SCTE STANDARDS JOURNAL

VOLUME 3 NO. 2 JULY 2023

SCTE TECHNICAL JOURNAL

SCTE
a subsidiary of CableLabs®

SCTE STANDARDS JOURNAL

SCTE TECHNICAL JOURNAL

VOLUME 3, NUMBER 2

July 2023

Society of Cable Telecommunications Engineers, Inc.
140 Philips Road, Exton, PA 19341-1318

Table of Contents

Editorial Correspondence: If there are errors or omissions to the information provided in this journal, corrections may be sent to our editorial department. Address to: SCTE Journals, SCTE, 140 Philips Road, Exton, PA 19341-1318 or email journals@scte.org.

Submissions: If you have ideas or topics for future journal articles, please let us know. All submissions will be peer reviewed and published at the discretion of SCTE. Electronic submissions are preferred, and should be submitted to SCTE Journals ,journals@scte.org.

Can we talk about cable without mentioning television or residential broadband? Just watch us!

It's a sign of how our business has expanded that this edition of the SCTE Technical Journal talks about how our industry is driving change on the roads, in the workplace, and in corporate vehicle fleets – everywhere but in the home.

As SCTE's Explorer initiative, Energy Management standards subcommittees and other programs have helped our members break new ground, the SCTE Technical Journal has become increasingly essential as a source of industry knowledge. This month's edition includes:

- "**Practical AI-Powered IoT Solution to Help Cities Solve Traffic Problems,"** by Charter's Vishal Gajanan Chopade, Daniel Sjoestroem, Rohith Kumar Punithavel, Mohamed Daoud, Charles Hubbard, and Ankita Himanshubhai Bhagat. The article discusses how Charter Communications leveraged an off-the-shelf technology solution that integrates an IoT Edge device with camera and radar sensors, Artificial Intelligence, and Computer Vision techniques to detect and predict train arrivals and blockage times to reduce issues at at-grade crossings.

- "**Electric Vehicle Workplace Transition Plan for an SCTE Member Company**," by Villanova University RISE team members Queen Okon, Priya Arya, Mariah Bodine, Ryan Campbell, Yen Leng Chong, and Reid Upthegrove, with faculty advisor Karl Schmidt. The article assesses one cable operator's current inventory of internal combustion engine (ICE) vehicles and develops a fleet-level transition strategy.

- "**Worker Safety: A Robust On-Premise & Cloud Based AI Solution,"** by Charter's Rohith Kumar Punithavel, Vishal Gajanan Chopade, Charles Hubbard, and Mohammed Daoud. This article details a Proof of Concept (PoC) developed by Charter Communications for an industrial application that monitors the safety of drill press workers, with a particular focus on the role of AI in businesses and the need for on-premise solutions in safety applications.

I am continually impressed by how the willingness of cable technology professionals to share knowledge is powering our industry's expansion into exciting new areas. I hope you all will mark your calendars for two important upcoming dates within our community: the September 15 deadline for abstracts for consideration for the Fall edition of the SCTE Technical Journal, and – of course! – SCTE Cable-Tec Expo October 16-19 in Denver.

Thank you as always for your participation in SCTE and for your support in helping our industry continually to forge new paths and make history in telecommunications!

Practical AI-Powered IoT Solution to Help Cities Solve Traffic Problems

A Technical Paper prepared for SCTE by

Vishal Gajanan Chopade, Senior Software Engineer,
Charter Communications,
6399 S Fiddlers Green Circle, Greenwood Village, Denver, Colorado, 80111
Vishal.chopade@charter.com
+1 646-215-1036

Daniel Sjoestroem, Principal Wireless Engineer II,
Charter Communications,
6399 S Fiddlers Green Circle, Greenwood Village, Denver, Colorado, 80111
Daniel.Sjoestroem@charter.com

Rohith Kumar Punithavel, Software Engineer,
Charter Communications,
6399 S Fiddlers Green Circle, Greenwood Village, Denver, Colorado, 80111
RohithKumar.Punithavel@charter.com
+1 480-241-3019

Mohamed Daoud, Director - Emerging Technology,
Charter Communications,
6399 S Fiddlers Green Circle, Greenwood Village, Denver, Colorado, 80111
Mohamed.Daoud@charter.com
+1 312-363-9864

Charles Hubbard, Network Engineer II,
Charter Communications,
6399 S Fiddlers Green Circle, Greenwood Village, Denver, Colorado, 80111
Charles.Hubbard@charter.com
+1 432-212-4801

Ankita Himanshubhai Bhagat, Machine Learning Engineer,
Charter Communications
6399 S Fiddlers Green Circle, Greenwood Village, Denver, Colorado, 80111
c-ankita.bhagat@charter.com
+1 267-306-1890

Table of Contents

List of Figures

1. Abstract

Many U.S. industrial cities have a large number of at-grade railroad crossings that create unpredictable traffic jams for residents and visitors due to numerous freight rail companies not publishing train schedules. To solve this problem, Charter leveraged an off-the-shelf technology solution that integrates an IoT edge device with camera and radar sensors, artificial intelligence (AI), and computer vision techniques to detect and predict train arrivals and blockage times. The pilot test took place in the city of Lima, Ohio and deployed nine IoT edge devices on the East-West rail line and observed a significant increase in model accuracy with more historical data.

The paper covers the smart city solution architecture, the IoT apparatus built, data collection process, machine learning (ML) models training and inference for train detection and arrival time prediction, computer vision techniques, radar and sensor fusion, solution deployment, and operation and maintenance insights for the solution in Lima.

2. Introduction

2.1. Motivation

U.S. industrial cities are usually located at major crossroads for several railroad lines; this often results in prolonged delays for drivers and commuters trying to get across a city. These railroads are used by freight trains that can be a mile or more long and stop for extended times at intersections.

The railroads do not publicly publish freight train schedules, resulting in major traffic blockages affecting citizens and emergency medical services (EMS). Ultimately it becomes extremely hard for people in these industrial cities to plan their commutes while city officials spend years looking for a solution to this problem.

Lima, Ohio is an industrial city with more than 40 railroad crossings. The frequent and lengthy trains passing through the city cause significant traffic backups and delays, and the lack of alternative routes exacerbates the problem. The impact of these delays on the city's economy and quality of life is significant, with businesses struggling to receive deliveries and workers finding it difficult to commute to their jobs. Furthermore, emergency responders can be delayed, which can have grave consequences.

Another issue is the lack of alternative routes for drivers to take when trains are blocking roads. The city has limited options for detours, which means that traffic can come to a standstill when trains are passing through.

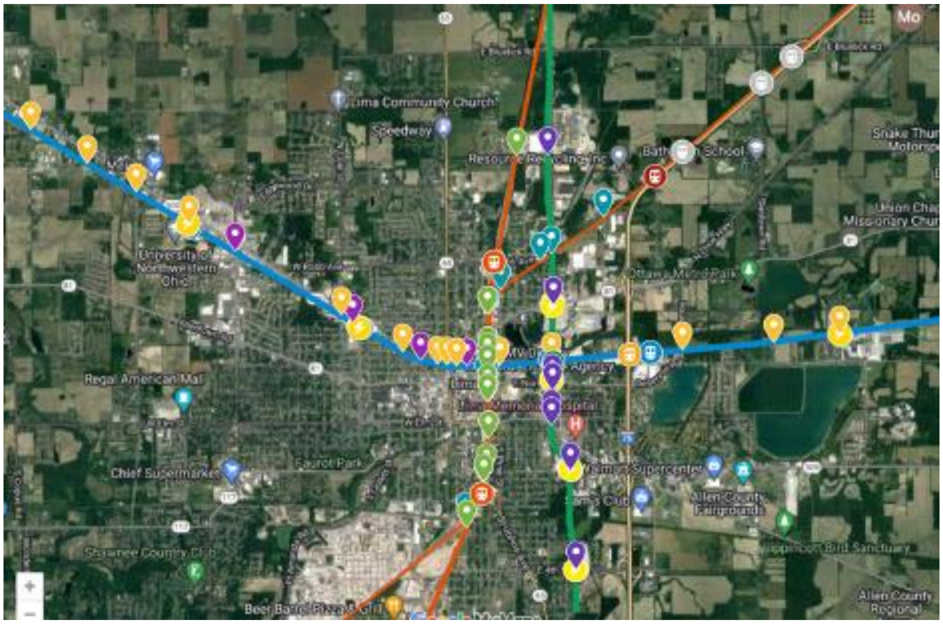

Figure 1 - Lima, OH Train Crossings

Although attempts have been made to address the issue, such as discussing scheduling with the rail companies, finding a long-term solution to the traffic problems caused by freight trains in Lima remains a challenge.

2.2. Existing solutions

Various attempts have been made to tackle the issue of train blockages, such as constructing overpasses or advising people to utilize less congested intersections. However, none of these endeavors have resulted in a viable long-term resolution. Typically, cities opt to build overpasses or underpasses at strategic locations to facilitate smooth traffic movement. Nonetheless, obtaining approvals and constructing such structures is both expensive and time-consuming. Moreover, during peak hours, when everyone tries to avoid train crossings, these overpasses and underpasses can themselves become traffic bottlenecks. As a result, cities are now contemplating an alternative solution that would eliminate the need for costly overpass construction. They are exploring the concept of a smart city project, which would provide real-time updates to users regarding intersections and train traffic, ultimately saving costs and improving efficiency.

Charter Communications worked with the City of Lima, OH and several entities to create a long-term solution for the train blockage problem based on the latest technology leveraging IoT sensors, machine learning, computer vision, and 5G/LTE.

3. Apparatus

3.1. Apparatus Description

The custom-designed apparatus is the crux of this solution. This apparatus is driven by a combination of a processing unit, sensors, remote plug, and a modem-router powered by Spectrum Mobile. All components are assembled in NEMA 3R enclosures and deployed in proximity to railway crossings on top of poles.

Figure 2 - Apparatus Block Diagram (left) and Custom-Built Apparatus (right)

3.1.1. Processing Unit

The processing unit is the brain of any smart application. Single board computers are inexpensive, smaller, and may or may not have a GPU. The embedded edge compute used in this application has 6 CPU cores and one GPU with 48 Tensor cores and 384 CUDA cores. The presence of a GPU allows the apparatus to perform intense computational solutions with negligible latency.

3.1.2. Camera

The camera is an optical sensor that captures the scene to which it is focused, then encodes the frame and transmits the frames to the processing unit where the decision making occurs. The camera of this application runs at 2992x1680 at 5 FPS. These cameras are IP cameras and are powered by PoE (Power over Ethernet (PoE) injectors.

3.1.3. Radar

Radar is a radio wave sensor which detects motion, speed, direction, and range as a function of the transmission and magnitude of radio wave reception. The radar used in this application works in the 24 – 24.5 GHz band, detects speed in the range of 1 – 200 ft, and communicates over USB interface.

3.1.4. Remote Plug

A remote plug is a kind of electrical plug that can be connected to the Internet, allowing users to control the apparatus wirelessly and remotely.

3.1.5. GPS

GPS is a satellite-based communication system that returns the location of the apparatus. The receiver is operated via a USB interface.

3.1.6. Modem-Router

Modem-router allows the apparatus to connect to and provide internet connectivity to all connected components. The modem-router component that supports the Charter Spectrum application can handle gigabit class LTE connectivity, cloud access, GPS, etc. An external antenna has been added to improve transmission and reception.

