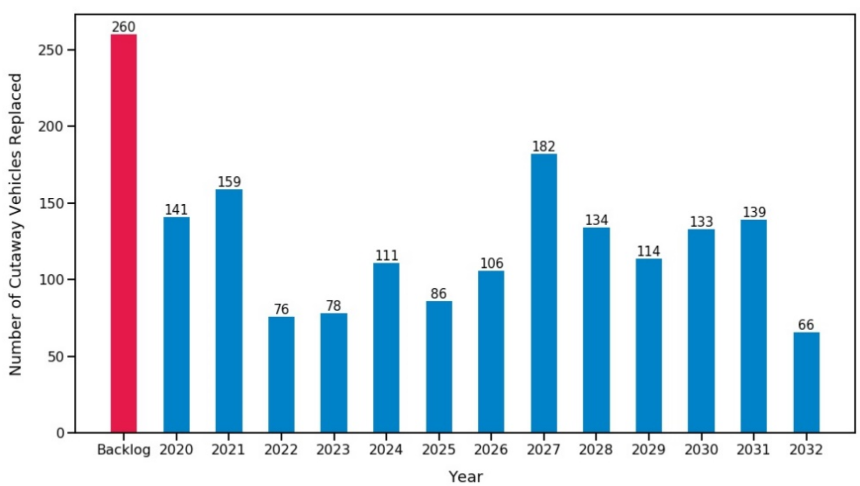
Backlog and Projected Replacement Costs for Revenue Vehicles



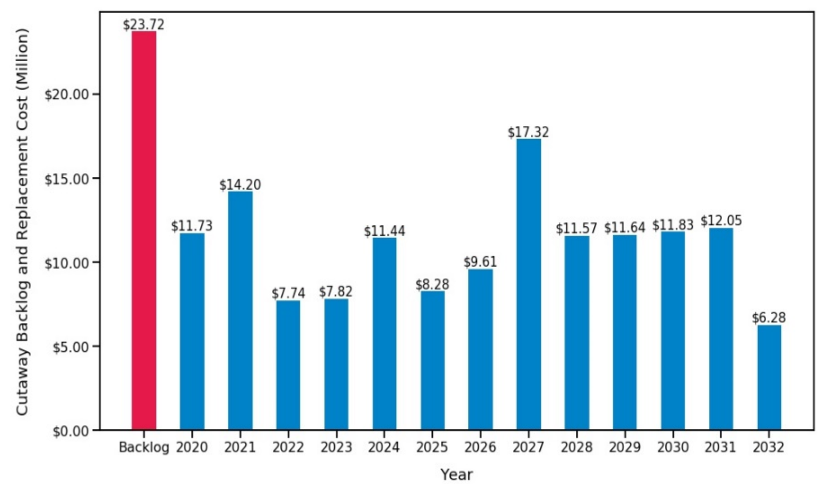
Backlog and Projected Replacement of Buses



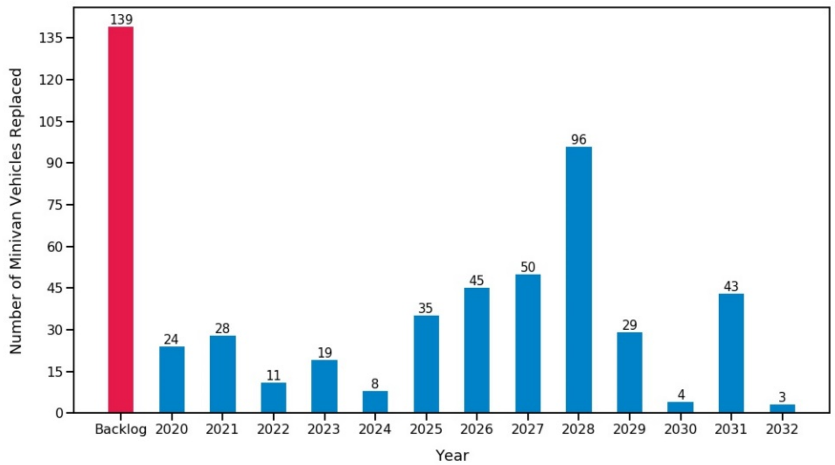
Backlog and Projected Replacement Cost for Buses



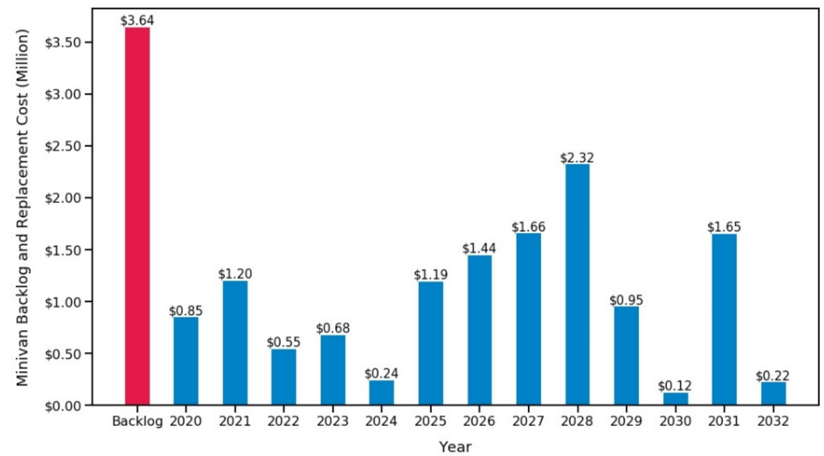
Backlog and Projected Replacement of Cutaways



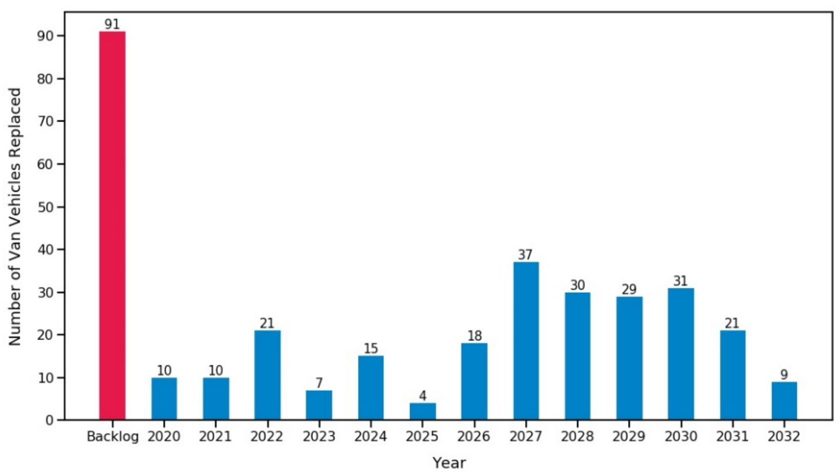
Backlog and Projected Replacement Cost for Cutaways



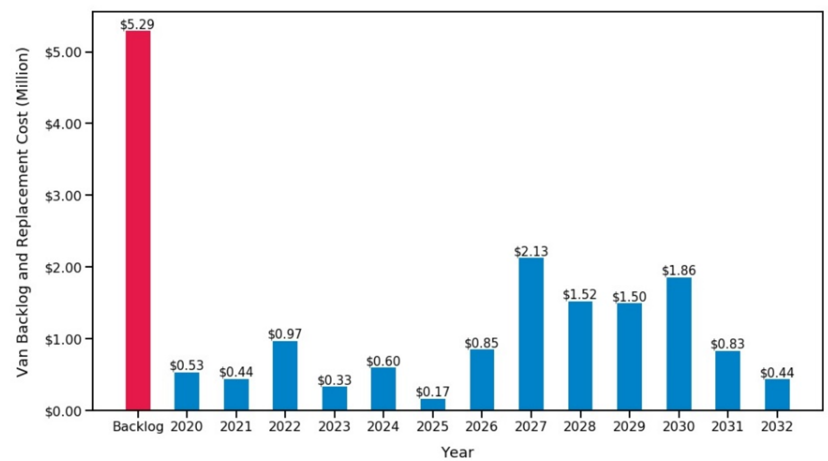
Backlog and Projected Replacement of Minivans



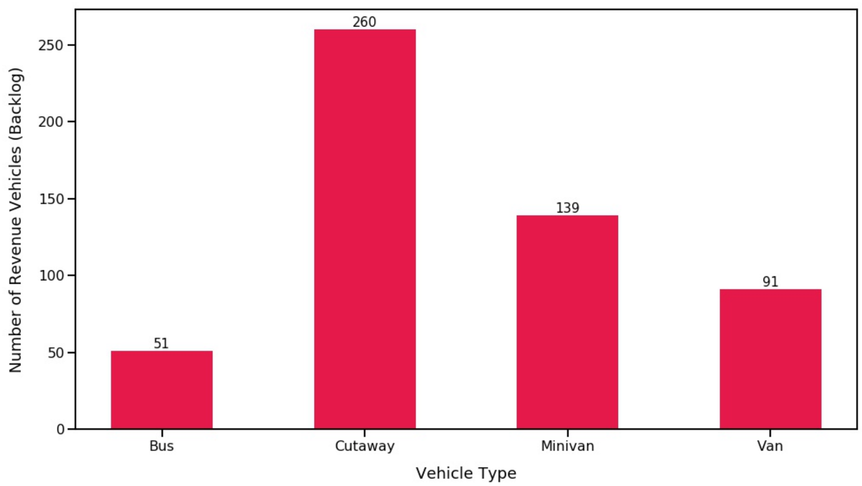
Backlog and Projected Replacement Cost for Minivans



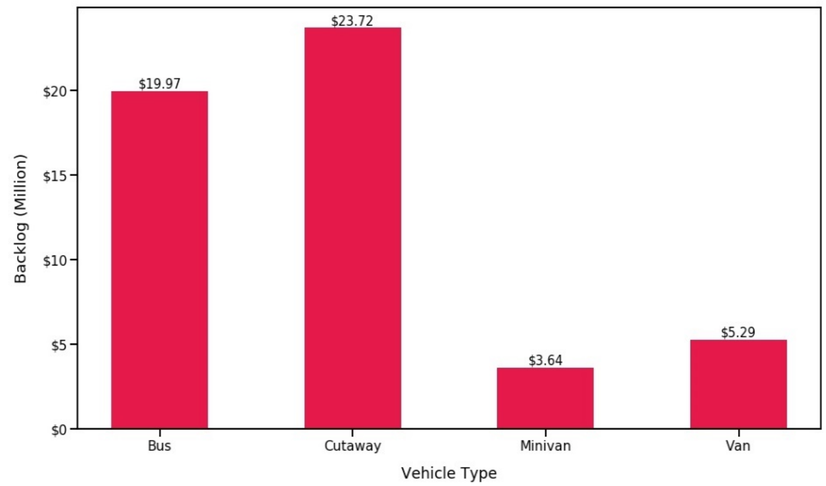
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

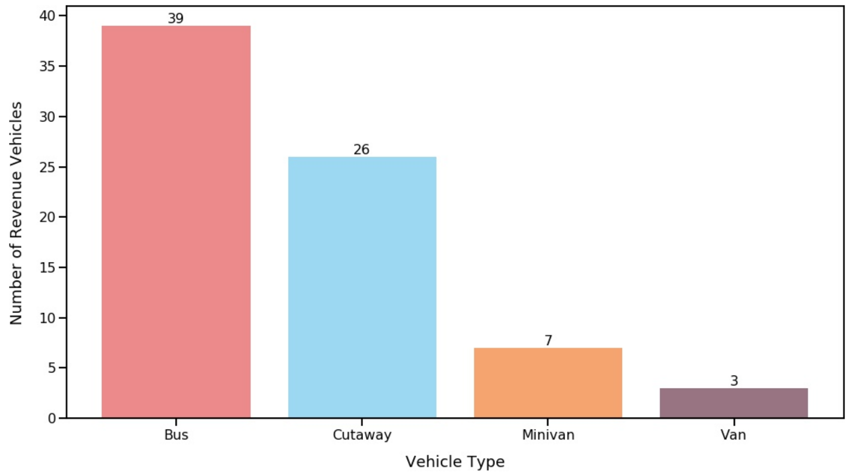


Backlog of the Revenue Vehicles by Vehicle Type

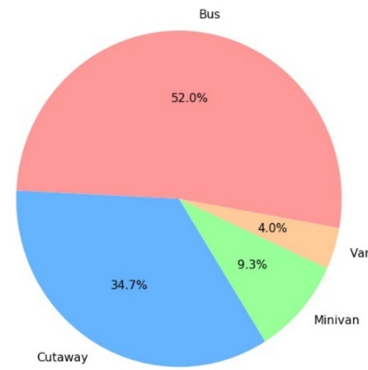


Funds Needed for Backlog by Vehicle Type

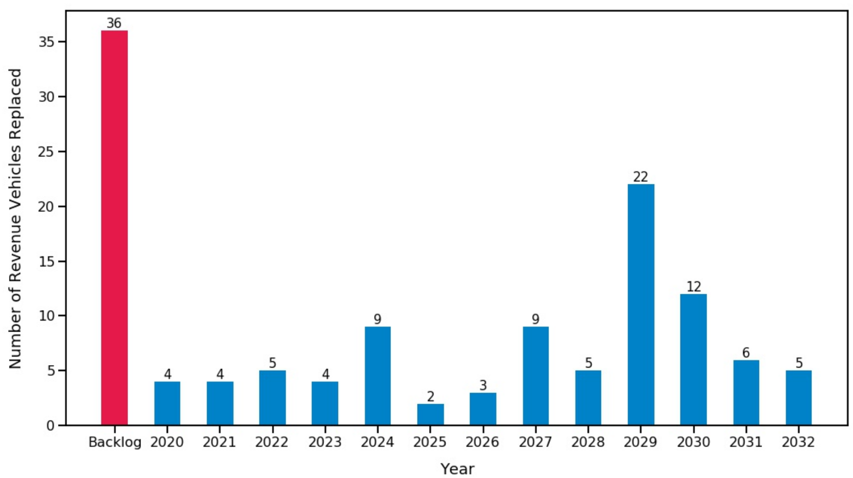
42 UT – Revenue Vehicles Information for Utah's Small Urban and Rural Transit Systems (NTD 2017)



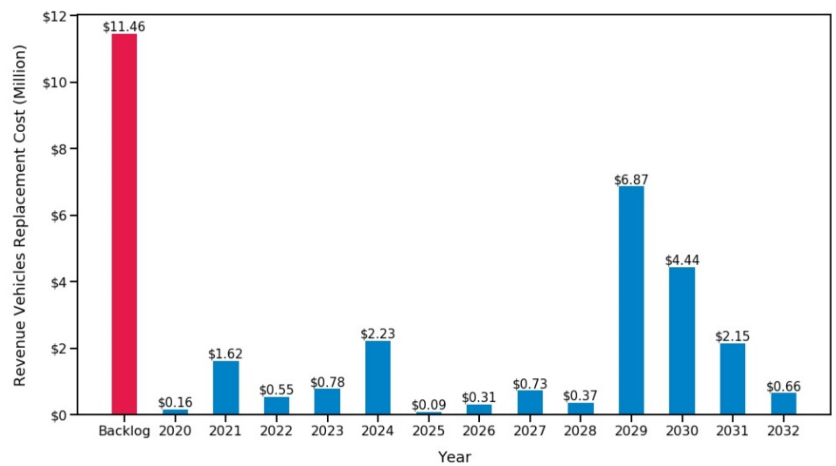
Number of Revenue Vehicles by Vehicle Type



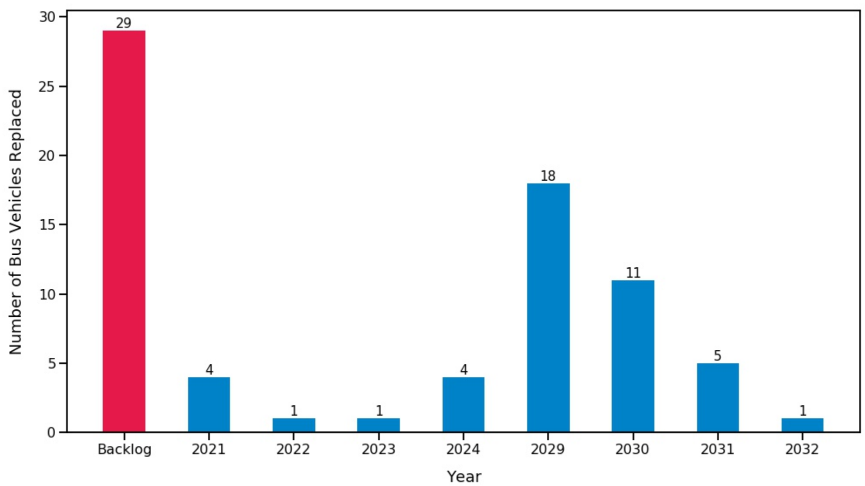
Percentage of Revenue Vehicles



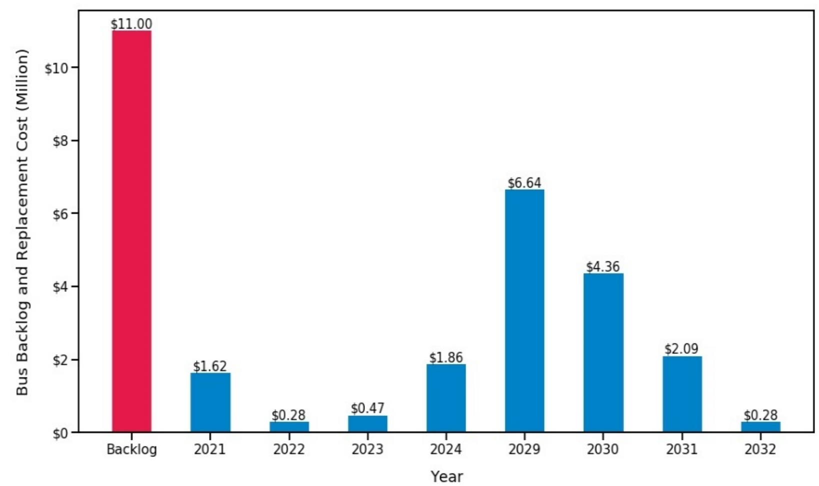
Backlog and Projected Replacement of Revenue Vehicles