3.2. Computer Vision

3.2.1. The Thought Process

The aim is to detect the train crossing the intersection and to determine if the junction is blocked or not. The initial thought process was to use any existing pre-trained model for the same, avoiding model training. If this ready-to-go model is well generalized on all distinct locations, this will reduce a huge amount of effort on custom dataset curation, image annotation, and AI model training and model management.

3.2.2. YOLO and Challenges

You only look once (YOLO) is a real-time object detection algorithm that identifies specific objects in videos, live feeds, or images. The YOLO machine learning algorithm uses features learned by a deep convolutional neural network to detect an object. YOLO has the advantage of being much faster than other networks and still maintains accuracy. Common objects in context (COCO) [2] pretrained weights on YOLO-v3 model were utilized for this initial experiment as “train” is already present as one of the classes in the COCO dataset. Out of 80 classes detected by COCO pretrained weights, only “train” class probability is being considered for train detection. On Nvidia Jetson Xavier NX, this model can process 5 frames per second during Real Time Streaming Protocol (RTSP) live stream inference.

The model performs well for some of the train cars; however, the performance is not as expected for different types of freight train cars. Also, the model is falsely detecting maintenance vehicles on railway tracks or school buses as a train. This led us to build another more reliable approach that can reduce misclassifications.

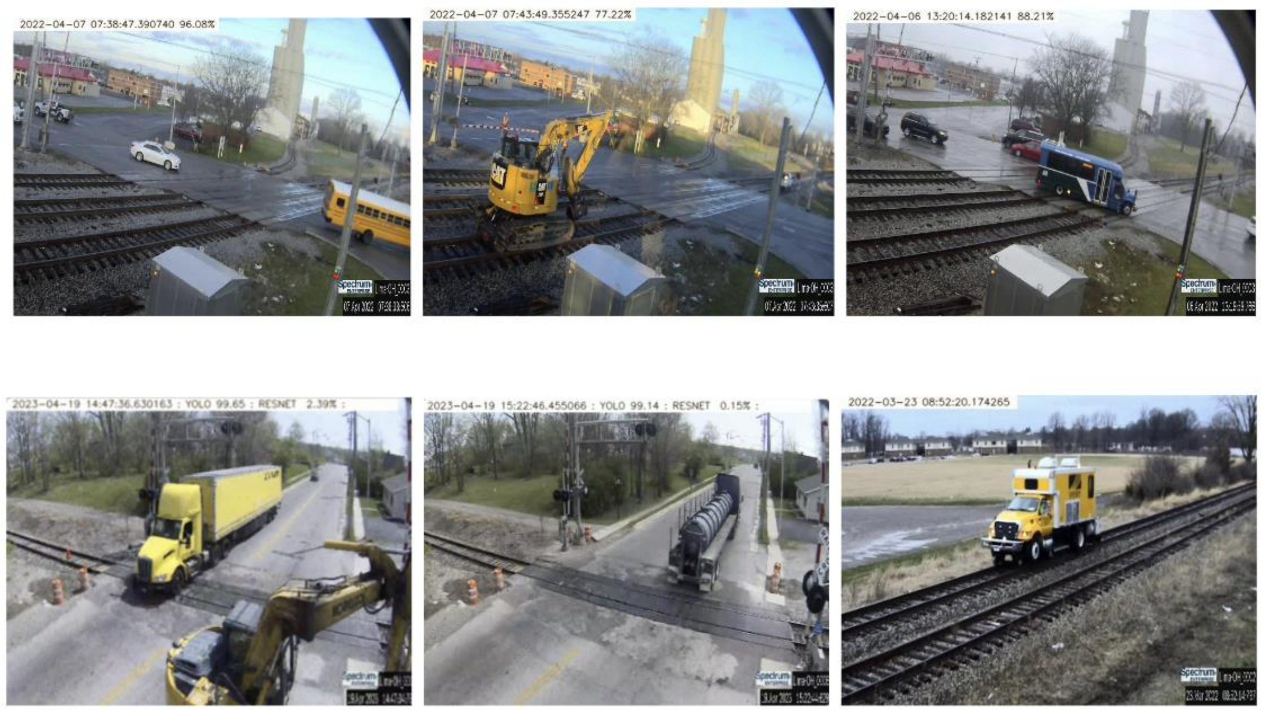

Figure 3 - YOLO Misclassifications

3.2.3. ResNet18

Training or fine-tuning the model on the custom dataset is the solution to resolving the challenges with the YOLO model. However, retraining the YOLO object detection model requires bounding boxes to be generated for the custom data. This is a time-consuming and resource-intensive process. The better idea was to fine tune a classification model in place of the object detection model. Also, fine tuning a smaller architecture will help with faster inference during a live camera stream.

ResNet-18 is a convolutional neural network that is trained on more than a million images from ImageNet [3] database. This is an efficient model in image classification. There are only 18 layers present in the model architecture, hence it is considered a compact model. The ImageNet pretrained weights were used to apply transfer learning on a custom dataset.

To curate the custom dataset, we utilized the cases generated with the help of the YOLO model, as well as manually recorded video instances. The model was struggling to differentiate maintenance vehicles on railway tracks from trains, hence the model was retrained with 2 different classes named “train” and “other”. Initially, a single ResNet model was used for multiple Lima locations, and data augmentation techniques were applied to enhance the dataset. However, augmented images were excluded from the dataset due to concerns that the increased diversity was making it difficult for the model to distinguish between the target class and other classes. The variations in background from different locations were impacting the model's perception and classification capabilities.

Evidently one single ResNet model was not generalizing quite well for all Lima locations. The reason was different backgrounds and traffic conditions per location. A few locations have buildings in the background which nearly match the color and texture of some of the freight train cars. Hence the model was confused in classifying such cases and generated false positive predictions. To get rid of such instances, multiple models were trained on combined datasets from those locations based on similarity of backgrounds.

For training and deploying the ResNet model, a jetson-inference repository has been utilized. It provides Python and C++ APIs for streaming from live camera feeds. For image classification, we have used ImageNet vision Deep Neural Network (DNN) library for Nvidia Jetson Xavier NX. It provides an API for faster inference with the help of TensorRT (an ahead-of-time compiler to optimize inference techniques on NVIDIA GPUs). With this approach, now more than 25 frames could be processed per second. The training and validation loss has been reduced significantly and accuracy improved while re-training the model as shown in Figure 4.

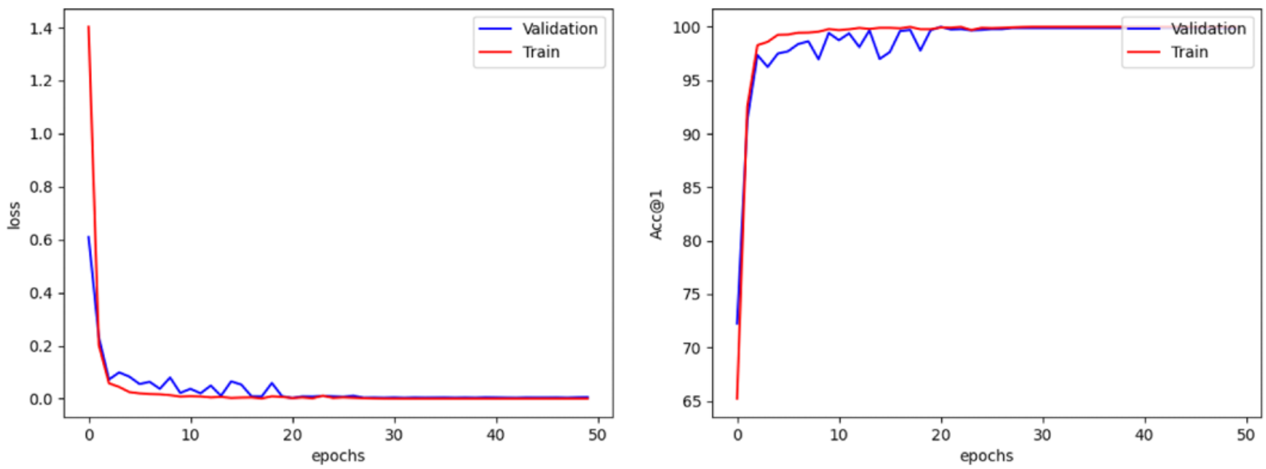

Figure 4 - ResNet Transfer Learning - Loss per Epoch and Top 1 Accuracy per Epoch

An accuracy score was used as a performance metric for the model as the custom dataset is balanced in terms of the train and other classes. Re-training ResNet18 with ImageNet pre-trained weights using the Transfer Learning approach achieved more than 98% accuracy score on the custom dataset.

3.2.4. Tracking Train Movement using Optical Flow

Train length is measured using a radar sensor deployed in the apparatus device. This data predicts the train arriving at a particular Lima junction. However, the signal noise in the data is noticeable during windy or rainy weather conditions. The train may appear steady from afar, yet the radar's ability to precisely capture its speed is compromised by the disruptive clamor of rain or wind. This resulted in inaccurate train lengths captured in the database. To resolve this issue, initially, we experimented with SEGNET of the jetson-inference [1] repository to explore the segmentation network. The idea was to segment the train from the rest of the scene and to capture the pixel movement in that region, to decide if the train is moving or steady. The pre-trained SEGNET model was not giving accurate results and generating labeled segmentation data to retrain the model is a time-consuming and resource-intensive task.

To build the equivalent solution faster, we used OpenCV Dense Optical Flow technique. The OpticalFlowFarneback [4] algorithm returns an optical flow object that can be used to estimate the direction and speed of the moving object in the video. When a train is crossing the junction there will be other traffic movements appearing on the road, which can also be detected by the algorithm. To eliminate those movements only 'X' axis direction pixel movements were considered and conditioned by a specific threshold value to decide if a train is moving or steady.

3.3. Radar

3.3.1. Working Off Radar

Radar, a technology based on radio waves, facilitates object detection and localization within its vicinity. Abbreviated from "RAdio Detection And Ranging," radar systems emit radio waves from a transmitter, reflecting off the objects of interest and detecting the reflected waves with a receiver. By examining the properties of the reflected waves and calculating the time it takes for them to return, radar systems determine several object attributes, including distance, direction, speed, and other position. Radar systems find wide-ranging applications across traffic control, navigation, and military surveillance.

The radar system provides a comprehensive short-range radar (SRR) solution that offers features such as motion detection, speed measurement, directional sensing, and range reporting capabilities. This system processes all radar signals onboard, and its application programming interface (API) offers processed data in a straightforward manner. The radar used in this application allows flexible control over reporting formats, sample rates, and module power levels, and its USB output enables easy connectivity to edge compute devices.

The sensor produces data in the JavaScript Object Notation (JSON) form containing key-value pairs, each of which represents the range in feet from the sensor and the reflection magnitude at that range (see example 1. below).

1. {"time": "2022-01-05 14:27:30.196996", "input": {"time": "11413.101", "unit": "ft", "magnitude": ["267.75", "139.00", "85.02", "80.43", "68.09", "65.14"], "range": ["11.42", "16.38", "92.17", "21.45", "81.96", "87.07"]}}
2. {"time": "2022-01-05 14:27:27.971921", "input": {"time": "11410.827", "unit": "fps", "magnitude": "10.06", "speed": "-38.41"}}

When an object comes into motion within the radar's range, the device calculates the object's speed and reflection magnitude (see example 2. above), which is subsequently used in the following equation to estimate the object's length:

Length of train = Length of train + (speed × delta time)

here, Length of train is always appended and modified by the calculation.

delta time is the difference between current time and time of previous speed.

3.3.2. Speed Pattern Filter

The implemented code incorporates advanced algorithms that eliminate noise to yield highly accurate length calculations, extending up to a length of 500 feet. However, the presence of heavy rainfall can challenge radar systems, as they may detect the speed of raindrops (rain fade phenomenon [6]), which could lead to a mistaken interpretation of object speed, such as a train. To mitigate such circumstances, we developed a specialized algorithm "Speed pattern filter" based on data gathered over several months of rainy conditions. This algorithm is integrated into the system to compare incoming data with average values derived from the collected data. If the incoming data falls outside the dynamic bounding boxes created by the algorithm, it is considered noise, and if it stays within the bounds, it is deemed valid train data. After thorough testing in both controlled environments and field trials, this algorithm has been successfully deployed to enhance train detection accuracy by eliminating several types of noise.

3.4. Sensor Fusion

3.4.1. Constraints

There are situations in which the camera and its AI/ML models do not perform well-enough to detect or classify a train in the view. This especially happens in bad light conditions at night, when either there are headlights from traffic that blind the camera or the lack of light sources at the scene resulting in a very dark view. During daytime, a low standing sun may also interfere with the camera if the angle of deployment is in a sun-facing direction.

Weather conditions such as fog, rain, sleet, or snow partially or even fully blocking the camera lens have affected the performance of the camera models. Raindrops on the camera housing window, especially in the dark, distort the view heavily and the models can hardly differentiate train cars from other road traffic.

The radar sensor is also affected by weather conditions. There is a trade-off in radar sensor configuration to have it detect indistinct speeds from slowly crawling trains but also not to pick up too many speed reports from signal noise, or the raindrop effect.

Weather conditions observed at the location of an apparatus are utilized by the camera model to confirm a train is active in the field of view to help differentiate speed detections caused by heavy rain and the actual speed of the train.

3.4.2. Sensors in Operation

Whenever radar speed detections form an expected pattern of a large train object, and a certain length of an object has been measured, a train entry observation is reported. The camera may help in classifying the type of object being present in the view and requires a large field of view for motion to be measured if a train is seen. When the radar sensor no longer detects train motion, the camera model may help decide if a train object is still sitting at the intersection or if road traffic may cross.

The utilization of the camera in those situations also differs with the location and mount of the apparatus. The time of the day, given there are artificial light sources after sunset, as well as the weather conditions are also considered.

3.4.3. Challenges

The decision of when to use camera model outcomes has been the biggest challenge in this area, as both camera and radar sensors may provide some incorrectness in their output.

The local weather conditions at the location of any apparatus are determined through calls to the *OpenWeather* API [5]. The times of various aspects of the sun at that location are also calculated to help set the requirements on the camera models.

Since weather-related factors such as weather, sunrise and sunset times tend to remain consistent for a minimum of 24 hours, short term internet connectivity issues may not have a significant impact on the device. However, it is important to consider that weather conditions can change rapidly, and reliable internet connectivity is crucial for the device to maintain up-to-date weather awareness in any given situation for decision making.

At some remote locations outside of the city where there are no streetlights or other sources of light that improve visibility, the apparatus may run, having camera perceptions only as an aid, after the sun has set. Contrary to this, at locations within the city that are always illuminated, the requirement on camera models would always be enabled and state whether an intersection is open for road traffic or not.

4. Train Schedule Predictions

4.1. Event-Based Train Arrival Predictions

Predicting train schedules can be used to develop efficient ways to advise drivers on wait time at railroad crossings, while also providing alternative route suggestions to save time. The train arrival time is predicted in minutes and seconds at a specific junction as determined by the current location, direction, and length of that train at that given moment.

The apparatus is pushing the train’s current location, direction, and length to the cloud at regular intervals until the train completely disappears at that Lima crossing or stops moving. Each of these events is logged with element status as initial, intermediate, or final. The final message contains the most accurate information on train length. Initial and intermediate messages will have incremental train length.

To train the predictive model, the first step was to generate the data which can be used for training. For data cleaning and training data preparation, we used a semi-automated approach. For each event on a train’s current position, the arrival of that same train to all other apparatus devices needs to be generated. This data becomes the ground truth for the model training.

4.2. Using a Linear Regression Model with an Average Speed

Another important aspect of a predictive model is to generate meaningful and correlated features with the target variable. There are two new features being generated here, Estimated Arrival Time based on the current train speed and Estimated Arrival Time based on the average speed of a train on a specific route.

To generate these features, the distance between two apparatus devices is utilized so the train current length is subtracted from this fixed distance to generate the most realistic distance the train has yet to cover. The generated remaining distance is then divided by the train speed. If we rely just on the current speed of the train to estimate arrival time, we notice the model underestimates the train speed and hence predicts the incorrect arrival time. The common rule is that the train usually picks up higher speed after crossing the junction. Hence two separate features were generated, one using the current train speed and another one with the average train speed for the route. The average train speed for the route was calculated by considering three months of data and outliers were removed before the average speed was extracted.

The target variable, Estimated Arrival Time, now must be predicted as a weighted sum of these two newly generated features. The obvious choice was the linear regression model to determine the weights of each feature based on its variance. Model training was performed on 3 months of data, as the data cleaning and transformation is a time-consuming process; we accumulated only a few months of train arrival data using the linear regression model and recorded an error of +/- 4.07 mins for ETA at Lima 0001, +/- 1.57 mins for ETA at Lima 0002 +/- 2.64 mins for ETA at Lima 0003 on the sampled test data. The error rate is high for test data, since occasionally the train might have started towards Lima 0001 but was parked somewhere in between. We don't have access to events happening between the apparatus devices. If we exclude the events where trains never arrive at the adjacent junction or took longer than usual, the errors will be +/- 3.21 mins for ETA at Lima 0001, +/- 1.47 mins for ETA at Lima 0002, and +/- 1.16 mins for ETA at Lima 0003. There is a post-process module, which eliminates negative prediction values and adjusts ETA predictions based on a train's direction.

4.3. Real World Problem and Challenges

The above approach works well for the cases in which the train arrives at the adjacent junction according to the moving direction and within an expected timeframe. However, there are a few instances when trains arrive at the junction with an increased delay of a couple of hours to a couple of days. The challenge here is that we don't have access to the events happening between the apparatus devices and hence we don't have any predictor variables to predict this delay.

Another issue is varying train lengths. At certain junctions following a rail switching yard, a train can append additional cars or remove existing cars, changing the overall length of the train. Hence the accurate arrival predictions can only be possible for the next or following adjacent junctions.

There is no fixed pattern of train schedules due to safety, security, and competitive reasons. Hence predicting train schedules far ahead of time is not possible. Event based prediction can be achieved for the scope of this project.

Many times, the train does back-and-forth movements while appending or removing cars. Due to this movement, the direction of the train represents continuous changes which makes the prediction of train arrival difficult.

5. Dashboard

5.1. Data Flow from Apparatus to Cloud

The data flow from the apparatus to the cloud is shown in the image below.

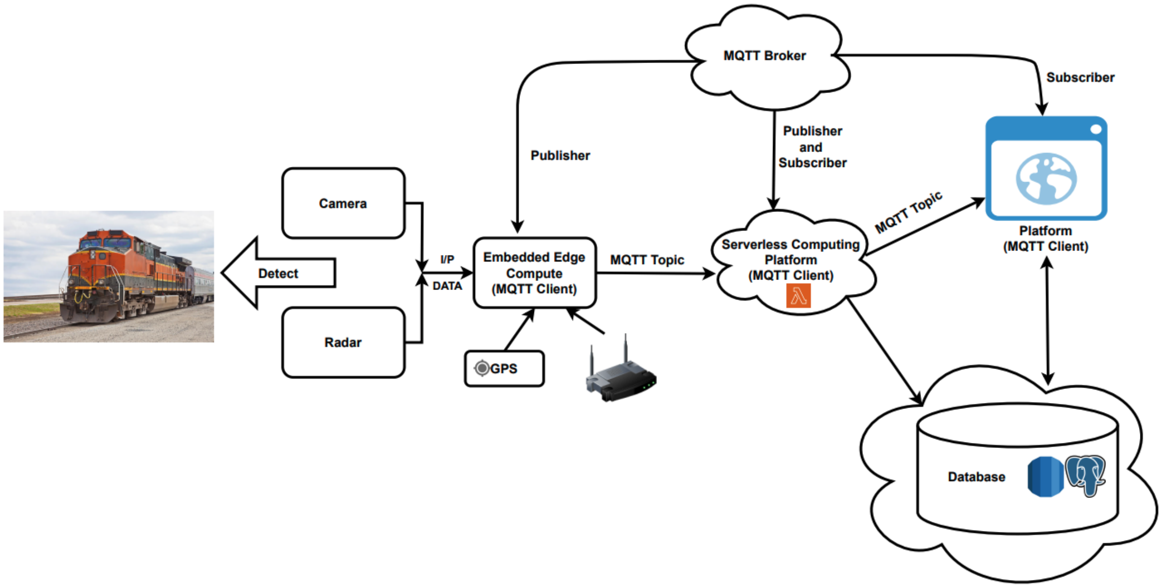

Figure 5 - Data Flow Architecture

The embedded edge compute module accepts input from the camera, radar, and GPS. The camera and radar algorithms work to detect train estimates such as train speed, length, direction, and time to cross the intersection. The apparatus generates a data payload that contains metrics associated with the train, the GPS location of the apparatus, and hardware-related metrics such as memory usage, GPU usage, temperature, etc. These generated payload messages occur at least every 60 seconds when the apparatus detects a train. The apparatus transmits instantaneous status update messages if a train suddenly stops or changes direction. If no trains have passed, a health check message payload gets generated every 60 minutes. The message transfer happens with the help of the Message Queuing Telemetry Transport (MQTT) protocol. MQTT is a standards-based messaging protocol, or set of rules, used for machine-to-machine communication. MQTT protocol has a broker which is hosted on the cloud and is the heart of this communication protocol, and then there is the client, which can subscribe and publish. A broker can have millions of clients connected. The broker is responsible for receiving all messages, filtering them, and determining which client should receive them. The messages are directed and filtered by topics.

The apparatus acts as an MQTT client and transmits payloads on an MQTT topic over LTE. These payloads trigger a serverless computing platform, which is another MQTT client hosted on the cloud that parses the payload into train and hardware data. For live information, a visualization platform receives the train data over an MQTT topic from the serverless compute process. This same process also parses and stores the train and hardware data in separate tables in a relational database for analysis.

5.2. Data Visualization

There are currently nine apparatuses deployed in the field. The data from the apparatus is visualized in three ways:

- Live Data Visualization

The payload from the serverless compute process is parsed and displayed on the map in Figure 6. The live data visualization lets users know where the train is so they can plan their travel accordingly. Various rail lines and their locations can be selected using the drop-down menu at the top to view their train count, average time blocked, and total time blocked for the past 24 hours.