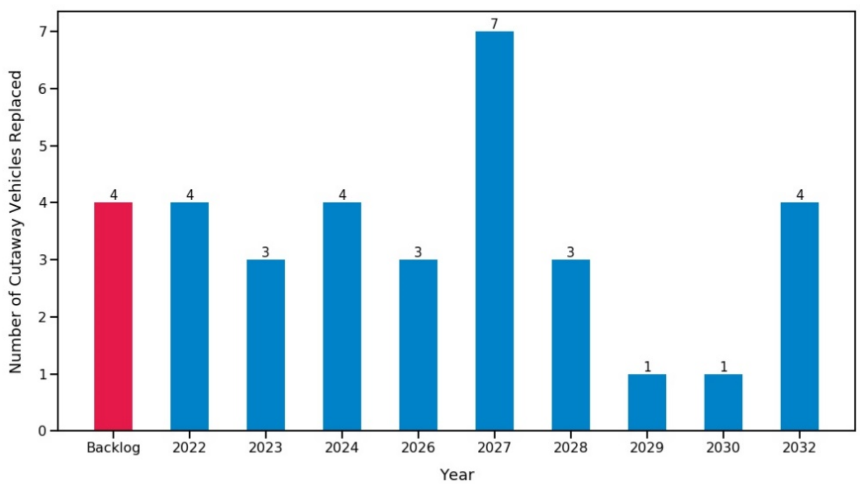
Backlog and Projected Replacement Costs for Revenue Vehicles



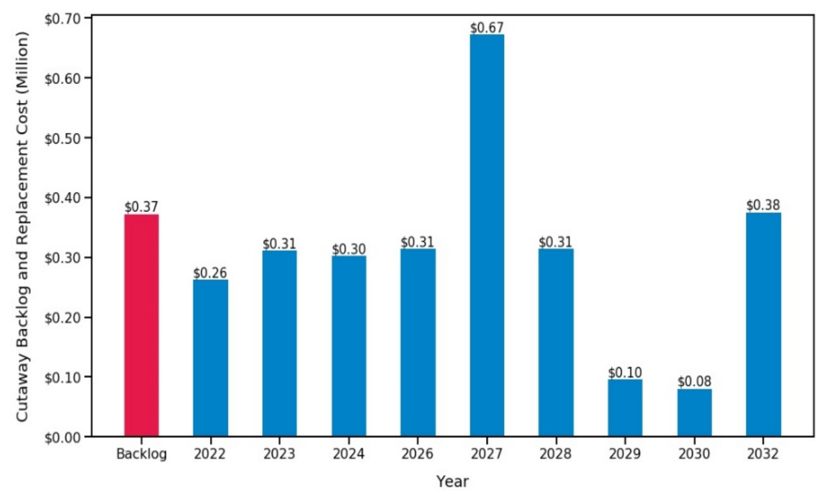
Backlog and Projected Replacement of Buses



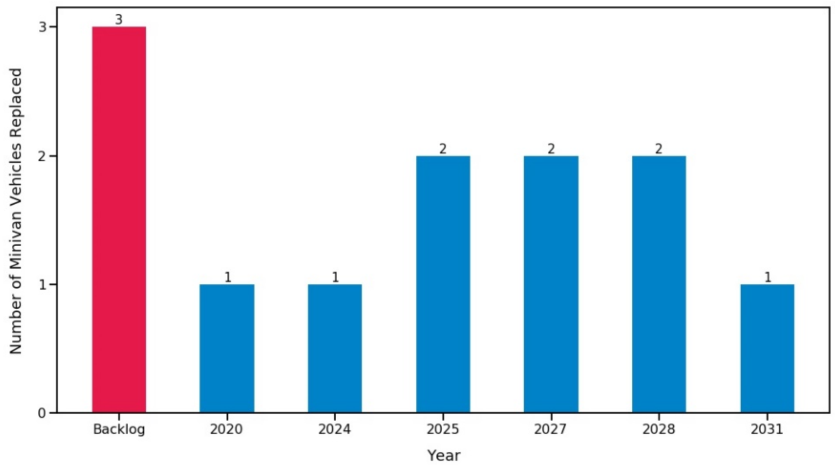
Backlog and Projected Replacement Cost for Buses



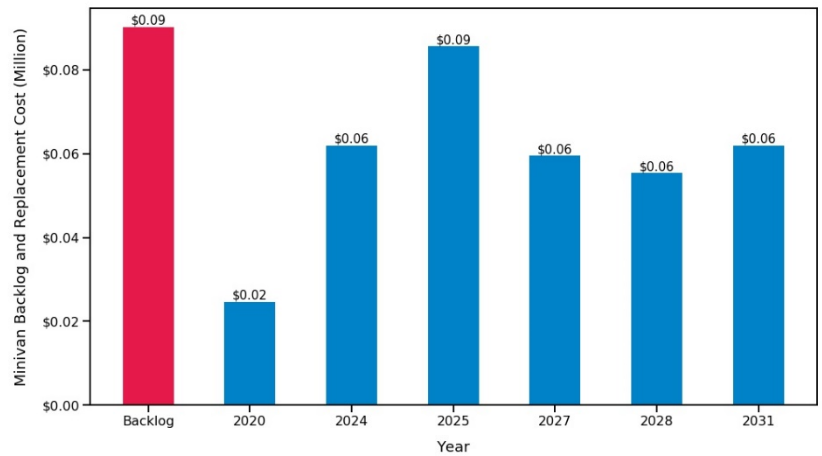
Backlog and Projected Replacement of Cutaways



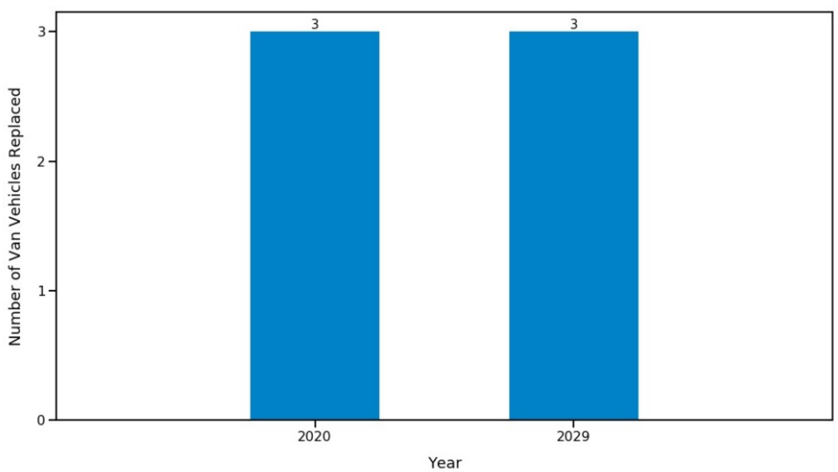
Backlog and Projected Replacement Cost for Cutaways



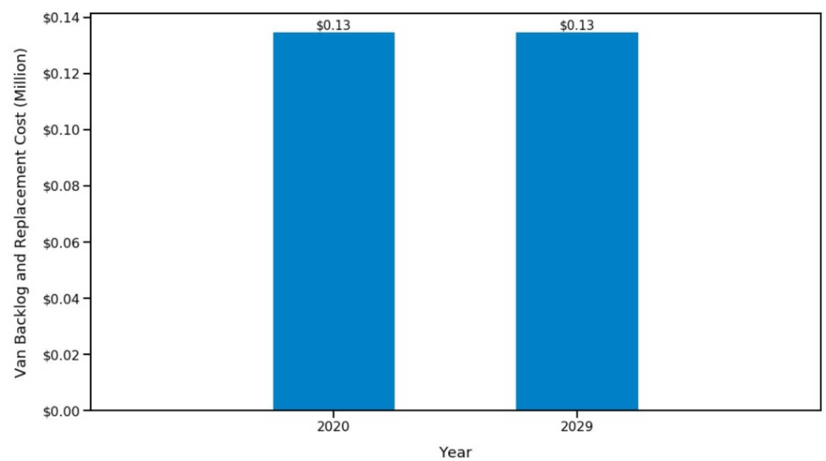
Backlog and Projected Replacement of Minivans



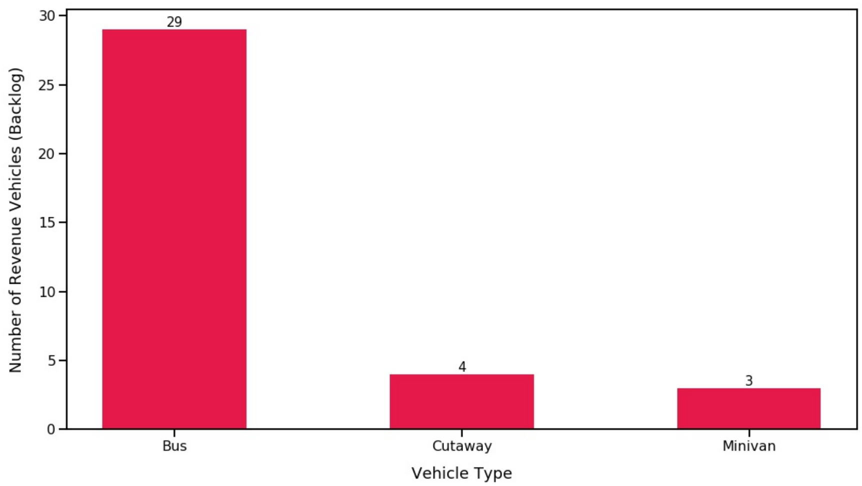
Backlog and Projected Replacement Cost for Minivans



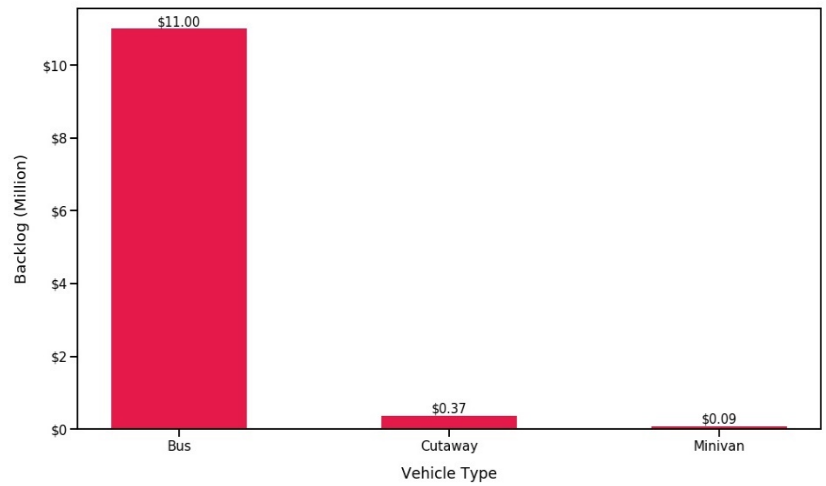
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

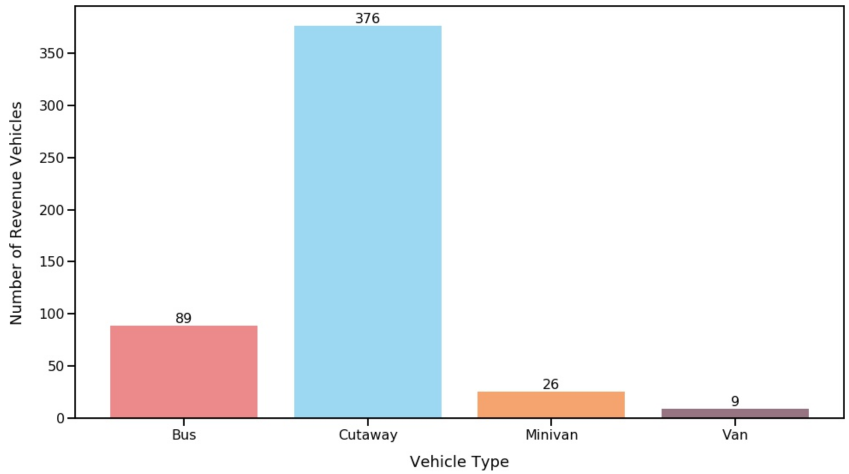


Backlog of the Revenue Vehicles by Vehicle Type

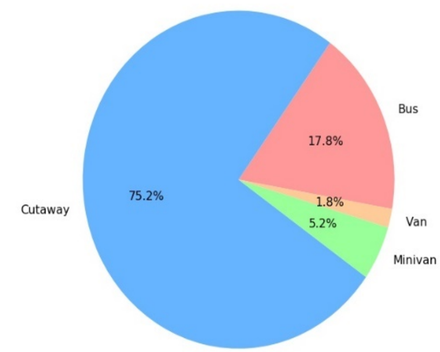


Funds Needed for Backlog by Vehicle Type

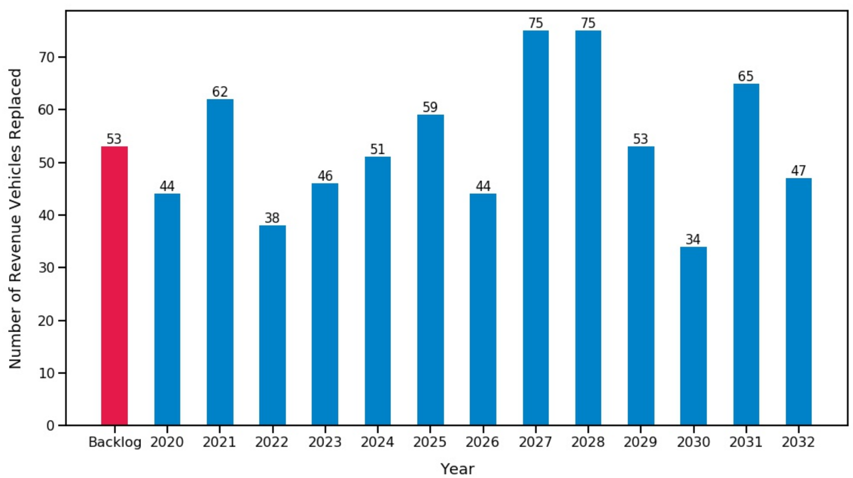
43 VA – Revenue Vehicles Information for Virginia's Small Urban and Rural Transit Systems (NTD 2017)



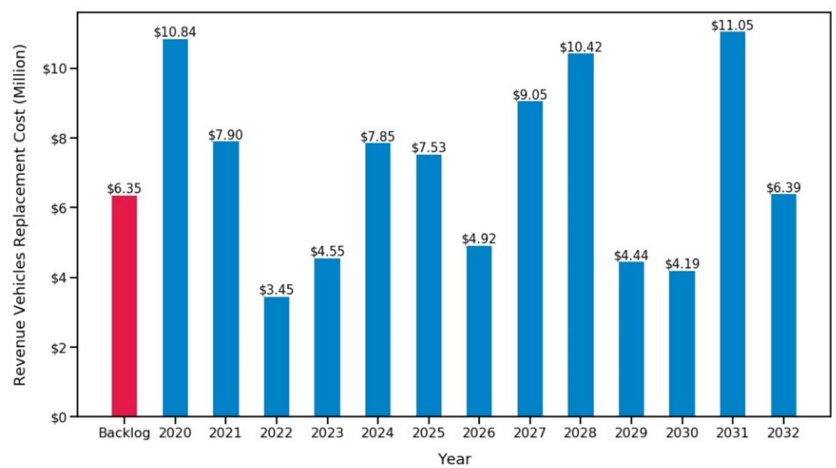
Number of Revenue Vehicles by Vehicle Type