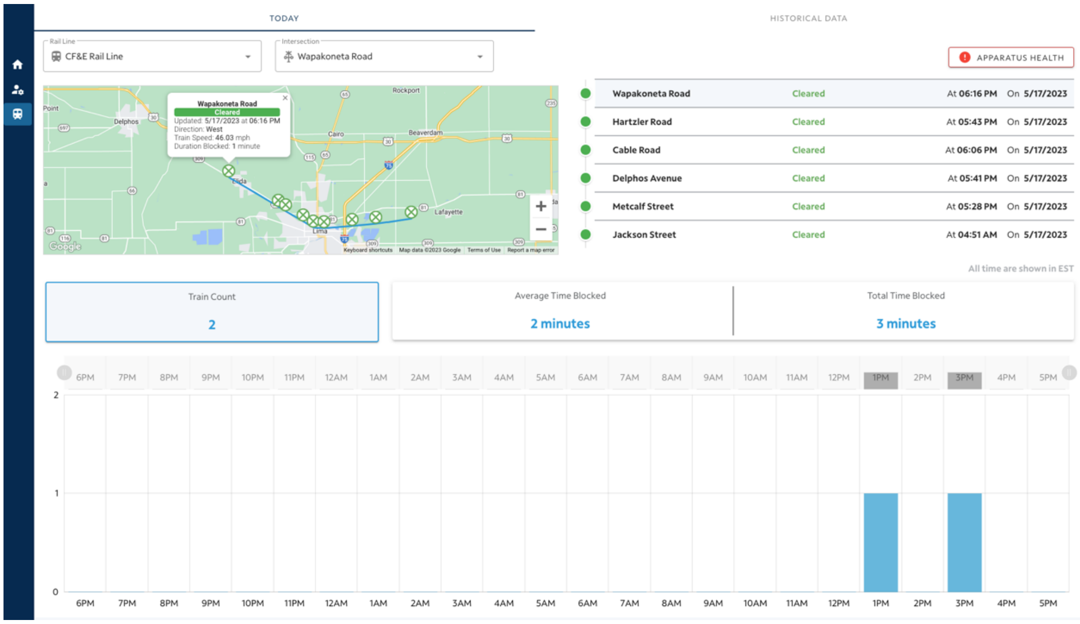

Figure 6 - Live Map User Platform Interface

- Apparatus Health Visualization

The apparatus health information transmitted from each field unit can be viewed and analyzed. In this, the data retrieved from the database is used for analysis. The user can access rail lines and the apparatus location from the options on the side. This tab gives information about the status of the apparatus, network outage, uptime of the apparatus, software version of the application running, disk percentage, memory percentage, CPU usage percentage, and CPU temperature for a range of calendar inputs. The chosen numerically-valued hardware variables also show plot visualization at the bottom. The selected data points can be exported externally as a CSV or JSON file.

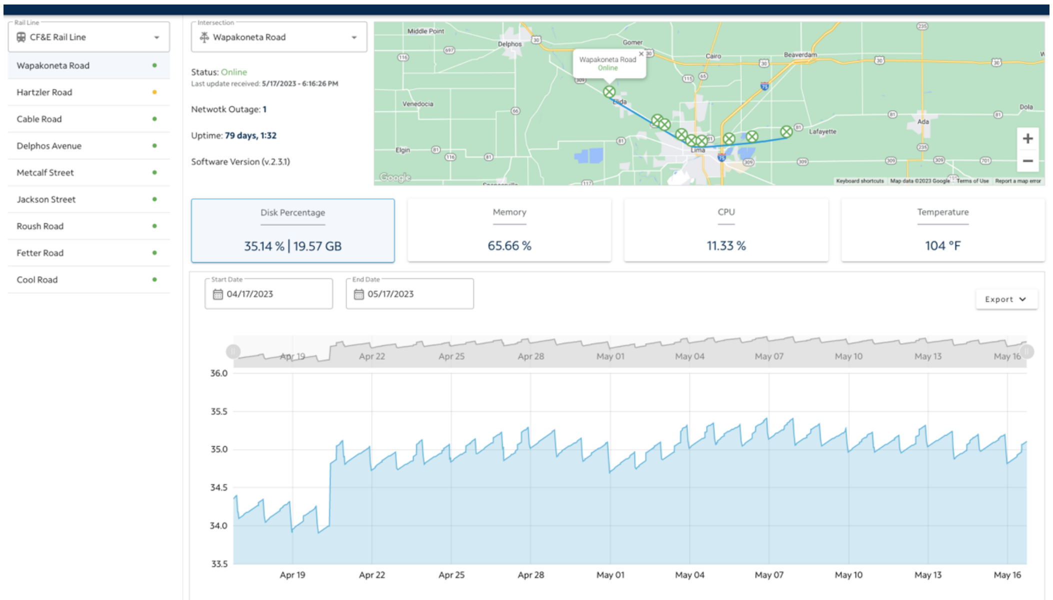

Figure 7 - Device Health User Platform Interface

- Historical Data Visualization

Data collected and stored from the apparatus is used for data analysis and visualization. This tab will let us choose the rail line, apparatus location, date range, direction, if applicable, and analysis parameter. The analysis parameters included are Train Count by Hour, Train Count by Day, Train Count Heat Map, Total Time Blocked, Average Time Blocked by Hour, and Average Time Blocked by Day. The selected data points can be exported externally as a CSV or JSON file. The plots generated are interactive.

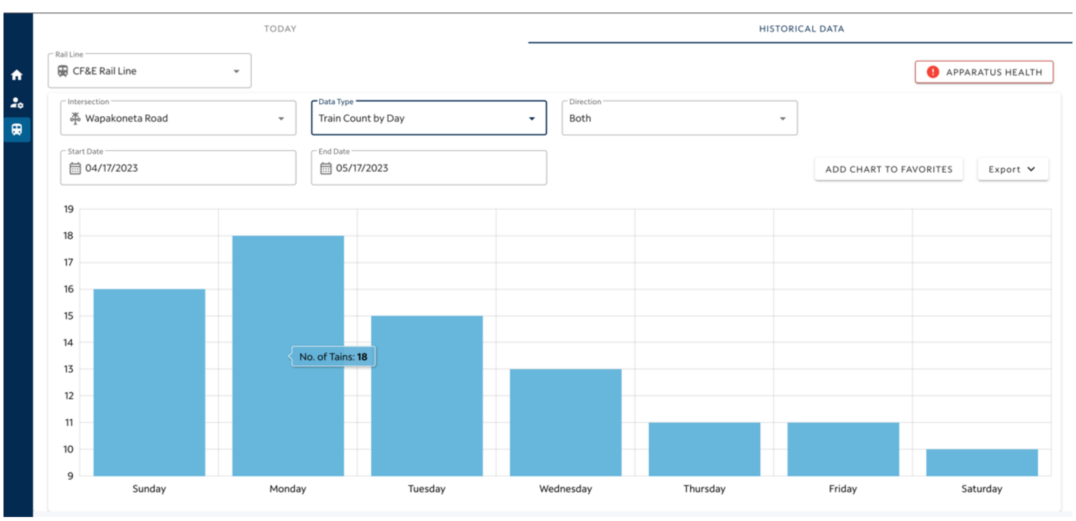

Figure 8 - Train Count by Day Visualization

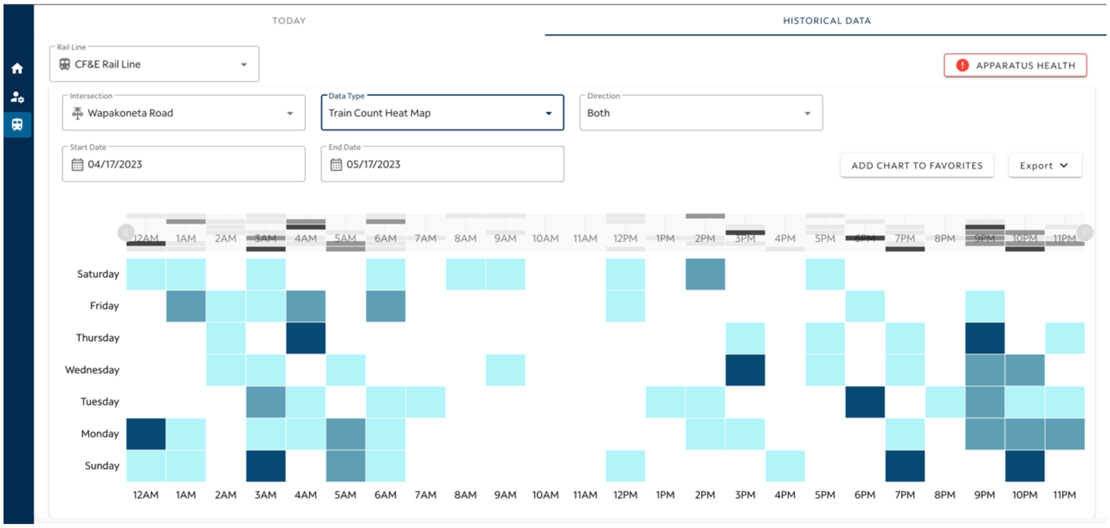

Figure 9 - Train Count Heat Map Visualization

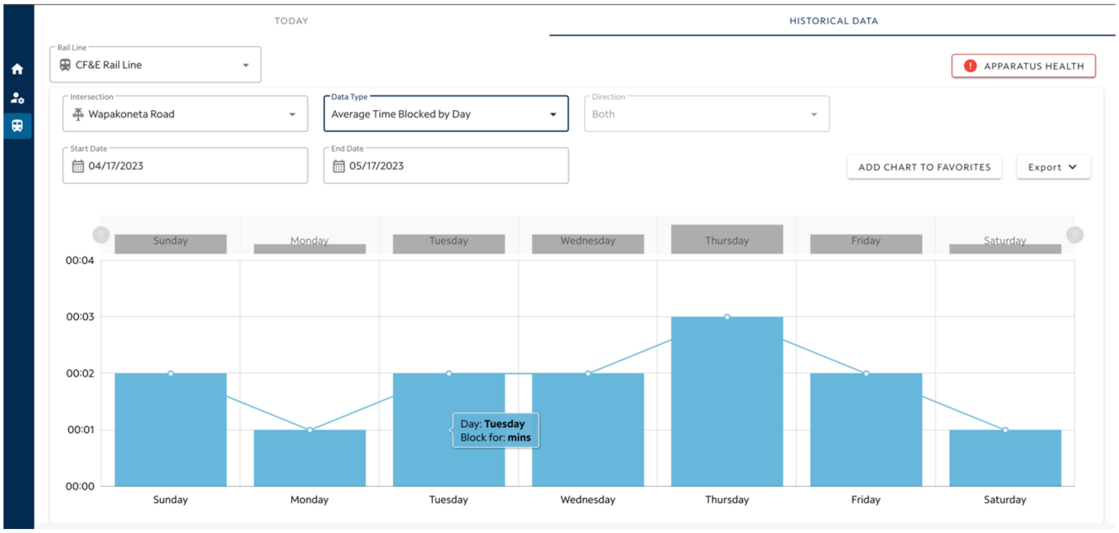

Figure 10 - Average Time Blocked by Day Visualization(X axis: Day, Y axis: HH:MM)

6. Conclusions

In summary, industrial cities in the United States, such as Lima, Ohio, face significant challenges due to the high number of railroad crossings. The constant flow of freight train activity, combined with the lack of publicly available schedules and alternative routes, leads to prolonged disruptions for drivers, commuters, and emergency services. As a result, the economy, standard of living, and public safety of these cities suffers negative consequences. To tackle these issues, an innovative approach that integrates embedded systems, networking, and artificial intelligence has been pursued.