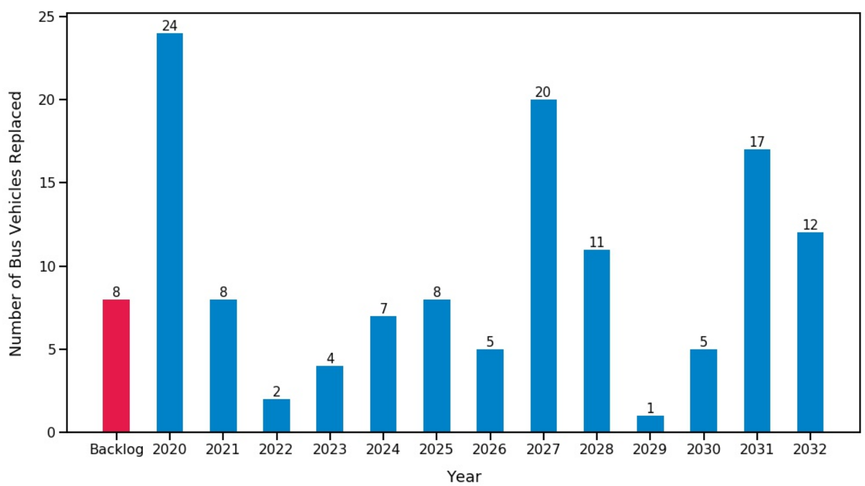
Percentage of Revenue Vehicles



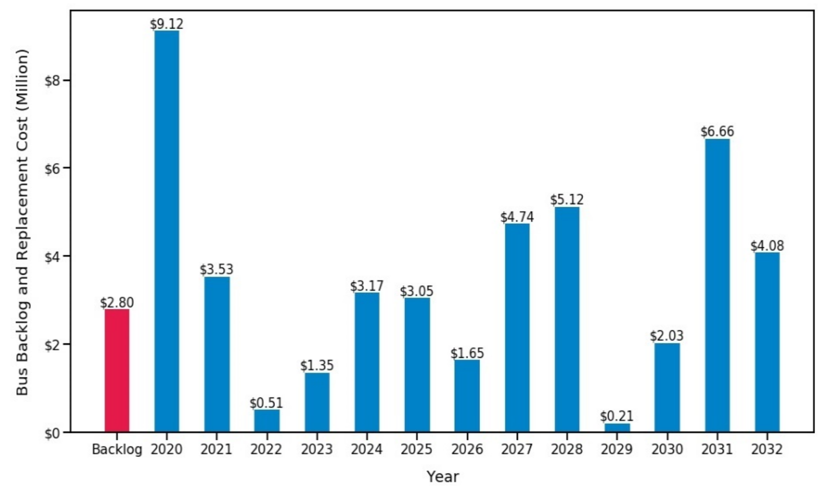
Backlog and Projected Replacement of Revenue Vehicles



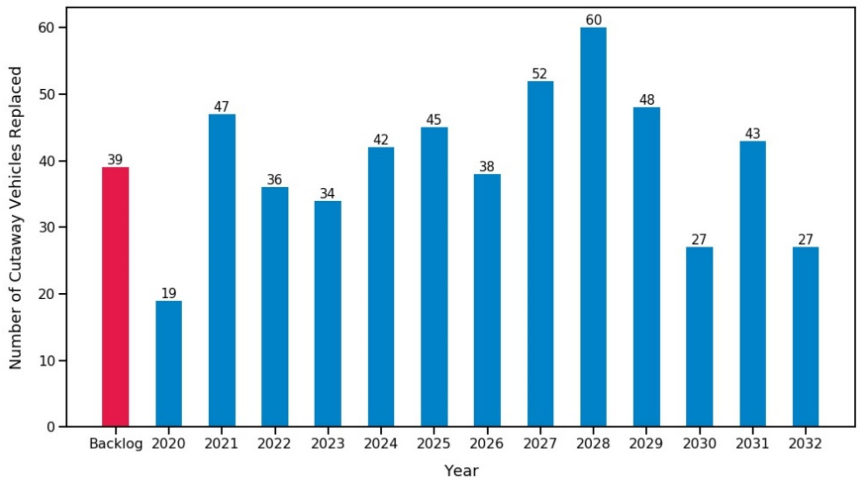
Backlog and Projected Replacement Costs for Revenue Vehicles



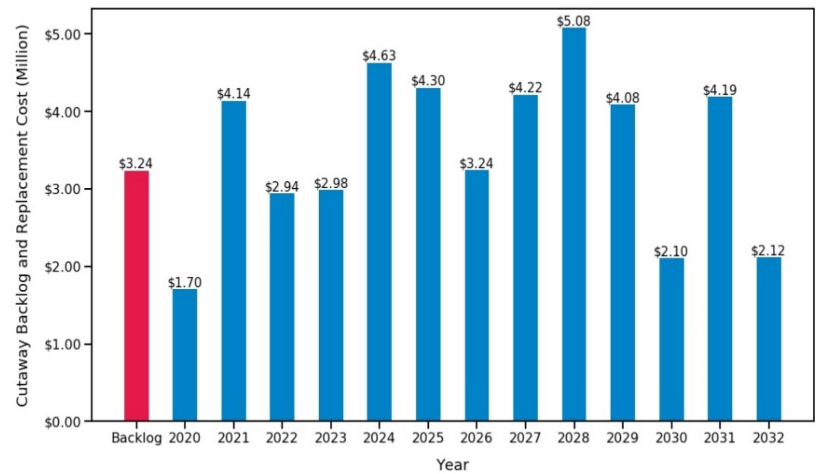
Backlog and Projected Replacement of Buses



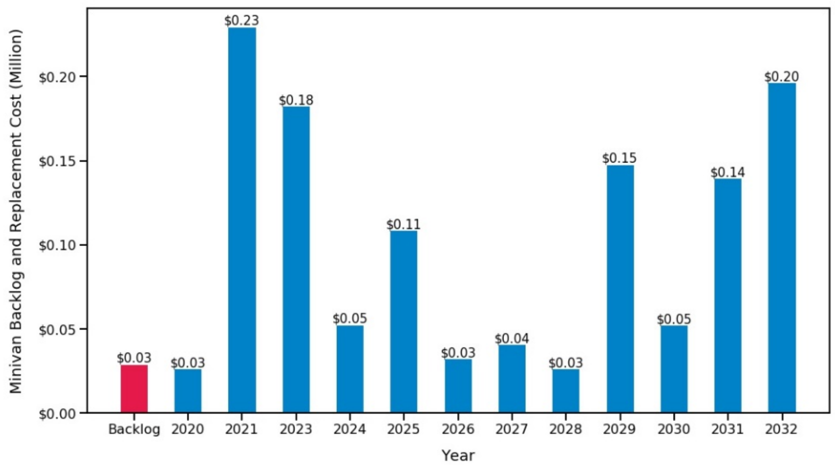
Backlog and Projected Replacement Cost for Buses



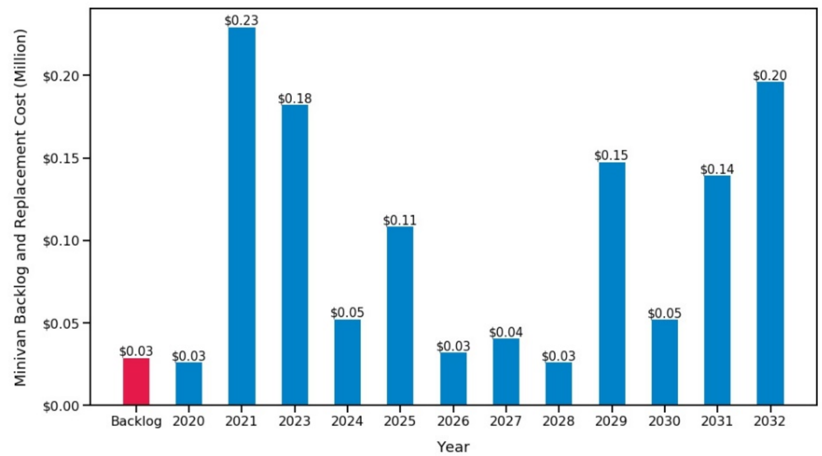
Backlog and Projected Replacement of Cutaways



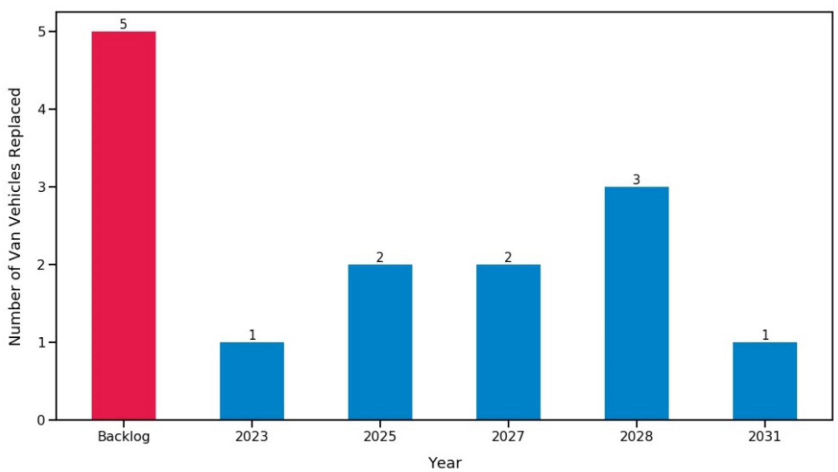
Backlog and Projected Replacement Cost for Cutaways



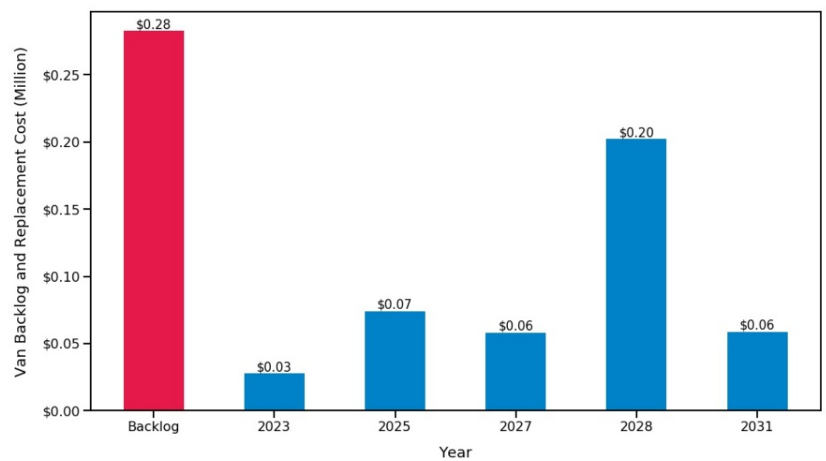
Backlog and Projected Replacement of Minivans



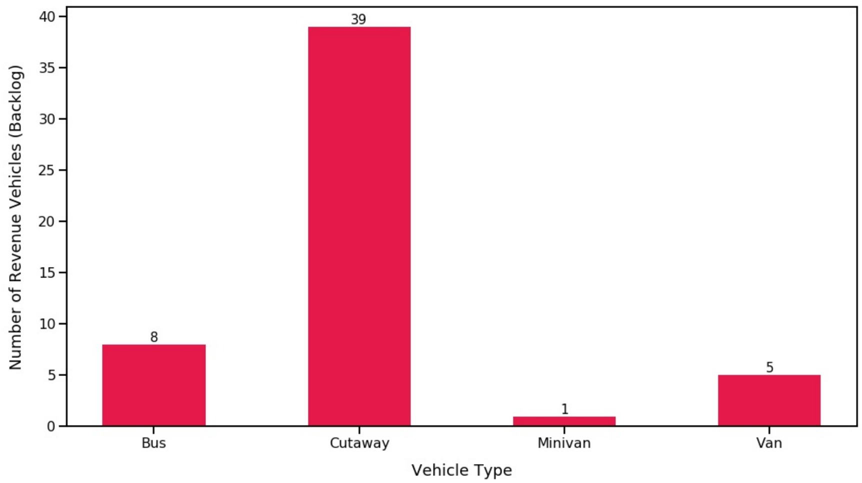
Backlog and Projected Replacement Cost for Minivans

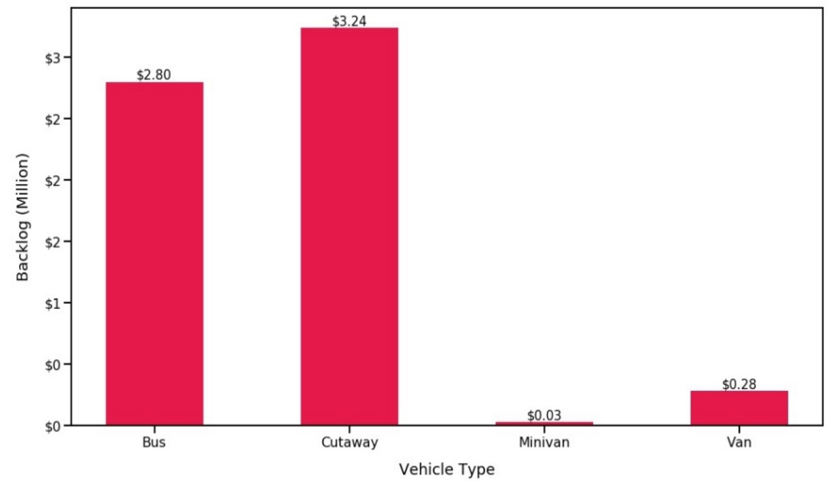


Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

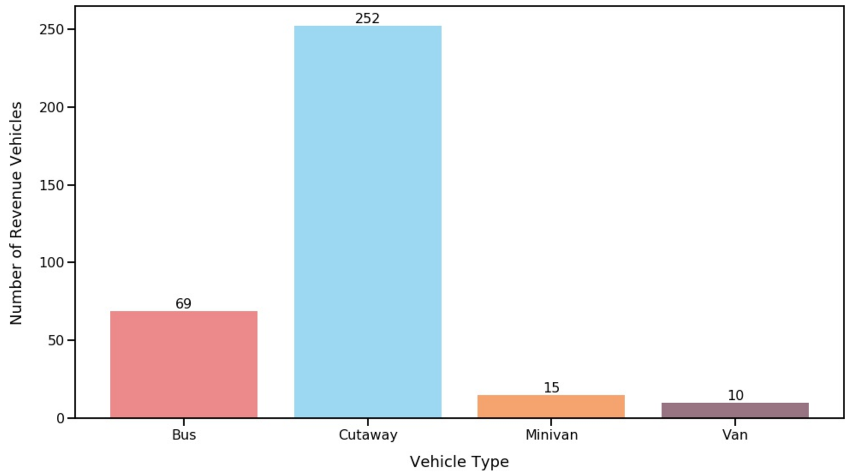




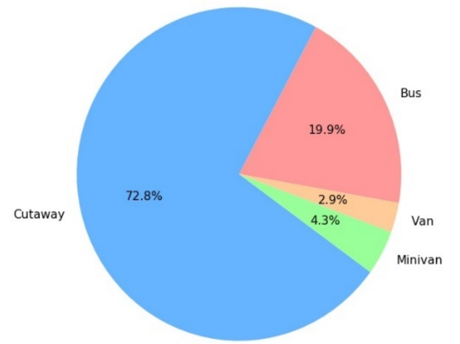
Backlog of the Revenue Vehicles by Vehicle Type

Funds Needed for Backlog by Vehicle Type

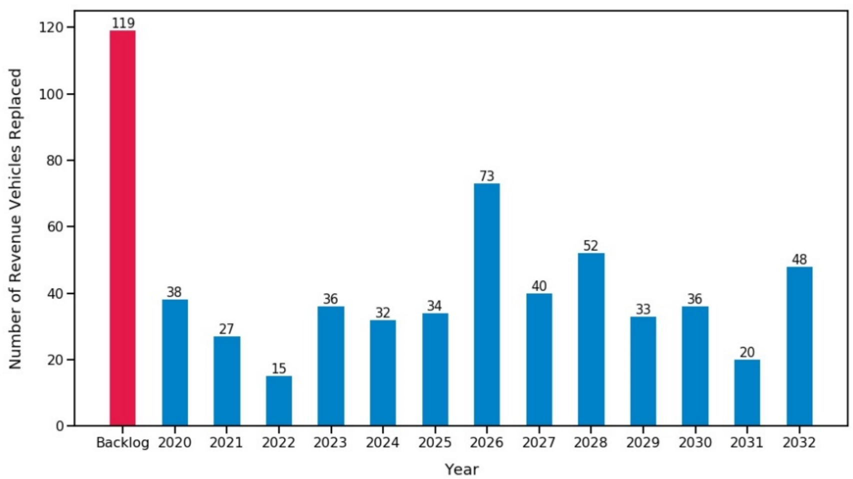
44 VT – Revenue Vehicles Information for Vermont's Small Urban and Rural Transit Systems (NTD 2017)



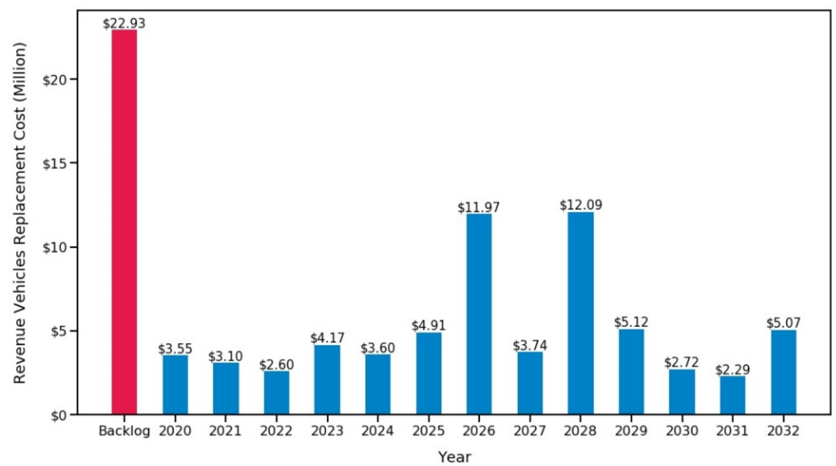
Number of Revenue Vehicles by Vehicle Type