By implementing embedded systems supported by advanced networking capabilities and sophisticated AI algorithms, it becomes possible to mitigate the adverse effects of traffic blockages, delays, and limited detour options. This comprehensive solution aims to improve the overall efficiency and well-being of industrial cities. By integrating computing technology into infrastructure elements through embedded systems and leveraging robust networking infrastructure, the movement of freight trains can be more effectively monitored and managed. Furthermore, the integration of AI algorithms enables the prediction and optimization of train schedules, leading to improved traffic management and better coordination among transportation networks.

This project has the potential to scale up and be utilized by local municipalities and individuals, particularly benefiting first responders by avoiding delays. Currently, local officials are already testing the project, and the MQTT infrastructure can be replaced with more robust and scalable cloud infrastructure to process larger amounts of data without interruptions.

Cable operators can also benefit from this solution as reliable internet connectivity is crucial. As the project expands to multiple cities, the network operators' customer base would increase due to the growing number of internet-enabled devices. Installing the solution in remote areas can serve as a valuable test point for network operators, allowing them to assess network coverage, latency, and consistency.

Effectively addressing these challenges requires a comprehensive strategy that combines technological innovation, collaboration with railway authorities, and engagement with local stakeholders. By deploying embedded systems, leveraging networking capabilities, and harnessing AI, industrial cities can strive to create a more streamlined and efficient transportation ecosystem. This approach promotes economic growth, enhances quality of life, and ensures public safety for all residents.

7. Abbreviations and Definitions

7.1. Abbreviations

AI	artificial intelligence
API	application programming interface
COCO	common objects in context
CPU	central processing unit
CUDA	Compute Unified Device Architecture
DNN	Deep Neural Network
EMS	emergency medical services
FPS	frames per second
ft	feet
GHz	gigahertz
GPS	Global Positioning System
GPU	graphics processing unit
IoT	internet of things
IP	Internet Protocol
JSON	JavaScript Object Notation
LTE	Long Term Evolution
ML	machine learning
MQTT	Message Queuing Telemetry Transport
NEMA	Natural Electrical Manufacturers Association
PoE	power over Ethernet
radar	radio detection and ranging
ResNet	residual network
RTSP	Real Time Streaming Protocol
SRR	short range radar
USB	universal serial bus
YOLO	you only look once

7.2. Definitions

No definitions are applicable.

8. Bibliography and References

[1] Dusty-nv. jetson-inference: Guide to deploying deep learning inference networks and deep vision primitives with TensorRT and NVIDIA Jetson. GitHub, https://github.com/dusty-nv/jetson-inference

[2] COCO Dataset: a large-scale object detection, segmentation, and captioning dataset. https://viso.ai/computer-vision/coco-dataset/

[3] ImageNet Dataset: image database organized according to the WordNet hierarchy, in which each node of the hierarchy is depicted by hundreds and thousands of images. https://www.image-net.org/

[4] Title: "opticalFlowFarneback" - MathWorks Documentation. Website: MathWorks. URL: https://www.mathworks.com/help/vision/ref/opticalflowfarneback.html

[5] OpenWeatherMap. (n.d.). OpenWeatherMap API. Retrieved from https://openweathermap.org/api

[6] Title: "What is Rain Fade?". Website: Everything RF Community. URL: https://www.everythingrf.com/community/what-is-rain-fade

Electric Vehicle Workplace Transition Plan for an SCTE Member Company

SCTE in Partnership with Villanova University as a Member of the Sustainable Engineering RISE Forum

A Technical Paper prepared for SCTE by
Villanova University RISE Team Members:

Queen Okon
linkedin.com/in/okonqueen

Priya Arya
linkedin.com/in/priyaarya/

Mariah Bodine
linkedin.com/in/mariah-bodine-9b28b6124/

Ryan Campbell
linkedin.com/in/ryan-campbell-388538b/

Yen Leng Chong
linkedin.com/in/yen-leng-yl-chong-65362013a/

Reid Upthegrove
linkedin.com/in/rtupthegrove/

Faculty Advisor:

Karl Schmidt, Professor of Practice, Villanova Faculty Advisor

Acknowledgment

This project was completed by a team of six Villanova students in the Master of Science in Sustainable Engineering (MSSE) program and Master of Business Administration (MBA) programs. This project was conducted as part of the program's Resilient Innovation through Sustainable Engineering (RISE) initiative. This RISE project was supported by Villanova faculty advisor, Karl Schmidt, and by the Society of Cable Telecommunications Engineers (SCTE). Thank you SCTE and its partners for all their guidance and support throughout this project, with special thanks to Derek DiGiacomo, Margaret Bernroth, and Sam Khola.

Table of Contents

List of Figures

List of Tables

1. Introduction

1.1. Transportation's Contribution to Climate Change

The transportation sector is one of the major sources of anthropogenic U.S. greenhouse gas (GHG) emissions as it accounted for 28% of total U.S. GHG emissions in 2021. The majority of GHG emissions from transportation are carbon dioxide (CO_2) resulting from the combustion of petroleum-based products, such as gasoline and diesel fuel in internal combustion engines. The largest sources of GHG emissions are light-duty vehicles (37%), and medium-heavy-duty vehicles (23%), and the remainder are passenger cars, aircraft, rail, pipelines, ships, and boats.

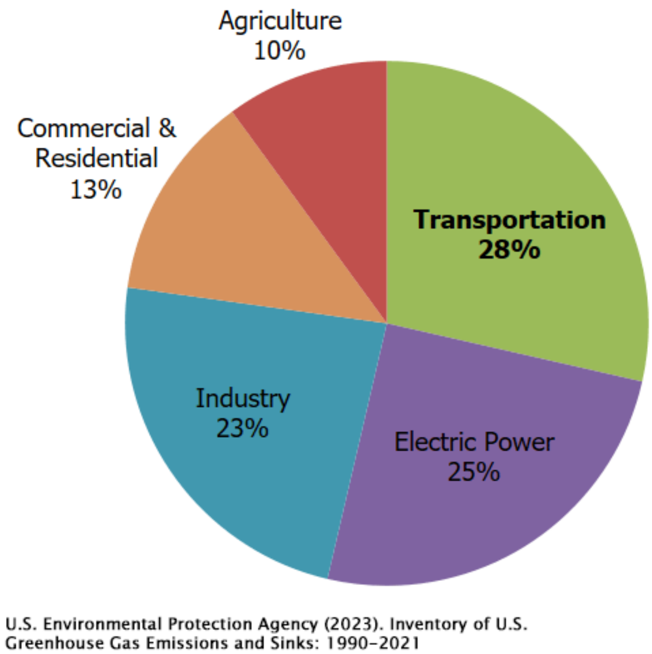

Figure 1: Total U.S. Greenhouse Gas Emissions by Economic Sector in 2021

Many global and major companies are starting to set targets and take actions to shift their fleets to electric vehicles (EVs) and install charging stations to pursue a net zero emission pathway. According to the International Energy Agency (IEA), there are more than 100 global companies in 80 markets committed to using electric vehicles by 2030. By 2020, these companies had already deployed 169,000 zero-emission vehicles, double from the previous year. Even though companies had difficulty in identifying EV equivalents for commercial vans and heavy-duty vehicles, the number of commercial electric vehicles rose 23% in 2020, including a threefold increase in electric trucks [2].

1.2. Villanova University & SCTE RISE Partnership

SCTE is a global nonprofit professional association for the advancement of the deployment of technology, technical standards, and workforce development education in the cable telecommunication industry. SCTE has also been a long-time RISE forum member in partnership with Villanova University's graduate Sustainable Engineering program. In the RISE program, engineering students work on real-world problem-solving solutions to help advance the sustainability goals of the participating partner organizations.

2. Objectives

2.1. Goal & Scope

In this project, one of the member companies of SCTE has set a climate goal, which it hopes to achieve partly by gradually transitioning its operating fleet to electric vehicles. The goal of this study has been to assess the company's current inventory of internal combustion engine (ICE) vehicles and to develop a fleet-level transition strategy. This necessitated a rather broad research scope, spanning financial and policy-level enablers, current infrastructure and technological capabilities, existing and upcoming EV options, and possible emissions and financial savings. While all of these items were in-scope for the internal evaluation, the company name and state-location information are omitted from this paper for the sake of maintaining company anonymity. Instead, a more general roadmap of fleet electrification is explored for other companies interested in employing a similar electrification strategy. Various factors that play a crucial role in transitioning the corporation fleet to EVs are highlighted in this study, such as geographic locations, national infrastructure development, state, and federal incentives, total cost of ownership (TCO), EV selection, and many others. After considering all factors, results and analysis are presented with recommendations for implementing the transition successfully in the future.

2.2. Approach

The approach employed for this project consisted of several steps. The first task was to collect and understand qualitative insights regarding the best strategies to evaluate large commercial fleets of light-to-heavy duty vehicles from literature, company staff, and expert interviews. With this information it was then possible to conduct an analysis of the best opportunities for electrification of fleet by location. After geographic prioritization, the team turned its attention towards vehicle-type, and utilized company-provided fleet data and a review of available research electric vehicle equivalents to understand electrification opportunities by vehicle class. At this point, key metrics were used to prioritize vehicle replacement and to develop preliminary replacement recommendations by vehicle class and location for the company. To maintain the confidentiality of the company's identity, the company's name and states of operation are not mentioned in this study.

3. Methodology

3.1. Strategy Development

To collect company-specific information and develop an effective fleet transition strategy, interviews with company staff and industry experts were conducted along with a thorough literature review. The interview topics included understanding company goals related to overall emissions, the top KPIs for decision-making, and how the pace of transition would affect the CAPEX and OPEX budgets. The literature review topics included successful fleet electrification plans in other industries; the national and state-level contexts for EVs; identification of states that are the most "EV-friendly" through incentives, policies, and infrastructure; concerns around range; and the distribution of different charger types.

With this insight, three strategies were considered for this study on transitioning the company's commercial fleet to all-electric. The first strategy is based on identifying current vehicle leases that are nearing the end of their term of contract and would make for a seamless transition. The second strategy is based on in-place procurement contracts or established goals or partnerships with specific vehicle manufacturers. Without proper timing of these leases and contracts there are potential penalties and termination negotiations to consider proceeding. The third strategy calculates the projected total cost of ownership (TCO) of the ICE vehicles and recommends phasing out from highest to lowest. This calculation considers all costs associated with a vehicle over a specific length of time, including estimated total costs of depreciation, insurance, fuel, maintenance, repairs, and taxes and fees. Since the member company had no standing leases or contracts in place, this study proceeded with the TCO strategy.

3.2. Geographic Prioritization

As a telecommunications provider, the SCTE member company operates in many locations across the United States. To prioritize geographic areas for the phased rollout of fleet electrification, a hierarchy of influential factors was developed. Each state was evaluated for key components in four categorical tiers to understand the feasibility of electric vehicle transition in that state. Tier 1 starts with examining current contracts and obligations that directly influence the ability to make fleet changes as well as the realistic timeline to prepare for implementation and forthcoming regulations. This step includes evaluating existing agreements with suppliers, current local mandates for electrification, and any established state-wide sustainability commitments.