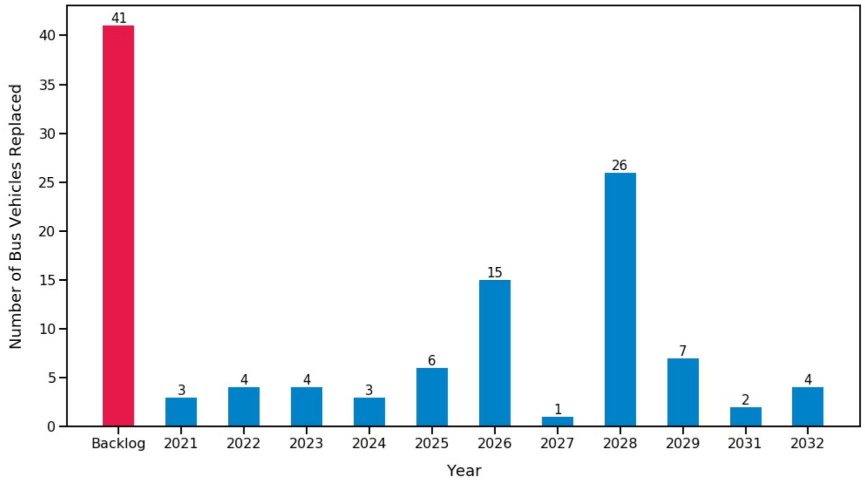
Percentage of Revenue Vehicles



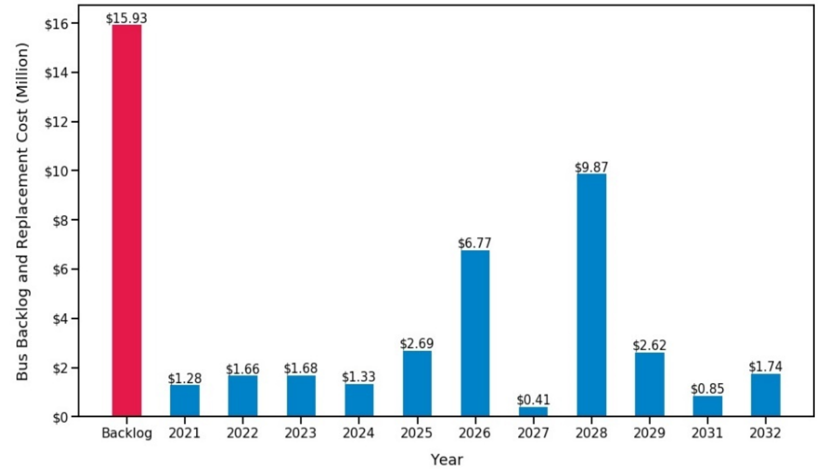
Backlog and Projected Replacement of Revenue Vehicles



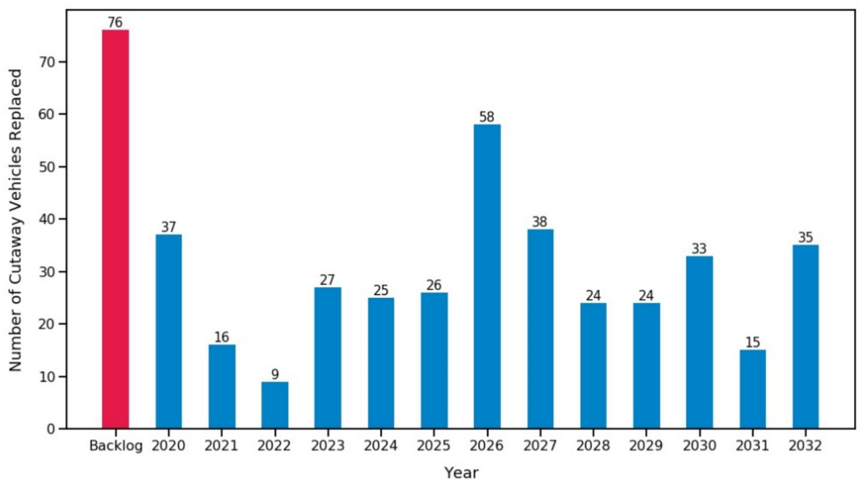
Backlog and Projected Replacement Costs for Revenue Vehicles



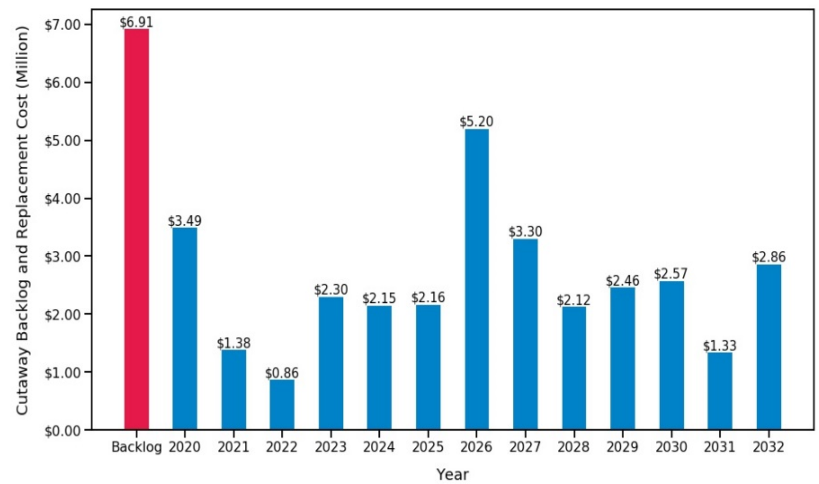
Backlog and Projected Replacement of Buses



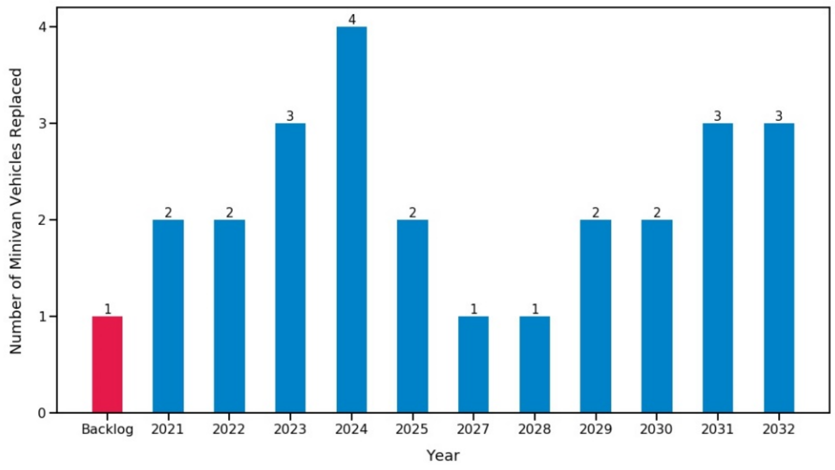
Backlog and Projected Replacement Cost for Buses



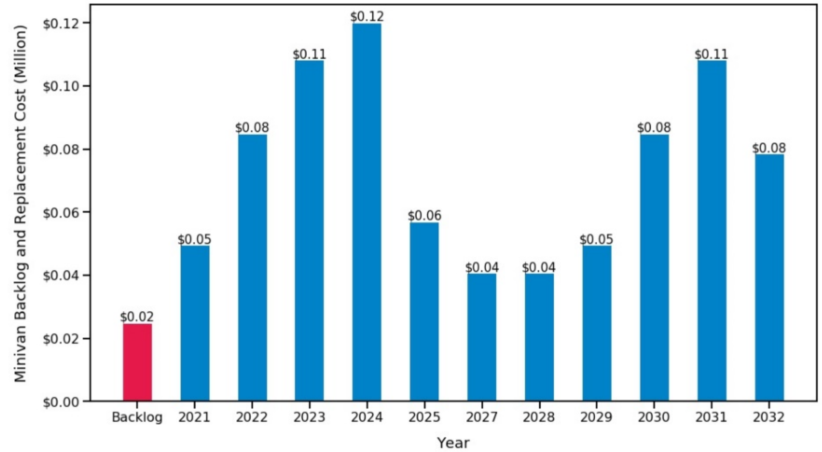
Backlog and Projected Replacement of Cutaways



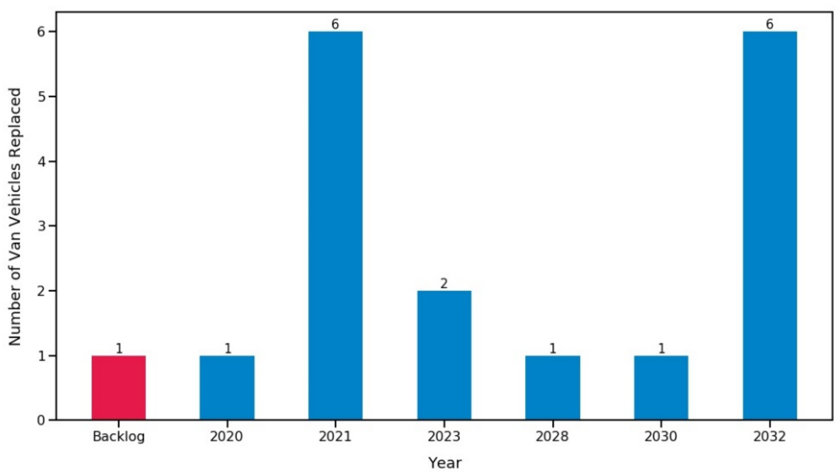
Backlog and Projected Replacement Cost for Cutaways



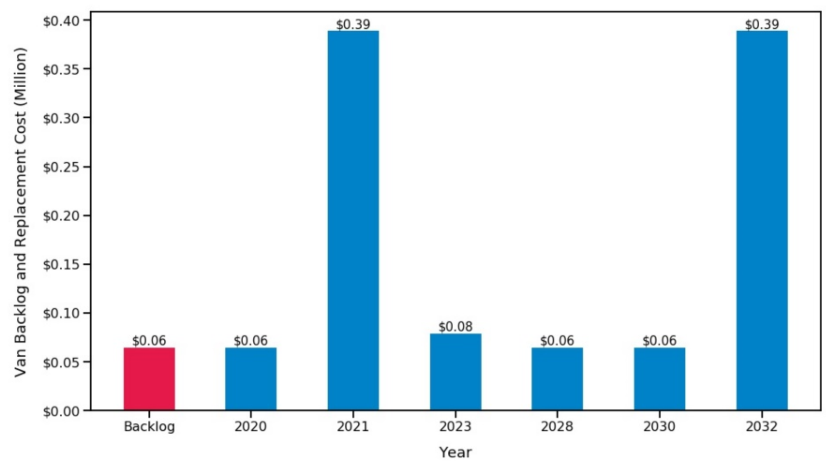
Backlog and Projected Replacement of Minivans



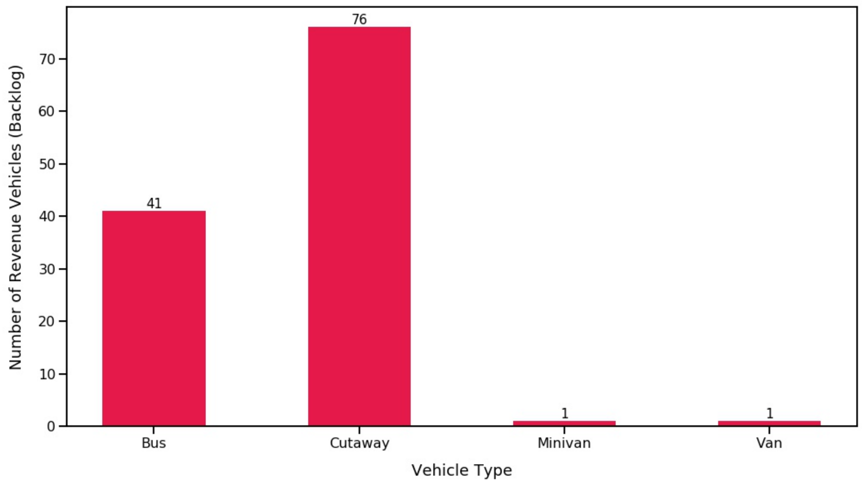
Backlog and Projected Replacement Cost for Minivans



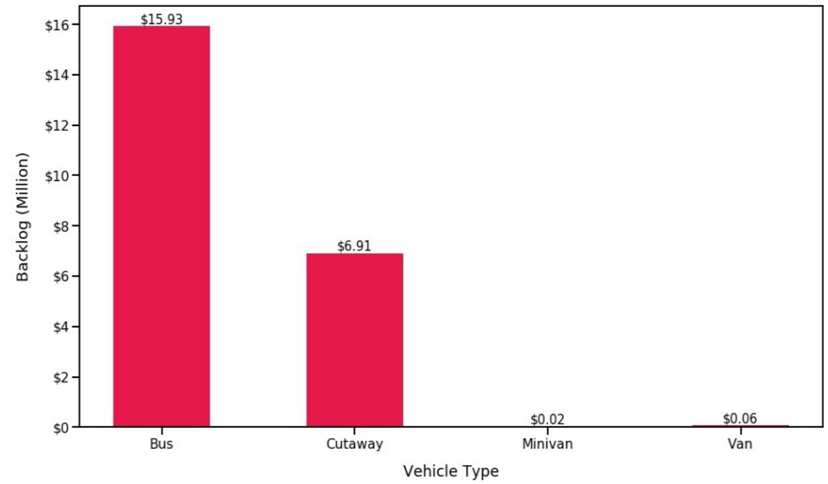
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

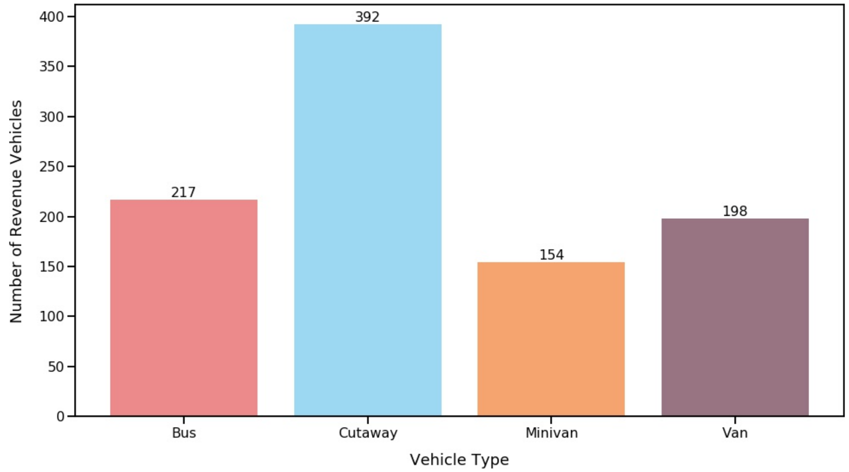


Backlog of the Revenue Vehicles by Vehicle Type

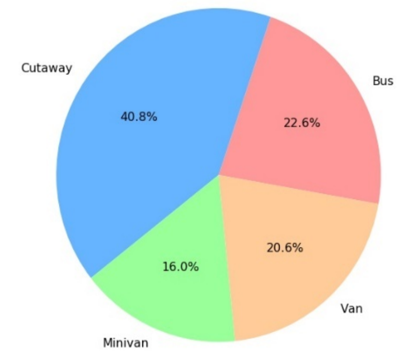


Funds Needed for Backlog by Vehicle Type

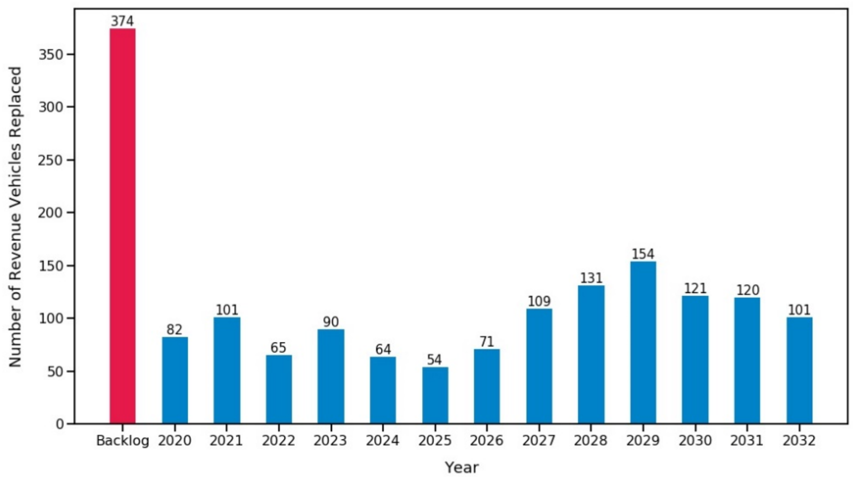
45 WA – Revenue Vehicles Information for Washington's Small Urban and Rural Transit Systems (NTD 2017)



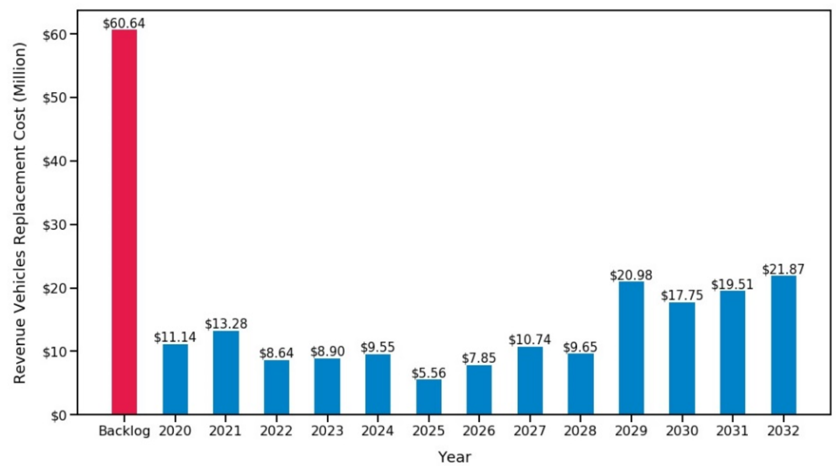
Number of Revenue Vehicles by Vehicle Type



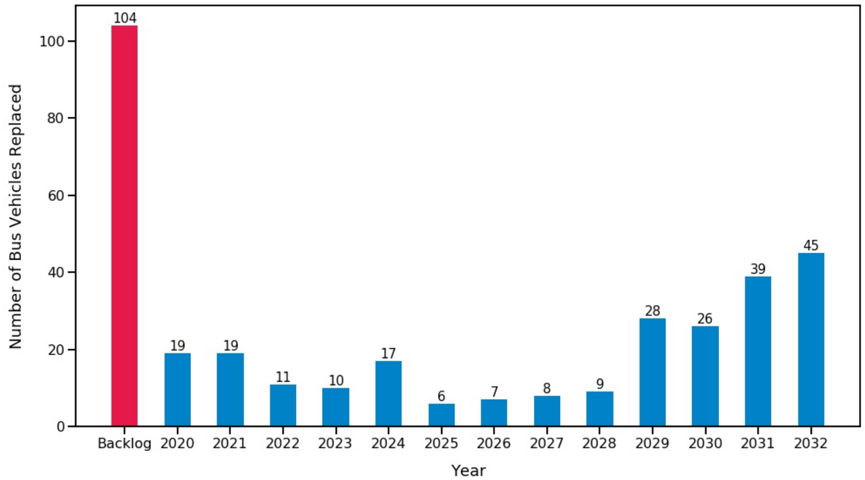
Percentage of Revenue Vehicles



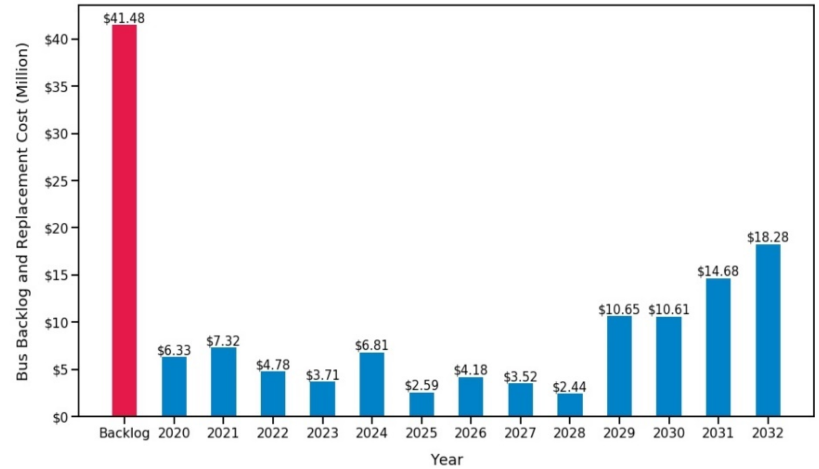
Backlog and Projected Replacement of Revenue Vehicles



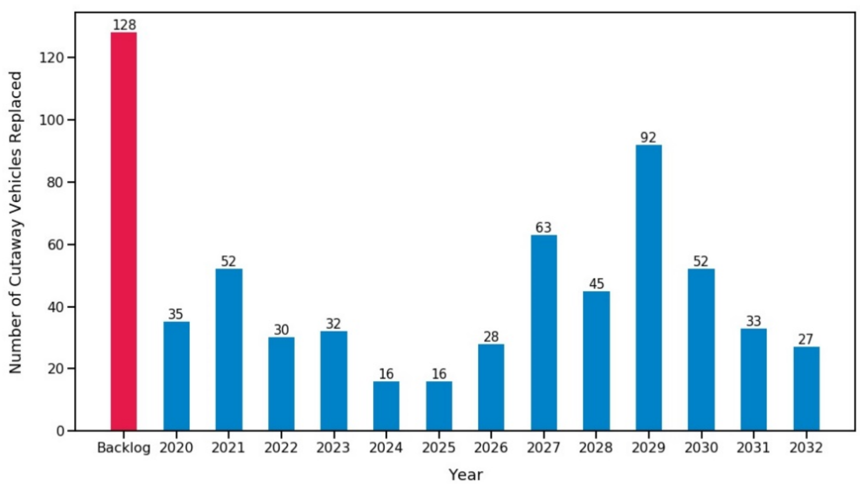
Backlog and Projected Replacement Costs for Revenue Vehicles



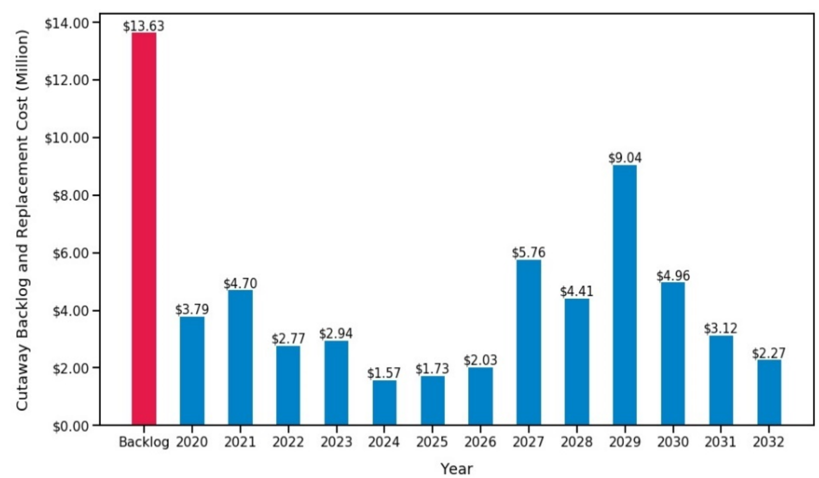
Backlog and Projected Replacement of Buses



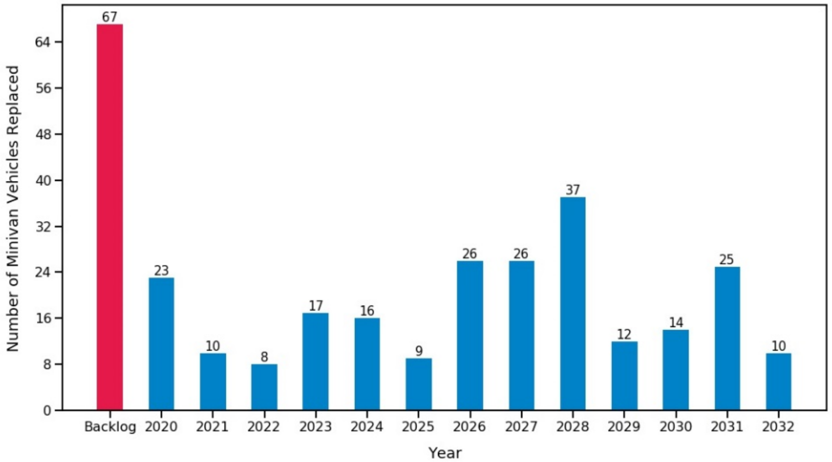
Backlog and Projected Replacement Cost for Buses



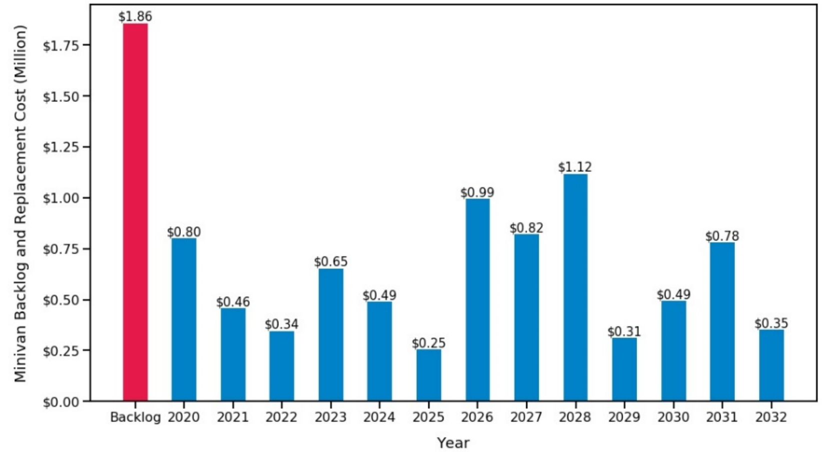
Backlog and Projected Replacement of Cutaways



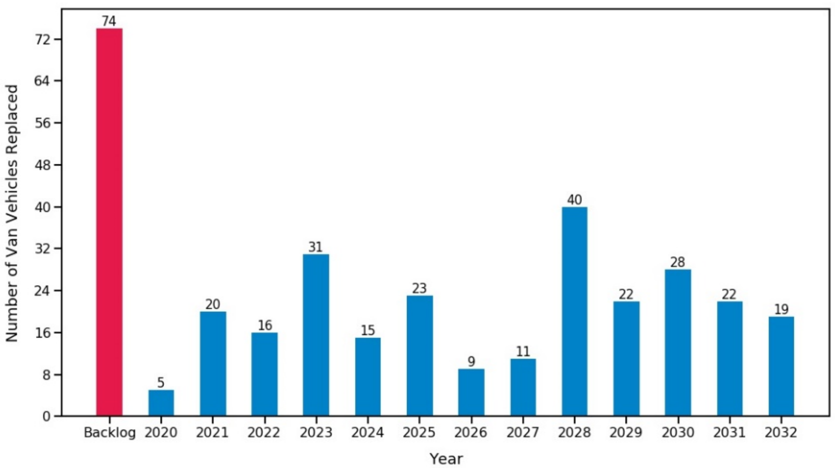
Backlog and Projected Replacement Cost for Cutaways



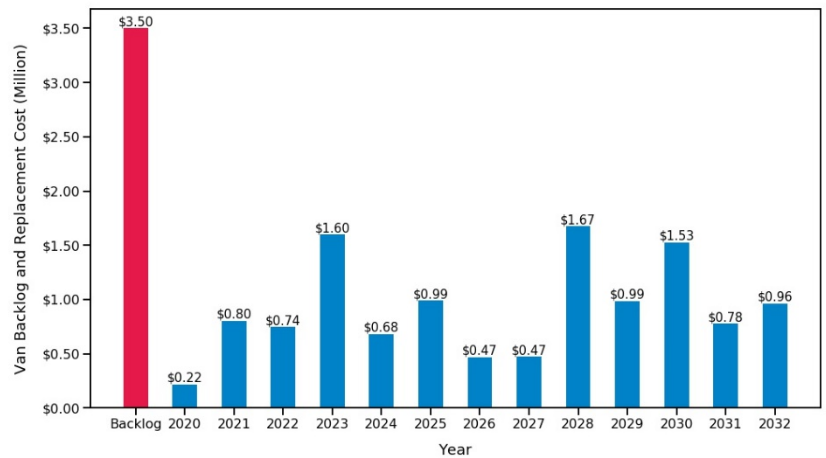
Backlog and Projected Replacement of Minivans



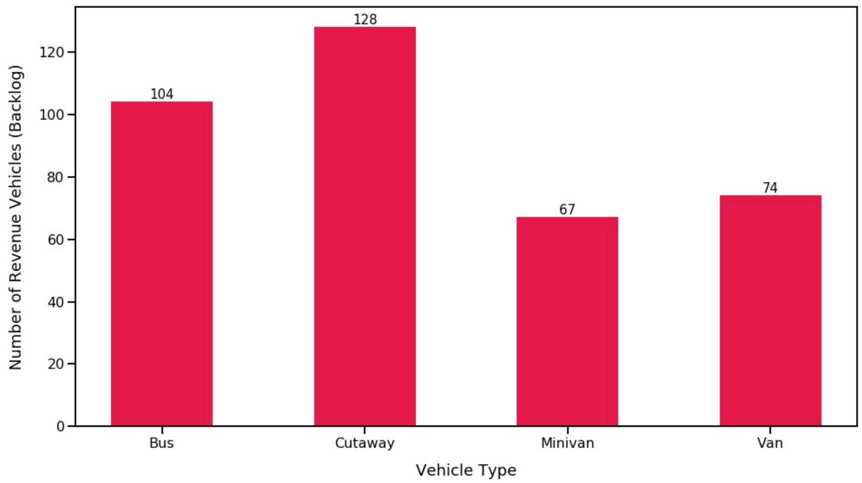
Backlog and Projected Replacement Cost for Minivans



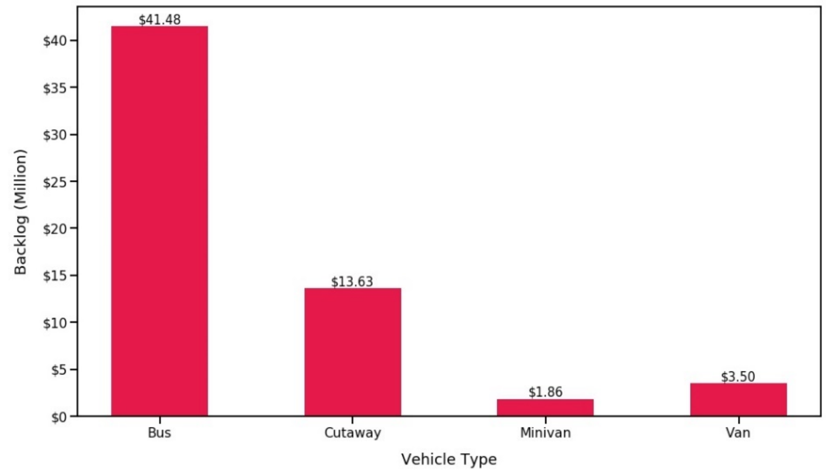
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

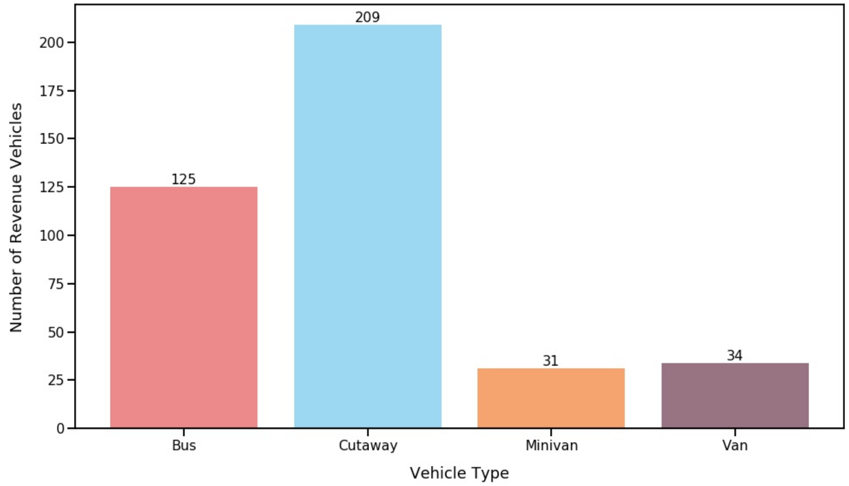


Backlog of the Revenue Vehicles by Vehicle Type

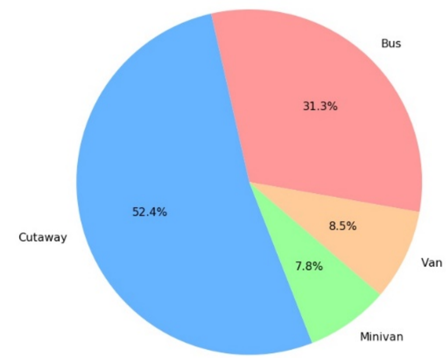


Funds Needed for Backlog by Vehicle Type

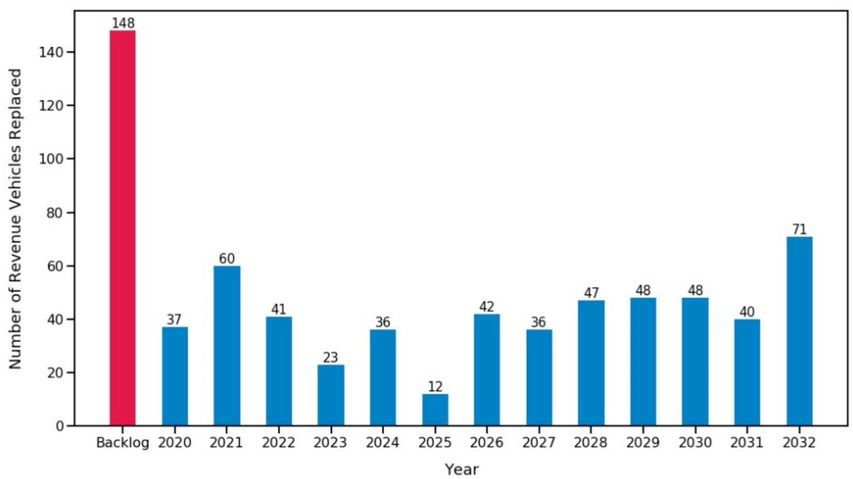
46 WI – Revenue Vehicles Information for Wisconsin's Small Urban and Rural Transit Systems (NTD 2017)