Tier 2 evaluates the available infrastructure and technologies to understand the current and near-future capacity to support electric vehicles within the state. This is done by identifying the total number and average distributions of charging stations and ports per population and per land area coverage. This tier also includes any available projections for the pace of technology transition to facilitate a higher future grid demand.

Tier 3 explores current financial incentives to accelerate electrification by identifying the state-level financial subsidies as well as private or utility financial enablers to be factored into the final cost calculations.

Finally, Tier 4 determines the energy mix by percent renewable to understand the energy source for electricity generation and therefore the relative positive impact from electrification.

The states that fulfilled the most categories, had the strongest infrastructure and energy mix, and/or were states of high interest for the company were chosen to be analyzed for this study. Through this analysis three states were identified as the optimal locations to proceed and serve as a model for future electric vehicle rollout.

3.3. Fleet Data Collection

3.3.1. ICE Vehicle TCO Calculations

Once the preferred states were identified, information was gathered on the current fleet in those areas. Vehicles were characterized by make, model, year, class, and VIN number to then calculate TCO over a five-year period. These calculations were done through a combination of the three different tools below, based on the available data for each, as none of the tools had sufficient databases for all vehicle types. The TCOs were then ranked from highest to lowest to identify which vehicles should be transitioned first in a cost-effective manner.

Table 1: TCO Calculation Tools for ICE Vehicles

Tool	Inputs	Outputs	Assumptions	Challenges
Department of Energy (DOE) Alternative Fuel Data Center Vehicle Cost Calculator*	Average Annual Mileage	Fuel and/or Electricity Cost and Use	City & highway fuel economy is retrieved from fueleconomy.gov with data sourced from Edmunds	Database did not include all makes and models
	Percentage City Driving	Cost/Mile	Emission factor is selected per fuel mix per state	The cost of purchase and installation of a charging system is not included in this tool
	Make	Annual Emissions of CO2	The default electricity price used is the regional average based on state	
	Vehicle Year	Annual & Cumulative TCO over 15 years (but we only need the TCO for the first 5 years for this analysis)	The average costs listed below are based on study by American Automobile Association (AAA) [3]: • Tires + maintenance = ¢5.38/mi • Insurance + license + registration = $1,616/year • Financed 90% of the vehicle price, five-year loan at 6% interest • Year One includes the 10% down payment	
	Number of days per Week	Vehicle Price		
	Number of weeks per year			
	Days Model (Transmission, Drivetrain, & Engine)			
			The tool does not consider the vehicle trade-in value.	
			For this analysis, it was assumed that: • Average daily driving distance = 40.816 miles	

Tool	Inputs	Outputs	Assumptions	Challenges
			• Number of days per week = 5 • Number of weeks per year = 49 • Percentage highway = 45% The above results in: • An annual driving distance of 10,000 miles • An annual city mileage of 5500 miles • An annual highway mileage of 4500 miles.	
Edmunds Inc. True Cost to Own Pricing System**	Zip Code	True Cost to Own	Operating costs are estimated for a 5-year period [4]	Only included vehicles for 2017 and newer
	Make	Total Cash Price	Average annual mileage is 15,000 miles [4]	The average annual mileage was manually adjusted to 10,000 miles
	Model	Ownership Costs: 5-Year Breakdown	The vehicle is assumed to be traditionally financed and not leased	The cost of purchase and installation of a charging system is not included in this tool
	Year	A breakdown of the TCO into the following seven cost categories: • Depreciation • Taxes and Fees • Financing • Fuel • Insurance • Repairs • Maintenance	An above-average credit rating was assumed for the purpose of determining finance rate [4]	
	Style (Includes number of doors, transmission, drivetrain, engine etc.)		A10% down payment was assumed at purchase [4]	
			Loan term is assumed to be 60 months [4]	
			Federal tax credit where applicable is applied	
VINChecker.Info Reports	Average Annual Mileage	Average market Value	Does not consider financing	Does not offer state-specific fuel cost customization

Tool	Inputs	Outputs	Assumptions	Challenges
Ownership Cost Calculator***	Current Mileage: Recalculated mileage from year of manufacture to date	Cost per mile		Does not offer state-specific electricity cost customization
	VIN	Annual & Cumulative TCO over 5 years		Occasional data discrepancies
	Time period (For this analysis, we choose a 6-month span)	Estimate Certainty		
		A breakdown of the TCO into the following six cost categories: • Depreciation • Taxes and Fees • Fuel • Insurance • Repairs • Maintenance		
		Vehicle Specifications		

* https://afdc.energy.gov/calc/

**https://www.edmunds.com/tco.html

***https://vincheck.info/check/report-summary.php?vin=1FDUF5GY2KEF90695

3.3.2. *EV Equivalent Identification*

The next step was to identify appropriate EV equivalents to those currently in the fleet. The company stated preferences for OEMs with wide networks, as well as for vehicles manufactured in the latest model year available. The company also specified a preferred daily range of 200-300 miles. In order to match electric vehicles to those already in the fleet, the EV models should be equivalent to the existing model or should slightly exceed the rating, such as gross vehicle weight rating (GVWR), but mostly for light-duty to medium trucks, which will be discussed below. As such, the vehicle class was first determined by GVWR through a combination of the company-provided data, the DOE tool, and the Badger Truck & Auto Group Classification guide [5]. Then the class was inputted along with preferences for year, technology (electric, plug-in hybrid electric, or hybrid electric), and OEM into one of the available alternative vehicle search tools. These tools were selected based on the user interface's ease of use to search for available EVs by global region, desired class, function, fuel type, and OEMs. A combination of the DOE's Alternative Fuels Data Center (AFDC) Alternative Fuel and Advanced Vehicle Search platform, the Green Cars Buyer's Guide, and the Zero-Emission Technology Inventory (ZETI) were used. A range of tools was needed for EV selection because of their respective databases of vehicles of different classes. For example, ZETI is a tool specific for medium- and heavy-duty EV vehicle searches only. The resulting vehicles were then compared to the original ICE vehicle for payload, dimensions, and daily mileage range to ensure all specifications were commensurate, when possible, in comparison to the original ICE vehicles.

3.3.3. *EV TCO Calculations*

The TCO was then calculated for each identified EV equivalent utilizing the same tools as for the ICE vehicles when results were available. For vehicles that could not be found with the previously mentioned tools, two additional tools were utilized.

Table 2: TCO Calculations for EV and Hybrid Vehicles

Tool	Inputs	Outputs	Assumptions	Challenges
Atlas Public Policy Fleet Procurement Analysis Tool https://atlaspolicy.com/fleet-procurement-analysis-tool/	Zip Code	NPV Vehicle Total Cost	Federal Tax credit is assumed to be the total price of $7,500	It has less vehicle specificity of the model specification details
	Gasoline Price	NPV Cost/ Mile		It is more limited in the range of OEMs it offered
	Diesel Price	Wheel-to-Well CO2 Fuel Emissions per mile		Many of the inputs or additional factors cannot standardized against other TCO tools.
	Electricity Cost	Total Wheel-to-Well CO2 Fuel Emissions		Limited to Light-, Medium- and Heavy-Duty Vehicles only
	Public Charging Price			
	Vehicle drivetrain type, class, year, make, model			
	Annual Mileage			

Tool	Inputs	Outputs	Assumptions	Challenges
	Expected Years of Use			
	Percentage City Driving			
	Expected Years of Use			
	Percentage Annual miles City Driving			
	Fuel Economy			
	Federal Tax credit			
Zero-Emission Technology Inventory (ZETI)	Fuel Type	Range		Limited to Light-, Medium- and Heavy-Duty Vehicles only
	Year	Payload		
	Vehicle Platform/ type	Energy Capacity		
	Manufacturer	First available year		
	Model	Incentive if considered		

3.4. Overall Fleet Data Analysis

Once TCOs, emissions, and other relevant vehicle specifications were calculated for EV equivalents, adjustments were made for charger and installation cost, upfitting (where necessary), and available incentives to effectively compare with ICE vehicles in Table 3. More specifically, the only incentive applied to the EVs is the Commercial Electric Vehicle and Fuel Cell Electric Vehicle Tax Credit from the Inflation Reduction Act (IRA) [6].

Table 3: Company-Provided Additional Costs of EVs beyond TCOs and Initial Purchase

Cost Type	Cost Source	Cost Amount ($)
Charger	Purchase	800
Charger	Installation	2395.81
Upfit	Car - Car	0
Upfit	SUV - SUV	0
Upfit	Truck - Bucket Truck	135,000
Upfit	Truck - Cargo Box Truck	0

Cost Type	Cost Source	Cost Amount ($)
Upfit	Truck - Construction Bucket Truck	135000
Upfit	Truck - Construction Truck	135000
Upfit	Truck - Fiber Bucket Truck	135000
Upfit	Truck - Light Truck	6,000
Upfit	Truck - Specialty Truck	0
Upfit	Truck - Underground Construction truck	135000
Upfit	Truck - Utility Body Truck	135000
Upfit	Truck - Utility Body-Flush	135000
Upfit	Van - Bucket van	15000
Upfit	Van - Fiber Bucket van	15000
Upfit	Van - Full size 12 pass van	15000
Upfit	Van – Full-size cargo van	15000
Upfit	Van - full size SVC van	15000
Upfit	Van - Passenger minivan	0
Upfit	Van - Service Minivan	0

State and private company incentives were not included in the scope of this analysis for the purchase of EVs. In addition, incentives were not included for charger purchase and installation due to lack of eligibility confirmation regarding the company's preferred model of residential charging at the homes of employees through company-sponsored charger purchase and installation. Further, it is currently unknown which employees own their home, and thus, can approve or deny charger installation at the home.

3.4.1. Fleet Data Overview

Ultimately, 1,625 data points were provided by the company to represent a portion of the vehicles in three of the six states of interest shared on the onset of this project. Those states include States A, B, and E. It is important to note that some of these datapoints are excluded for various reasons in various parts of the analysis. One example is: of the fleet data, three items are definitively excluded from all analysis. One item represented a piece of equipment rather than a vehicle. The other two vehicles were not analyzed due to their information not being available to the tools used to determine TCOs of the vehicles in the current fleet. Another example addresses the fact that the existing fleet consists of predominantly ICE vehicles, but also includes 47 hybrid vehicles. Hybrids, though evaluated for their TCOs and annual emissions whenever possible, were not included in the data and results section because it is assumed that these vehicles would not be prioritized for full electrification. The remaining number of vehicles after those two examples of exclusions are 1,574. Also, 13 additional vehicles were excluded due to the lack of data available in the tools used to determine the TCO. Those vehicles consist of three light-duty vehicles and 10 heavy-duty vehicles. Furthermore, three vans do not have data regarding the state of operation and were also excluded. As a result, a total number of 1,558 vehicles remain for analysis, including the following:

Table 4: Vehicles analyzed from overall company-provided fleet data

Vehicle Type	Count
Cars	101

Vehicle Type	Count
SUVs (41) & Minivans (9)	50
Light-Duty Bucket Trucks	446
Medium-Duty Bucket Trucks	263
Heavy-Duty Bucket Trucks	0
Cargo Trucks (7) & Specialty Trucks (1)	8
Vans	690

Specialty and cargo trucks were excluded from the analysis due to their representing less than 1% of the dataset. Heavy-duty trucks -representing less than 1% of the fleet- were excluded due to data unavailability. Also, three light duty vans did not have state allocation data in general.

3.5. Carbon-Pricing Scenarios Analysis

After evaluating the overall sample set, the next part of the analysis entailed developing a crude baseline model of carbon pricing scenarios, more specifically involving a carbon proxy price, also known as a shadow carbon price [7]. A shadow carbon price is an internal cost that does not involve exchange of funds, but rather "is incorporated into cost analyses, as follows: the estimate of any emissions associated with a financial decision is multiplied by a carbon price and this figure is added to the costs" [7]. In other words, when considering fleet electrification, a carbon shadow price "attaches a dollar value to the carbon emissions that are saved by driving the electric vehicle" [8]. This tool adds value in modeling financial risks from future carbon regulations, helps set a value to the cost to society from damages, and aligns decisions with organizational goals [8]. Such prices can also be factored into lifecycle cost (LCC) assessments which consider more than just initial purchase costs, ultimately altering the overall LCC and payback periods as well [8].

Company prices for carbon have ranged from $2/ton to more than $800/ton of carbon dioxide emissions, but for the purposes of this report, two scenarios are explored with internal prices of carbon [9]. The first scenario involves setting the shadow carbon price at $51/ton of carbon emissions, which is from the Biden Administration [10]. The second scenario has the carbon shadow price set to the November 2022 recommendation from the Environmental Protection Agency (EPA) of $190/ton of carbon emissions [10]. This exercise was performed to develop a preliminary sense of the financial risks and opportunities of electrification of the fleet if carbon prices were adopted internally and/or mandated externally over the five-year period of the TCOs evaluated. Because the analysis requires that the current vehicles considered have both TCO and emissions data estimates, as well as determined EV equivalents with TCO and annual emissions data available, this exercise only uses a subset of the fleet sample set. This subset consists of 477 vehicles, just under a third of the total sample set. Those vehicles consist of:

Table 5: Vehicles included in Carbon Pricing

Vehicle Type	Count
Cars	79
SUVs (37) and Minivans (9)	46
Light-Duty Bucket Trucks	352

Thus, medium-duty and heavy-duty bucket trucks as well as vans are not part of this exercise because of the data gaps.

4. Results and Analysis

During the analysis, a range of data gaps as well as inconsistency of sourcing and assumptions arose along the various steps of the data analysis process, as outlined below.

4.1. Assumptions, Data Gaps, Challenges

4.1.1. Strategy Development

Significant assumptions and data unavailability or quality challenges did not occur during this phase.

4.1.2. Geographic Prioritization

Significant assumptions and data unavailability or quality challenges did not occur during this phase.

4.1.3. ICE TCO Determination & Emissions

The ICE TCO determination phase presented several challenges. One challenge, as mentioned in *section 3, Methodology* is that there is no single tool that has data on every single vehicle in the fleet subset, and so multiple tools had to be employed, even though they have different built-in assumptions. For example, one tool may have an assumed value for the aggregate of insurance and tax costs while another tool might outline these costs individually, the sum of which does not match the aggregate from the other tool. In other words, the assumed amount of the costs that comprise the TCO for the same vehicle may differ from one tool to the next. These inconsistencies are aggregated in the overall analysis because it assumed that the inconsistencies are not significant enough in the data sourcing and subsequent embedded assumptions to prevent the observation of relevant trends in ICE and EV TCO comparisons. Further, the only tool employed that offers annual emissions estimates is the DOE's AFDC Vehicle Cost Calculator tool mentioned in Section 3.

4.1.4. EV Equivalent Determination

The most significant challenge faced was that available EV and hybrid vehicle models are often outside of the scope of the company's preferred manufacturers. As a result, there were instances, especially for higher GVWR class vehicles, in which alternative manufacturers and retrofitting options, such as those of the company, SEA Electric, were considered to find a possible EV equivalent and potentially determine an EV TCO.

4.1.5. EV TCO Determination & Emissions

Other than facing a significantly smaller number of EV and hybrid alternatives available on the market, the assumptions, data gaps, and data quality challenges mirror those of the ICE TCO and emissions determination. In addition to the DOE tool, the *Atlas Fleet Procurement Analysis Tool version 1.31* is the only other tool that offers both TCO estimates and annual emissions estimates, especially for higher weight class EVs not included in the DOE tool.

4.2. Geographic Prioritization Results

Based on the geographic prioritization hierarchy developed in section 0, three states out of the six selected states were prioritized for phased roll-out of the company fleet. These states are namely States A, B and

E, and they are highlighted in shades of green in Table 6 below. These states were selected based on their respective electrification and associated infrastructure presence and enablers. For example, mandates are drivers and federal, state, and financial incentives are enablers.

Table 6: Attributes of States of Operations that are Barriers or Enablers to Electrification and Emissions Reduction

State	T1 – Existing Agreements w/ Suppliers	T1 – Mandates	T1 – Sustainability Commitment	T2: Total Number of Stations (Public) per location	T2: Pacing technology transition (rate of transition)	T3: State financial enablers	T3: Private/Utility financial enablers	Energy Mix: Total Renewables* (%)	Average Land Area Coverage (sq. mi.) per Station	Average Population Coverage per Station
A				457		✓	✓	45.5	182	3,063
B		✓	✓	13,664	✓	✓	✓	42.3	12	1,040
C		✓		481		✓	✓	31.0	252	2,149
D				1,466		✓	✓	11.6	41	2,890
E				898		✓	✓	13.3	127	2,970
F			✓	1,058		✓	✓	8.7	40	2,871

State B is a prudent and necessary selection because of a mandate driving electrification. The feasibility of complying with this mandate is supported by having the highest number of charging stations in this state of the sample of states selected, and.one of the highest renewable energy relative contributions to the overall energy mix. However, State A and E were selected based on company preference.

4.3. Overall Fleet Analysis

For this analysis, TCO was estimated for the below-listed vehicle types in all 3 states (A, B and E) excluding specialty, cargo vans, heavy-duty trucks, and 3 light duty vans that did not have state allocation data in general. This analysis also considers financial incentives offered by the Inflation Reduction Act (IRA) [11]. This federal incentive offers up to $7,500 as tax credit for vehicles that are less than 14,000 pounds and offers up to $40,000 for vehicles above 14,000 pounds [6]. It is assumed that full credit is available for all EV equivalents considered in this project. The overall portion of the company's fleet that was evaluated consists of the following:

Table 7: Number of Vehicles in Fleet by Vehicle Type

Vehicle Type	Count
Cars	144
SUVs (42) & Minivans (9)	51
Vans	694
Light-Duty (LD) Bucket Trucks	448
Medium-Duty (MD) Bucket Trucks	263
Heavy-Duty (HD) Bucket Trucks	9
Cargo Box Trucks (MD & HD)	8
Specialty Truck (LD)	1

4.3.1. TCO Trends in States A, B & E: Cars

4.3.1.1. State A - Cars

There are no cars in the fleet operated in state A.

4.3.1.2. State B - Cars

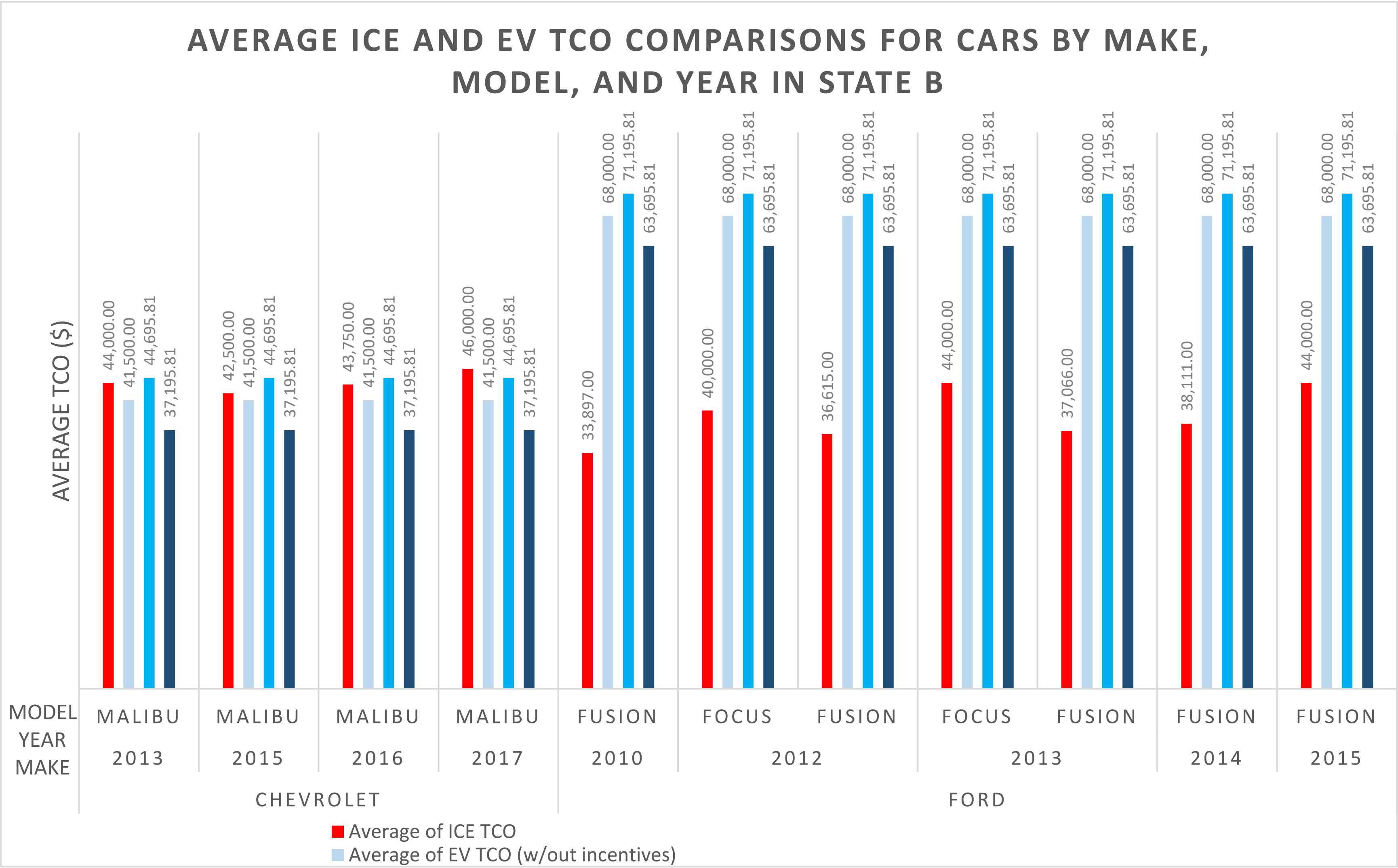

Figure 2: Comparison of ICE TCO to EV TCOs with and without additional costs and applied IRA subsidies for all cars in fleet in State B

The primary interpretation of the value of this graph is that the Ford Fusion and Ford Focus models are more expensive to replace with the 2023 Ford Mustang Mach-E. Thus, the best vehicles to prioritize for transition in State B are the 2023 Chevrolet Bolt EVs, which can help decrease the gap between the Ford Fusion/Focus and Ford Mustang Mach-E TCO. Even though upfront costs may be higher for EVs, they generally have cheaper TCOs over their lifetime compared to their ICE vehicles counterparts. This is due to fewer operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts, resulting in savings. Thus, when choosing an EV equivalent, the IRA Tax Credit can help decrease the TCO as observed in Figure 2, but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 1Table 8 contains a list of recommended EVs for the company regarding this analysis.