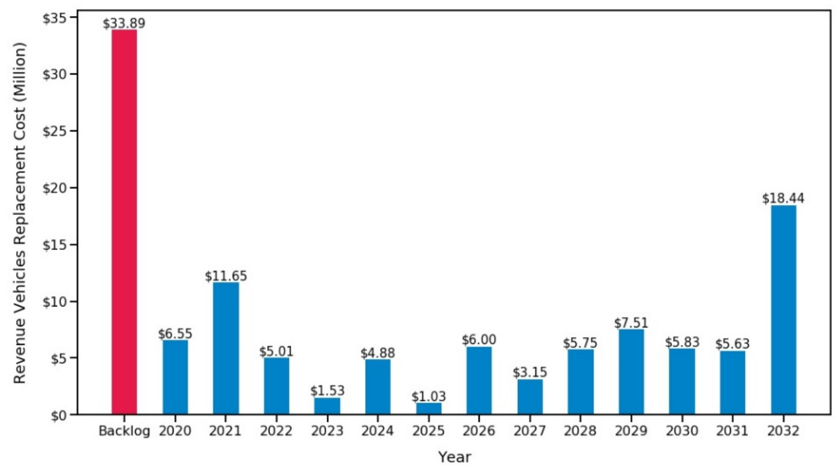
Number of Revenue Vehicles by Vehicle Type



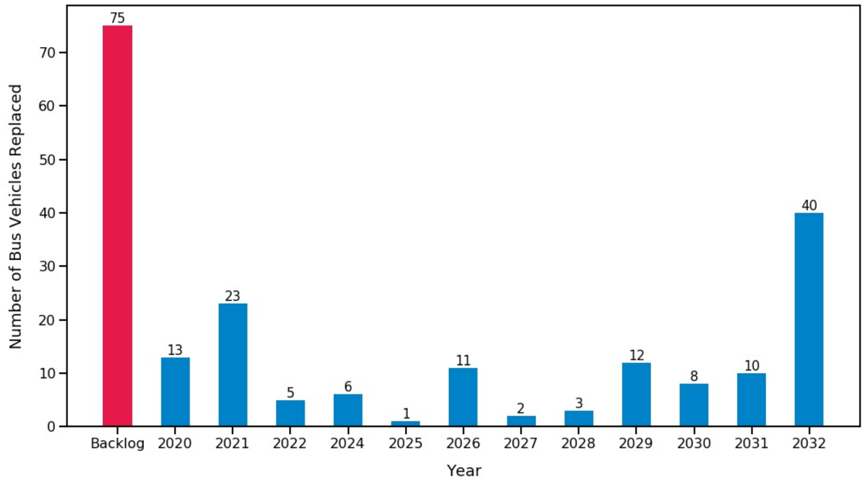
Percentage of Revenue Vehicles



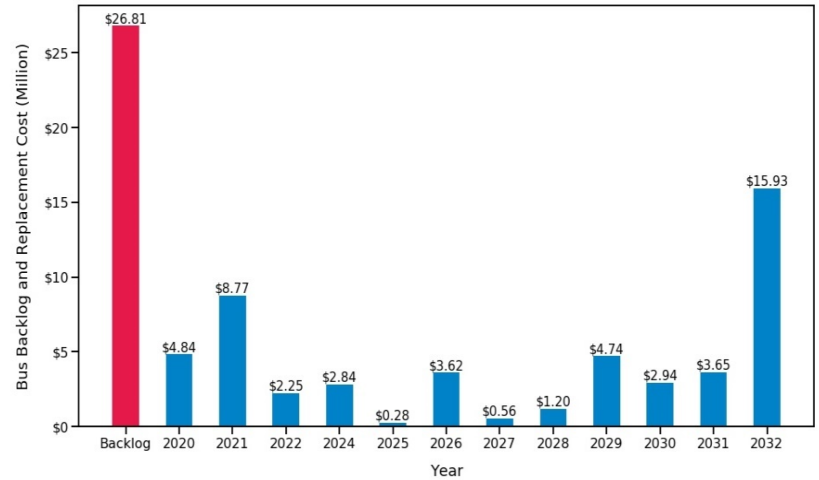
Backlog and Projected Replacement of Revenue Vehicles



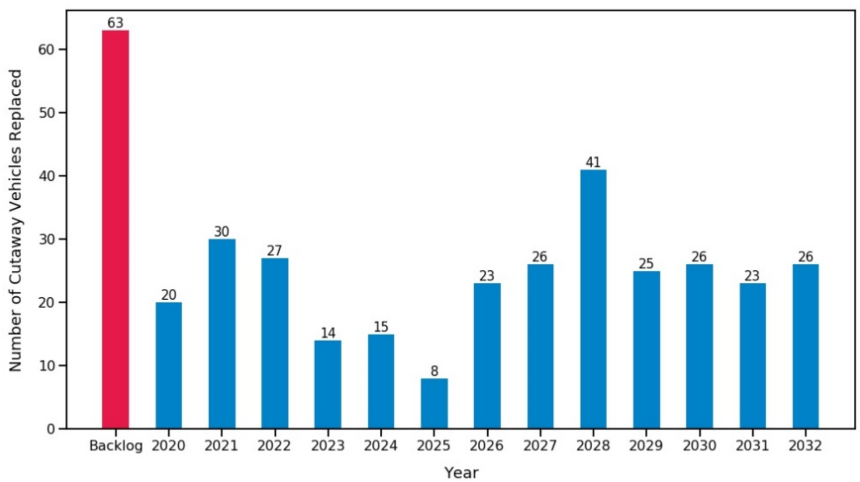
Backlog and Projected Replacement Costs for Revenue Vehicles



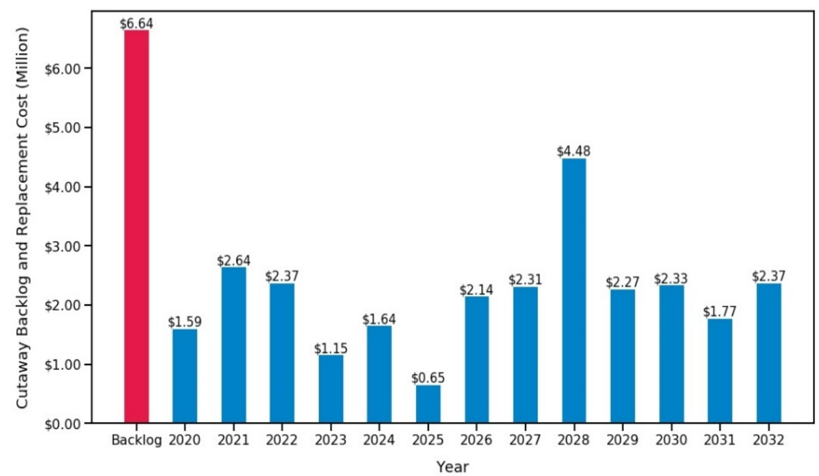
Backlog and Projected Replacement of Buses



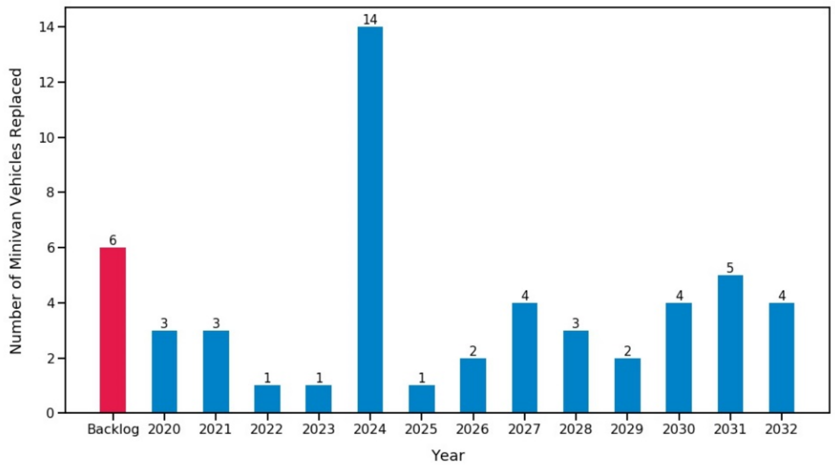
Backlog and Projected Replacement Cost for Buses



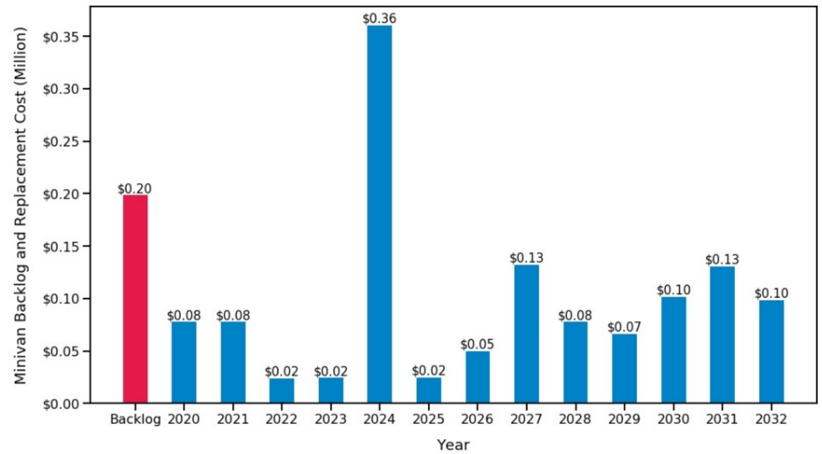
Backlog and Projected Replacement of Cutaways



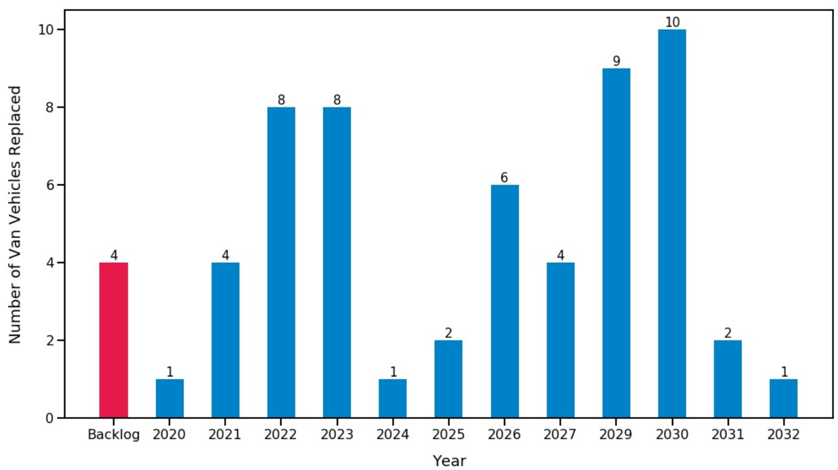
Backlog and Projected Replacement Cost for Cutaways



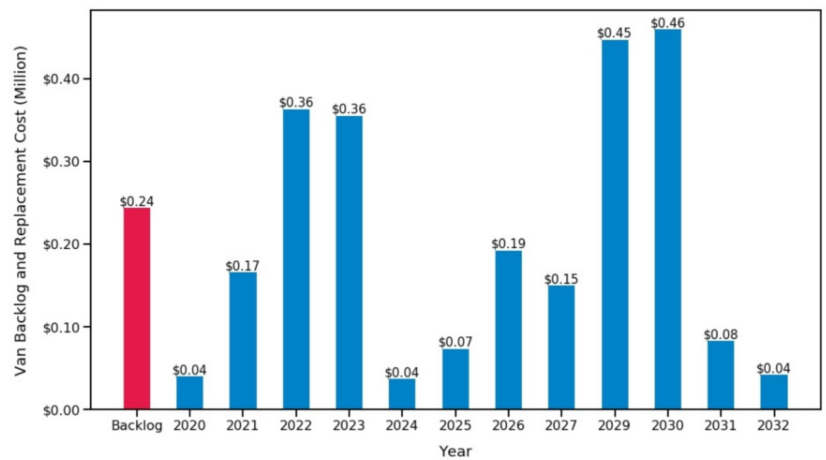
Backlog and Projected Replacement of Minivans



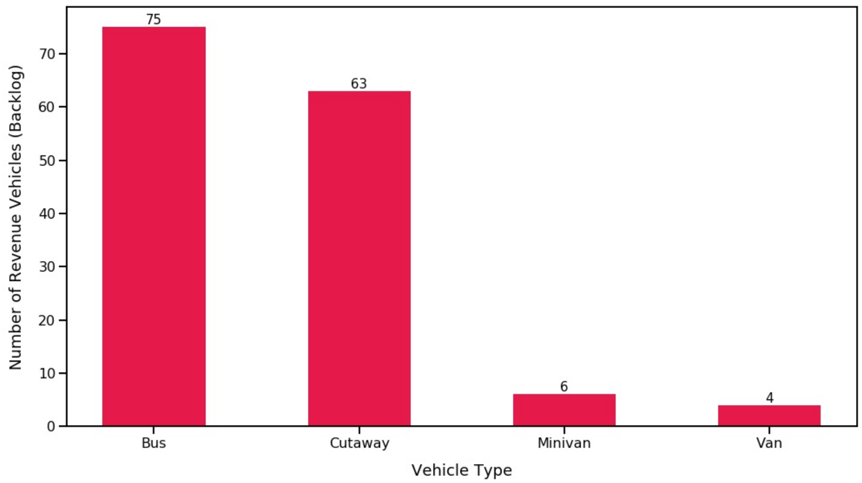
Backlog and Projected Replacement Cost for Minivans



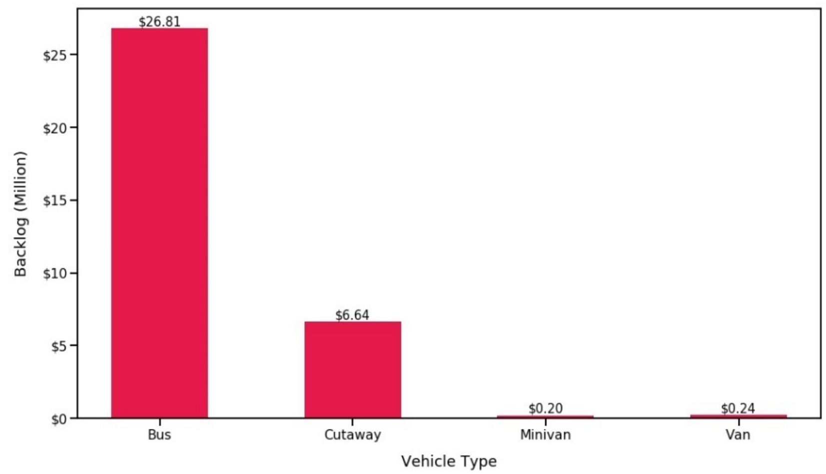
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

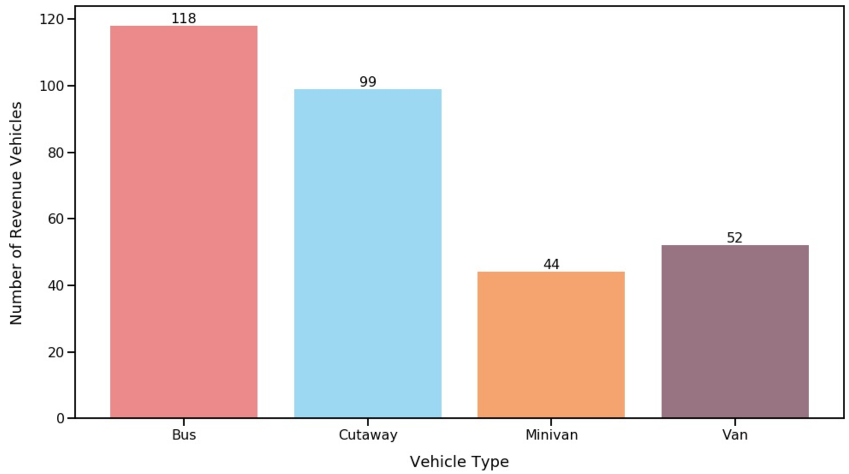


Backlog of the Revenue Vehicles by Vehicle Type

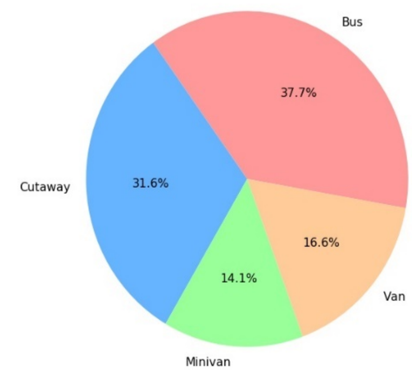


Funds Needed for Backlog by Vehicle Type

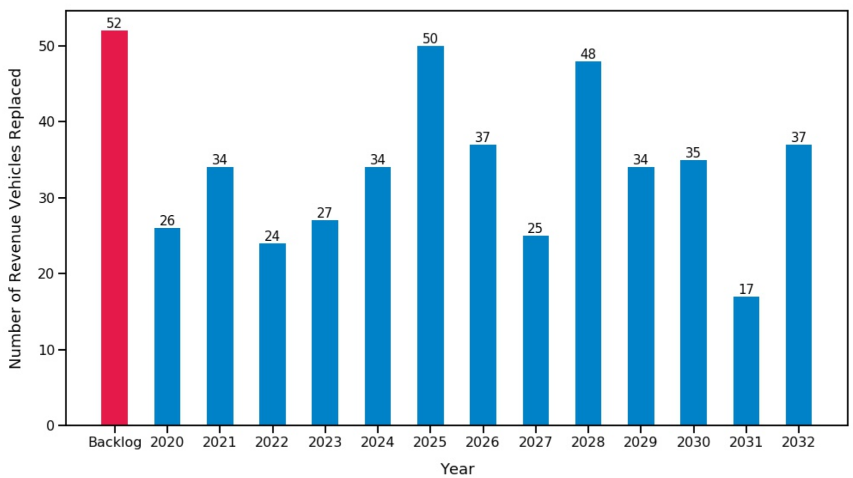
47 WV – Revenue Vehicles Information for West Virginia's Small Urban and Rural Transit Systems (NTD 2017)



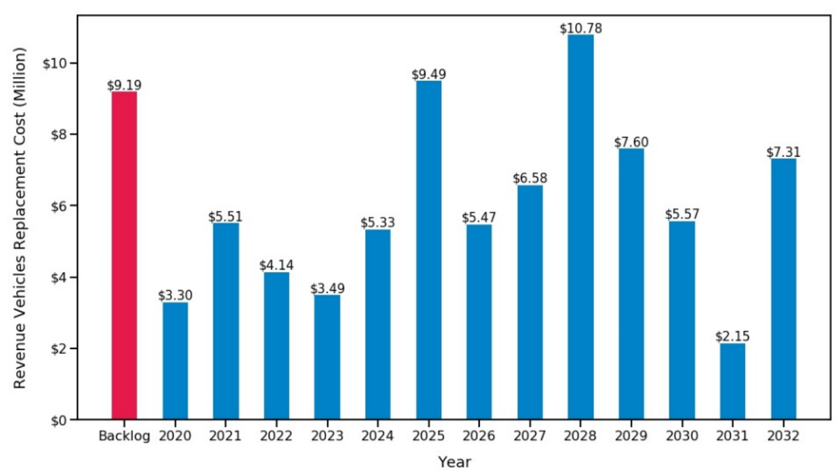
Number of Revenue Vehicles by Vehicle Type



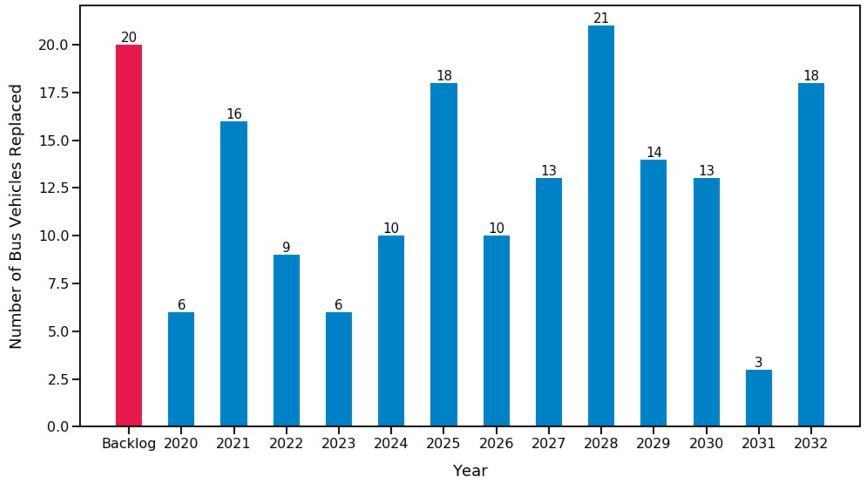
Percentage of Revenue Vehicles



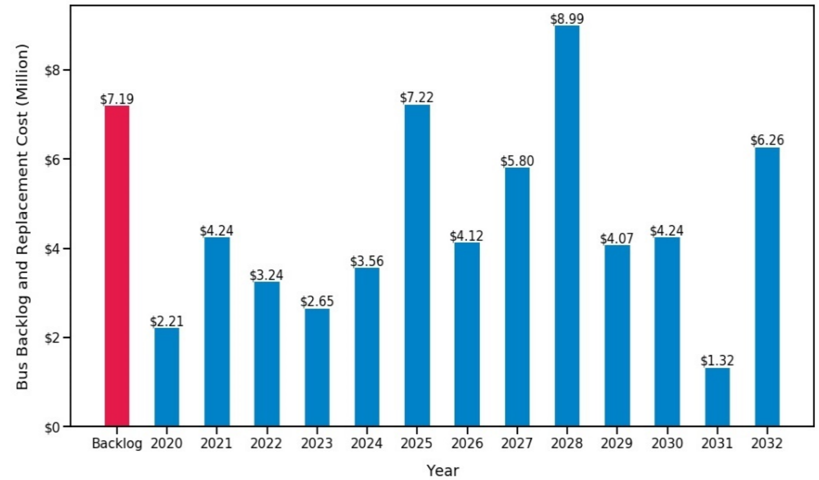
Backlog and Projected Replacement of Revenue Vehicles



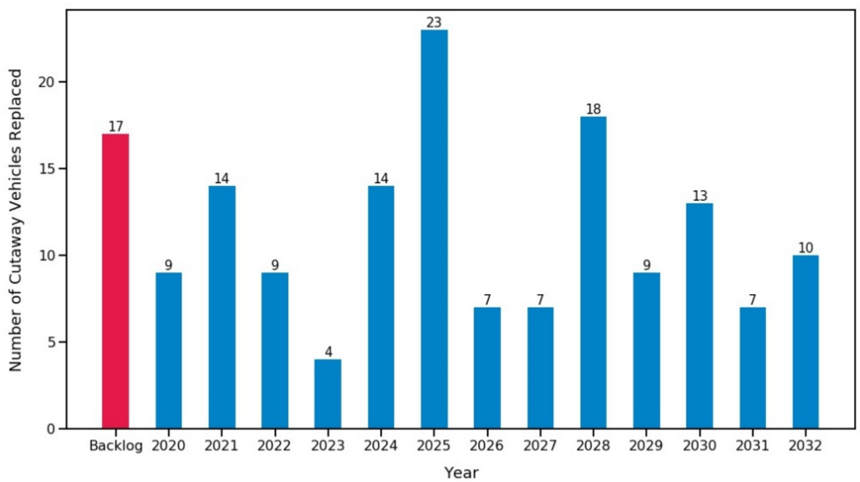
Backlog and Projected Replacement Costs for Revenue Vehicles



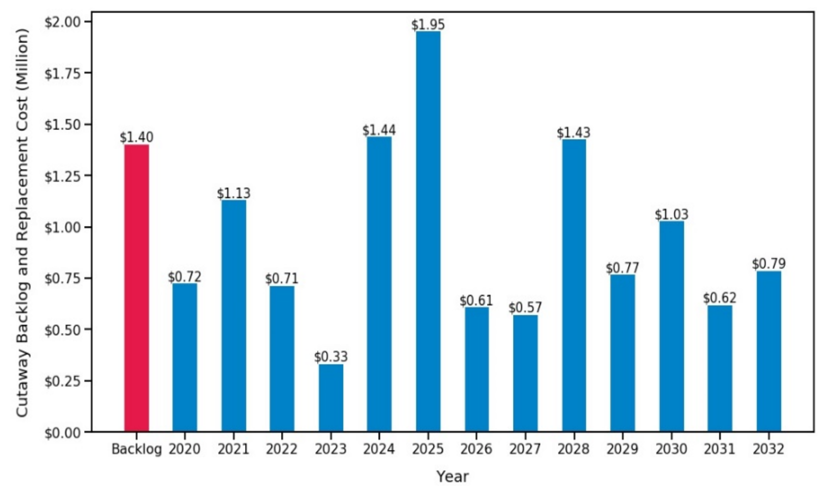
Backlog and Projected Replacement of Buses



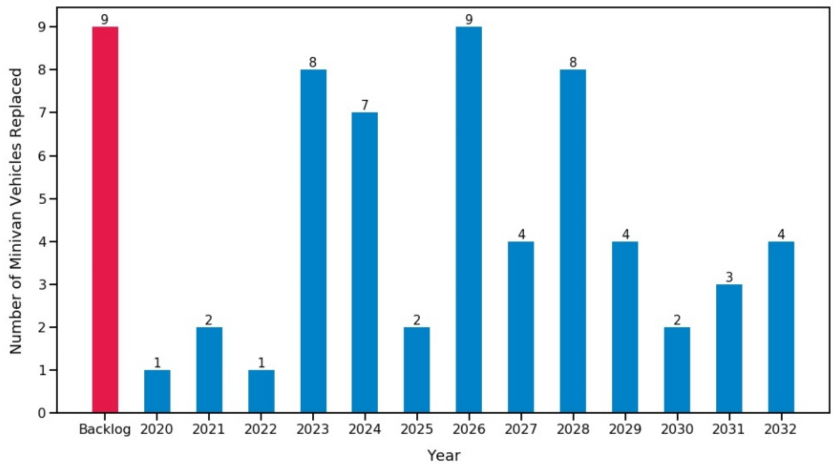
Backlog and Projected Replacement Cost for Buses



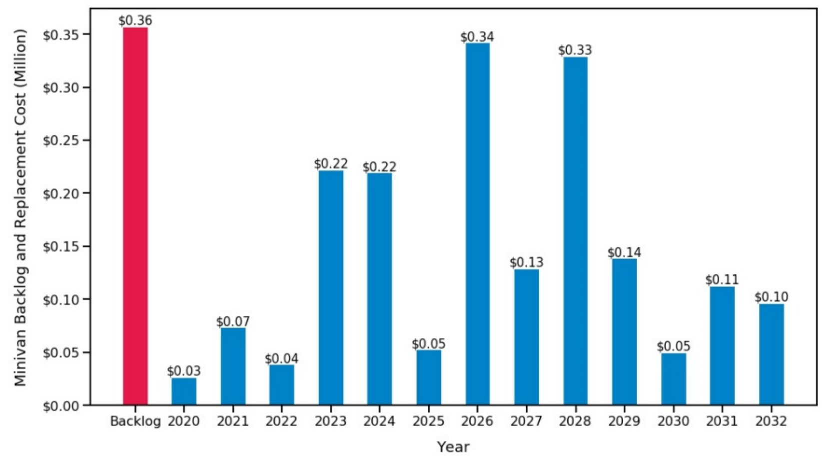
Backlog and Projected Replacement of Cutaways



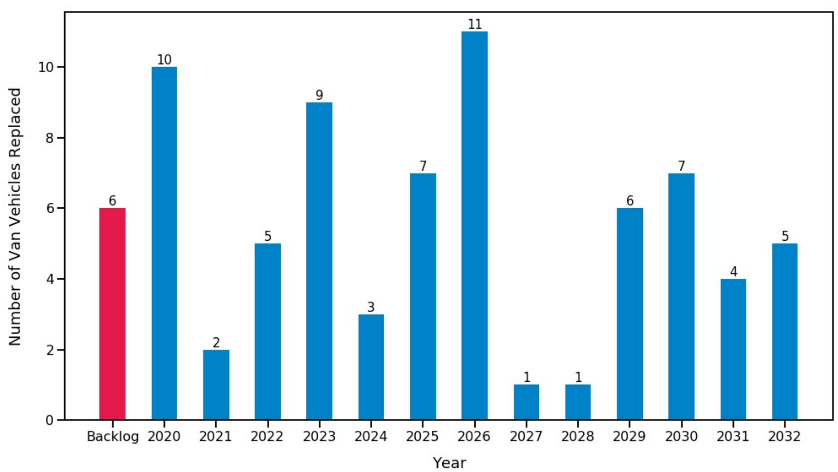
Backlog and Projected Replacement Cost for Cutaways



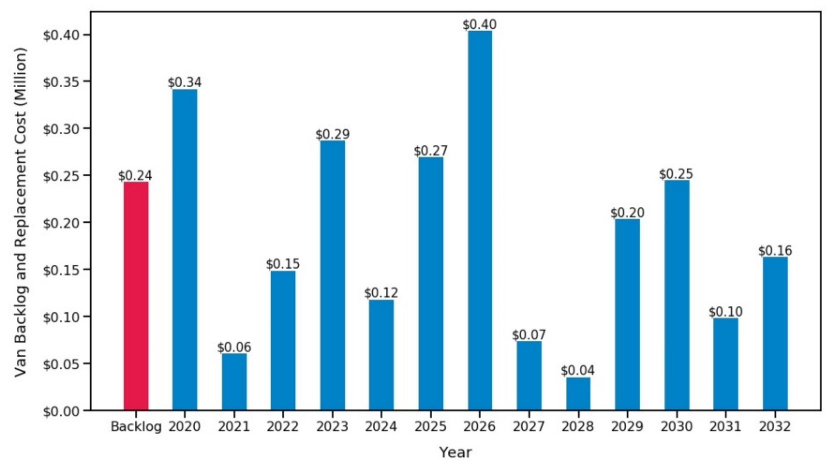
Backlog and Projected Replacement of Minivans



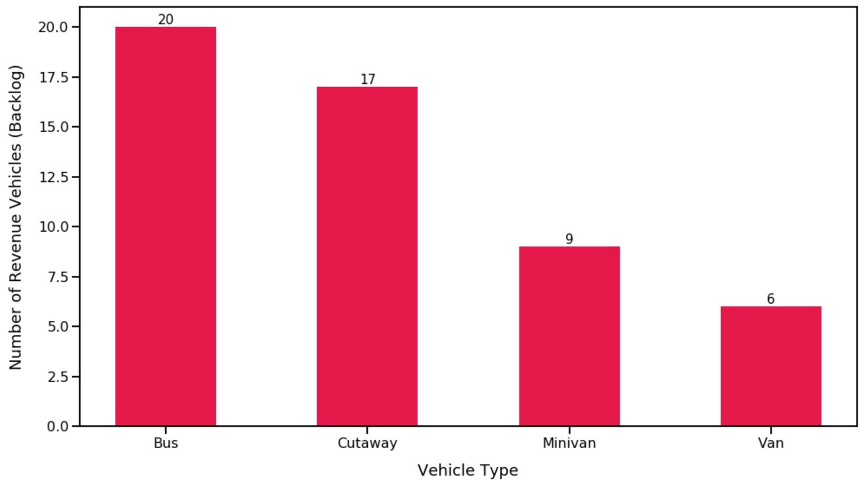
Backlog and Projected Replacement Cost for Minivans



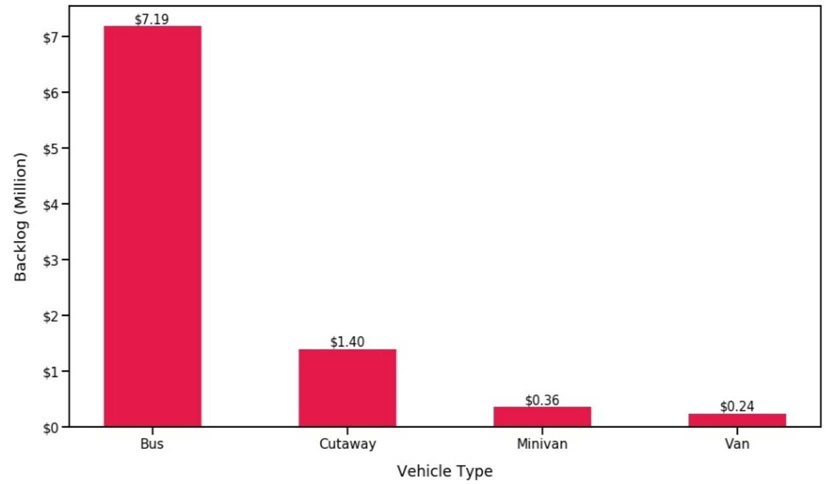
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans

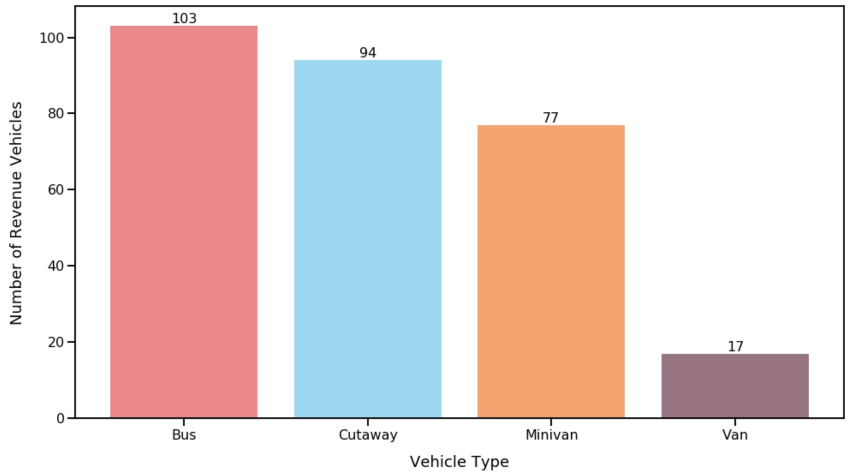


Backlog of the Revenue Vehicles by Vehicle Type

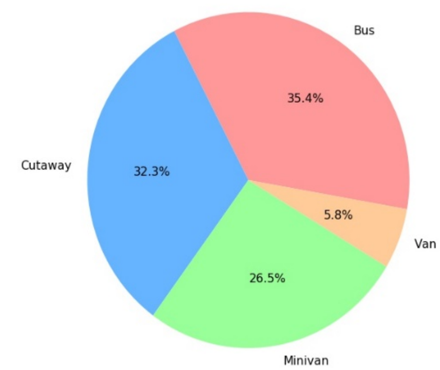


Funds Needed for Backlog by Vehicle Type

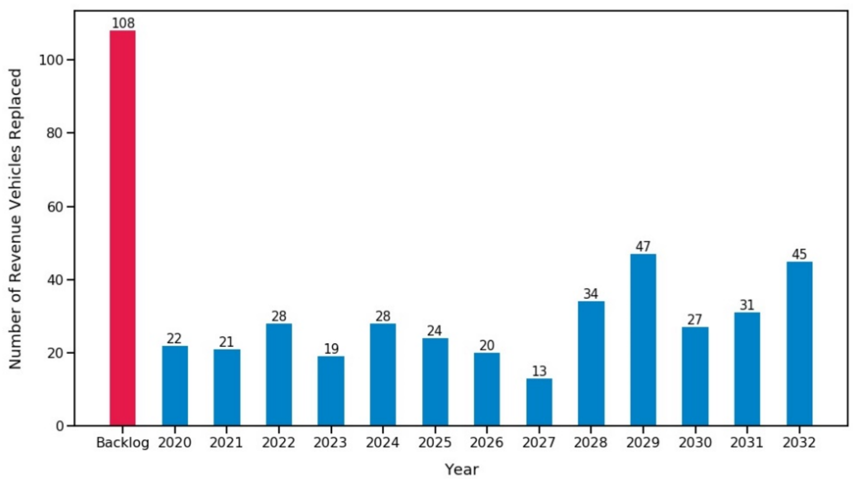
48 WY – Revenue Vehicles Information for Wyoming's Small Urban and Rural Transit Systems (NTD 2017)



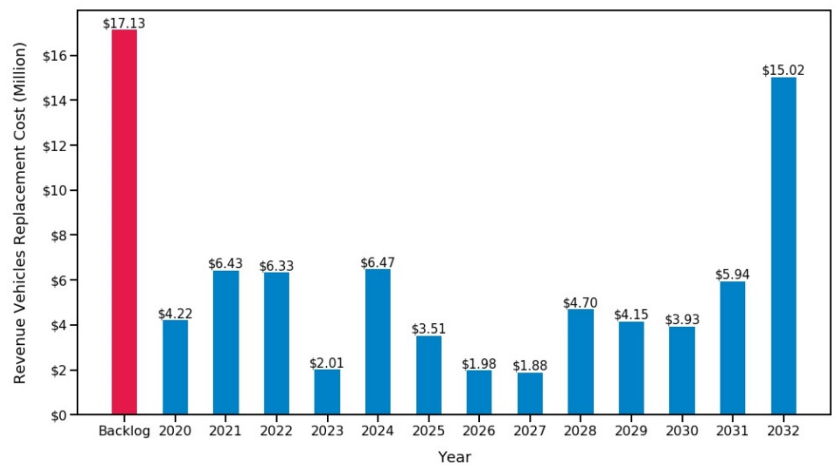
Number of Revenue Vehicles by Vehicle Type



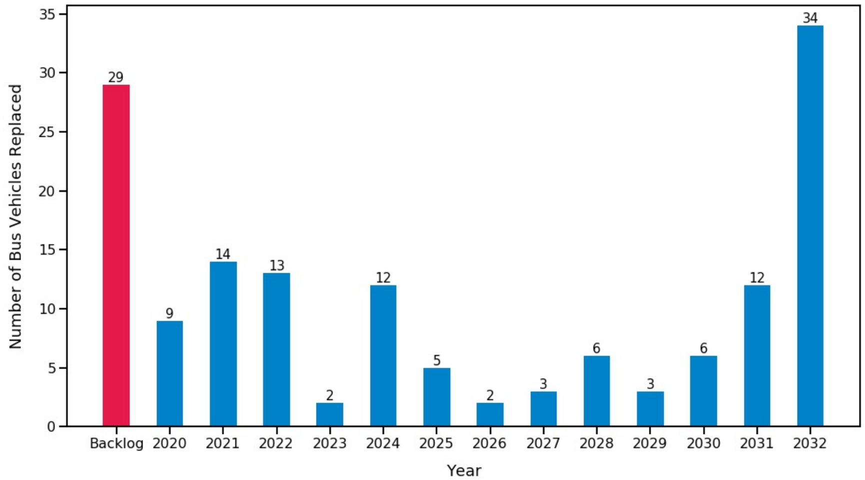
Percentage of Revenue Vehicles



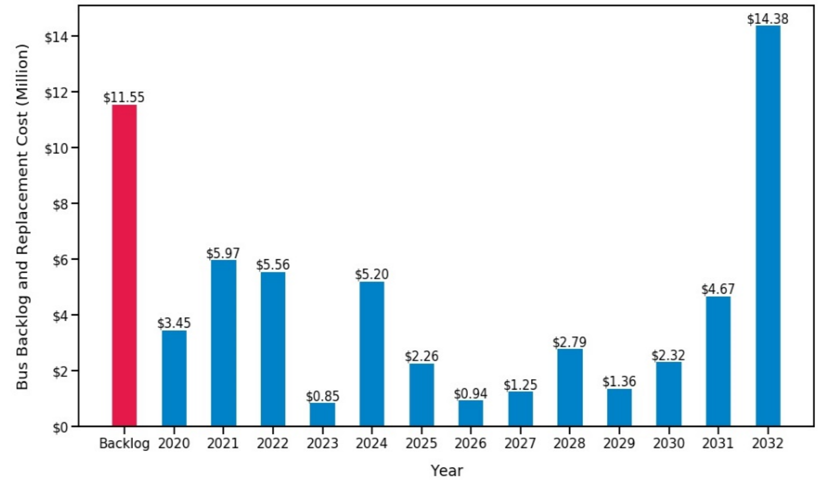
Backlog and Projected Replacement of Revenue Vehicles



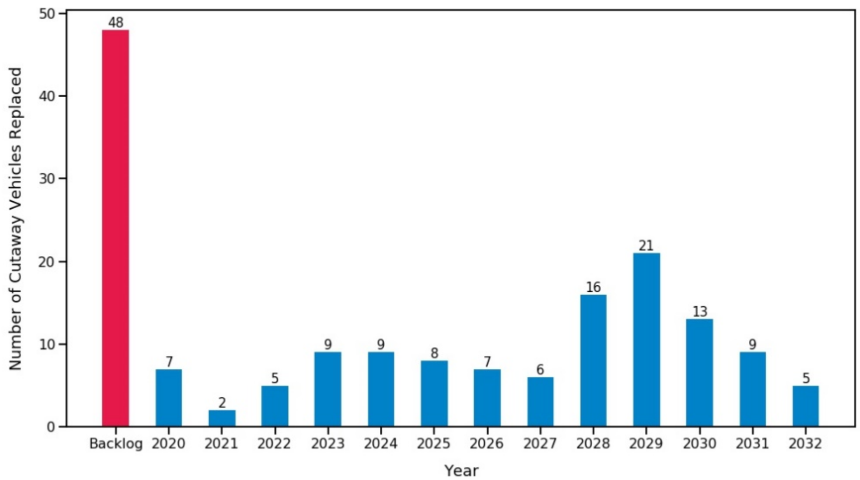
Backlog and Projected Replacement Costs for Revenue Vehicles



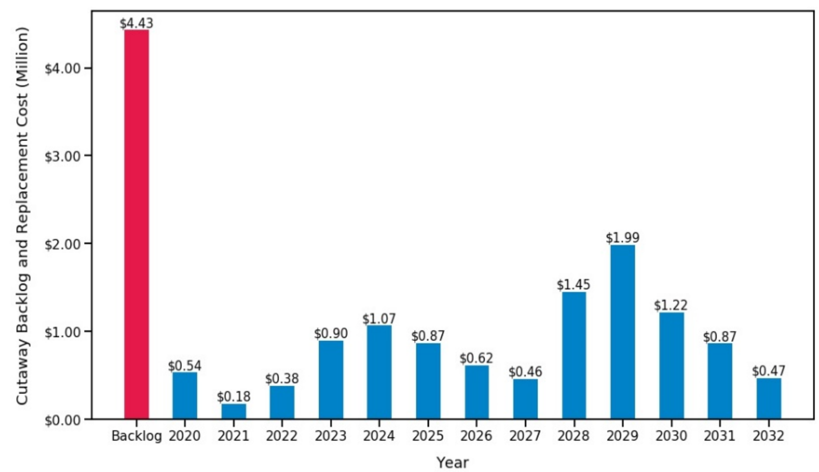
Backlog and Projected Replacement of Buses



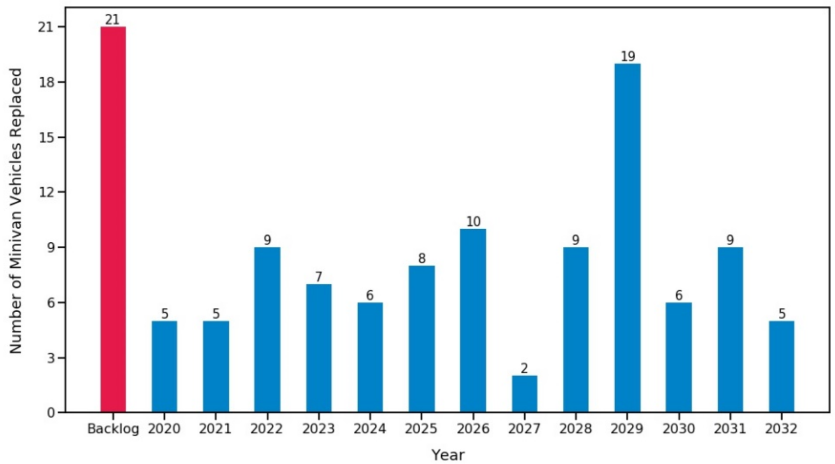
Backlog and Projected Replacement Cost for Buses



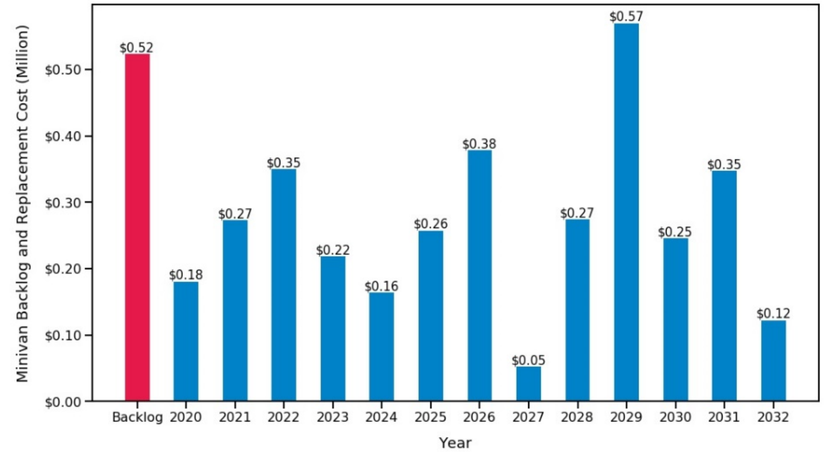
Backlog and Projected Replacement of Cutaways



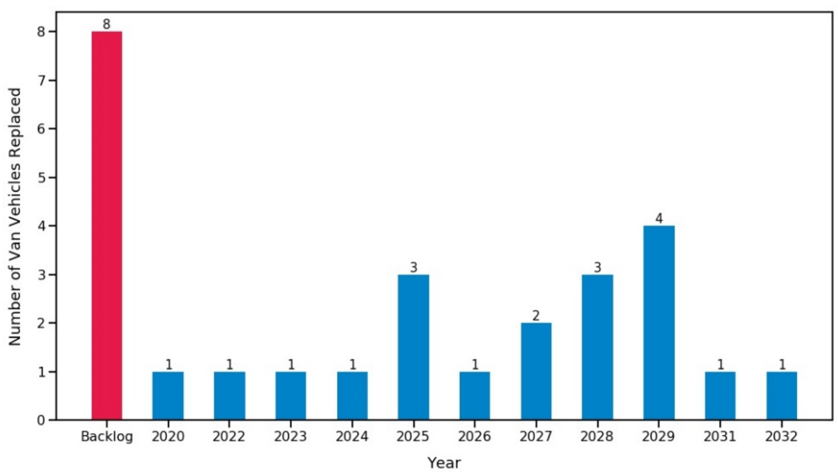
Backlog and Projected Replacement Cost for Cutaways



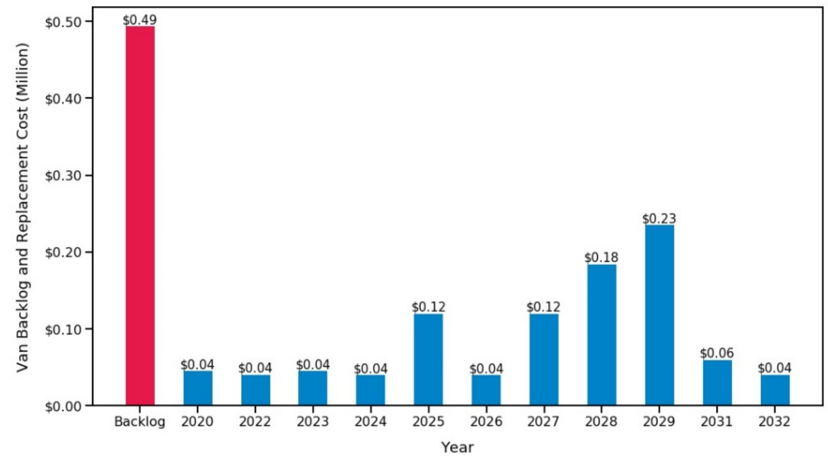
Backlog and Projected Replacement of Minivans



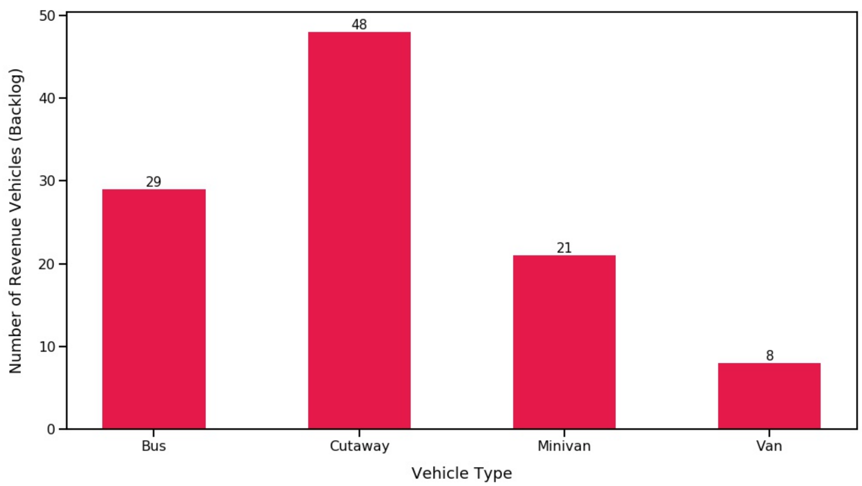
Backlog and Projected Replacement Cost for Minivans



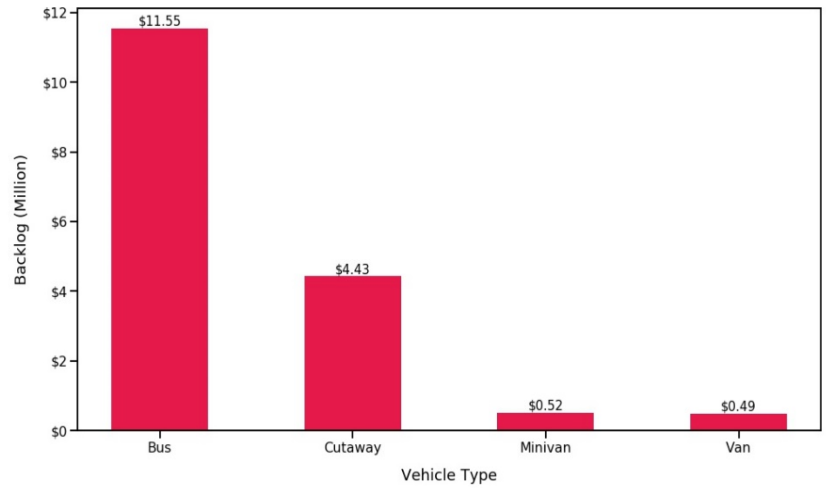
Backlog and Projected Replacement of Vans



Backlog and Projected Replacement Cost for Vans



Backlog of the Revenue Vehicles by Vehicle Type



Funds Needed for Backlog by Vehicle Type