Table 8: List of EV equivalents for ICE Cars Referenced in Figure 2

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Chevrolet Malibu (2010, 2013, 2017)	2023 Chevrolet Bolt EVs
Ford Focus (2012-2013)	2023 Ford Mustang Mach-E
Ford Fusion (20120, 2012-2015)	2023 Ford Mustang Mach-E

4.3.1.3. State E - Cars

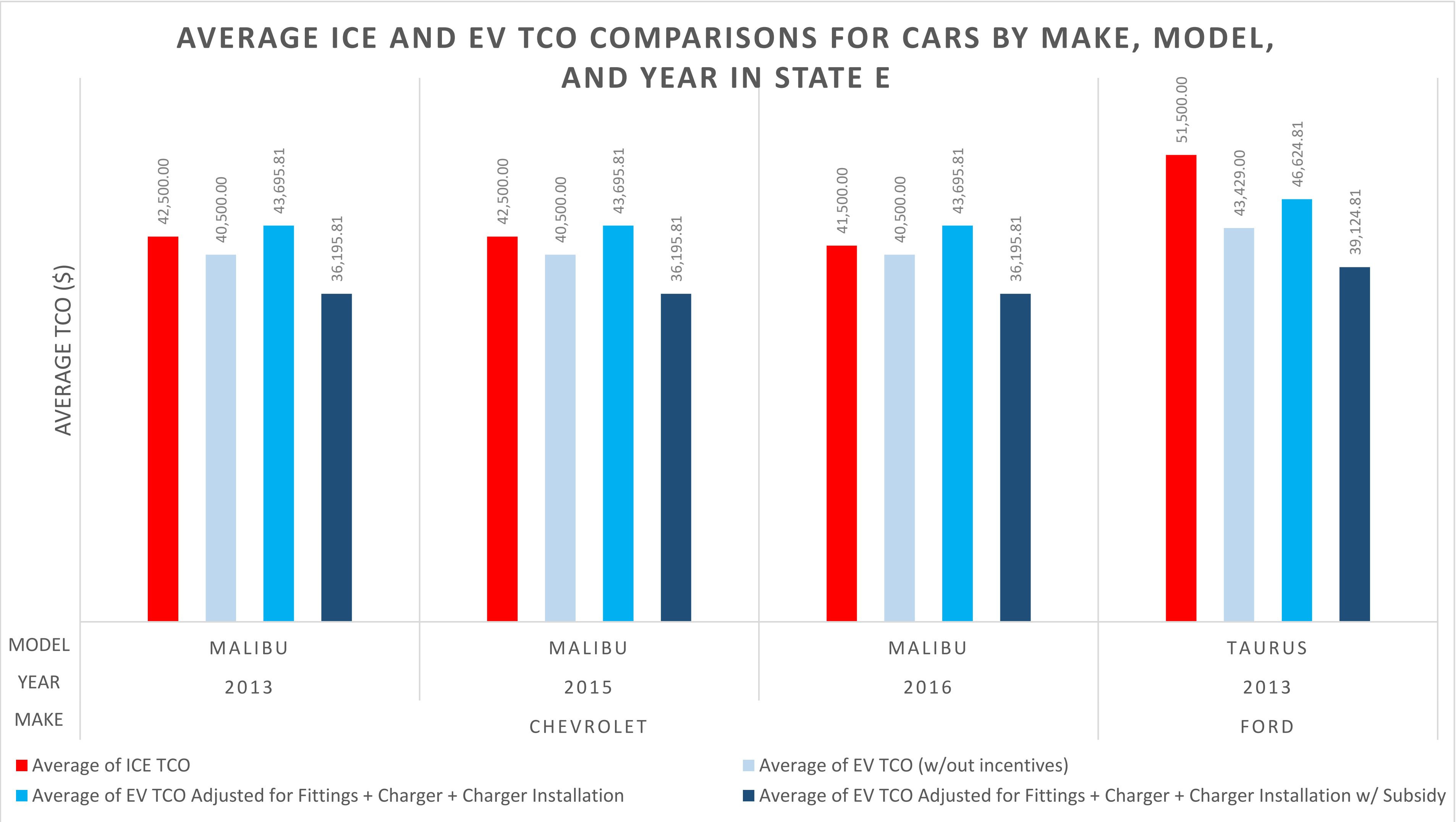

Figure 3: Average ICE and EV TCO Comparisons for Cars by Make, Model, and Year in State E

The primary interpretation of the value of this graph is that all the models are less expensive to replace with an equivalent EV model. Even though the EV TCO obtained for this analysis is less than that of the ICE vehicle, the EV TCO will further decrease over its lifetime making it a cheaper alternative. This is due to less operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts which adds up in savings. Thus, when choosing EV equivalents, the IRA Tax Credit can help decrease the TCO as observed in Figure 3 but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 9 contains a list of recommended EVs for the company regarding this analysis.

Table 9: List of EV equivalents for ICE Cars referenced in Figure 3

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Chevrolet Malibu (2013, 2015, 2016)	2023 Chevrolet Bolt EVs
Ford Taurus (2013)	2023 Chevrolet Bolt EUV

4.3.2. TCO Trends in States A, B, & E: SUVs & Minivans

4.3.2.1. State A

There are not any SUVs or minivans in the current fleet that are operated in State A.

4.3.2.2. *State B SUVs & Minivans*

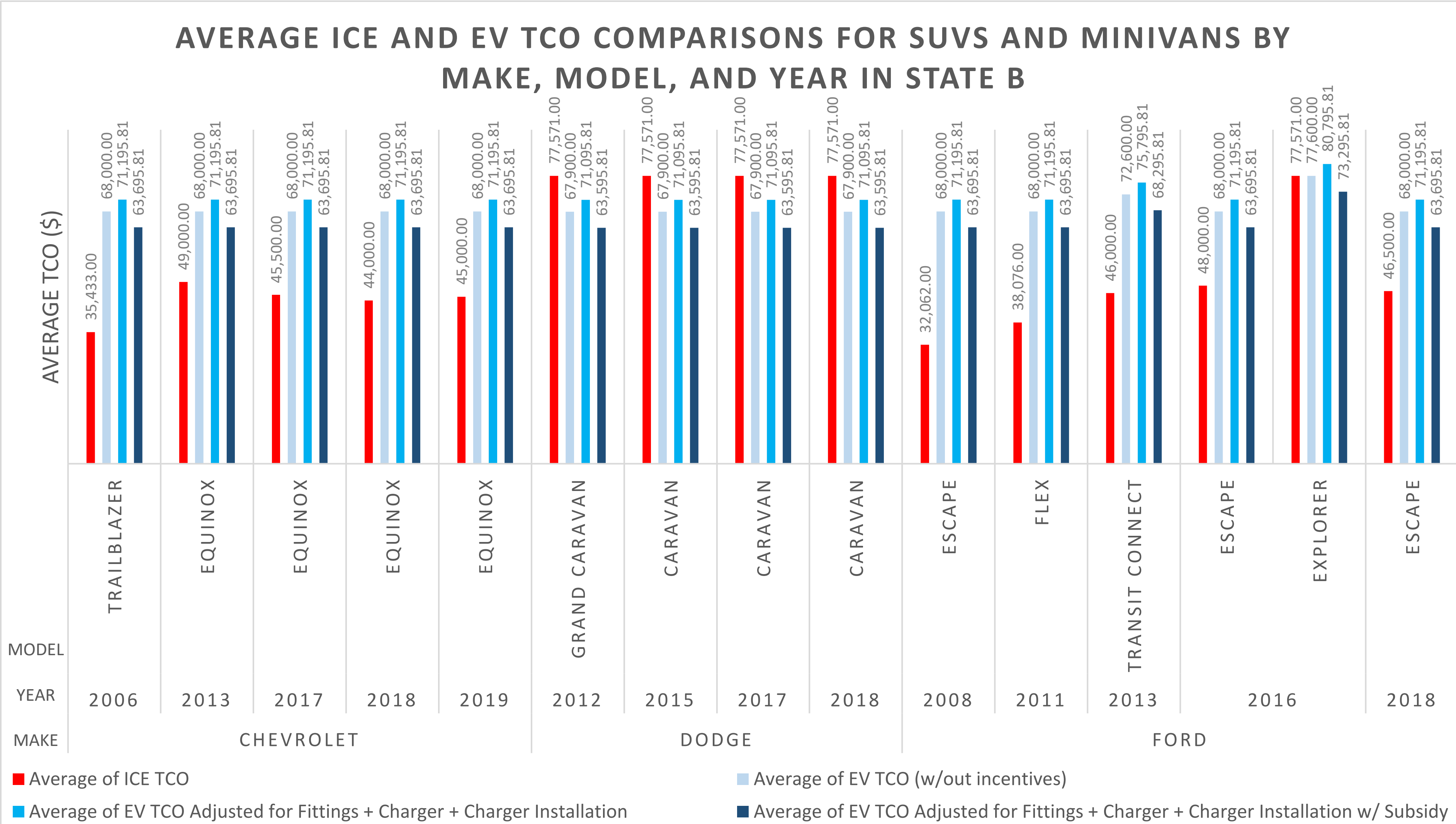

Figure 4: Average ICE and EV TCO Comparisons for SUVs and Minivans by Make, Model, and Year in State B

The primary interpretation of the value of this graph is that all the models are expensive to replace with an equivalent EV model. This increase can be attributed to the initial high MSRP (Manufacturer's Suggested Retail Price) of the equivalent EV and the upfitting cost to the EV TCO and the purchase and installation cost of the charger. Even though upfront costs may be higher for EVs, they generally have cheaper TCOs over their lifetime compared to their ICE vehicles counterparts. This is due to fewer operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts resulting in savings. Thus, when choosing EV equivalent, the IRA Tax Credit can help decrease the TCO as observed in Figure 4, but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 10 contains a list of recommended EVs for the company regarding this analysis.

Table 10: List of EV equivalents for ICE Cars Referenced in Figure 4

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Chevrolet Trailblazer (2006)	2023 Ford Mustang Mach-E AWD Automatic (A1) EV
Chevrolet Equinox (2016, 2017, 2018, 2019)	2023 Ford Mustang Mach-E AWD Automatic (A1) EV
Dodge Grand Caravan (2012)	2023 Chrysler Pacifica Hybrid (6cyl 2.6L Automatic Plug-in Hybrid)
Dodge Caravan (2015, 2017, 2018)	2023 Chrysler Pacifica Hybrid (6cyl 2.6L Automatic Plug-in Hybrid)
Ford Escape (2008, 2016, 2018)	2023 Ford Mustang Mach-E AWD Automatic (A1) EV
Ford Flex (2011)	2023 Ford Mustang Mach-E AWD Automatic (A1) EV
Ford Transit Connect (2013)	2023 Ford E-Transit Cargo Van
Ford Explorer (2016)	2023 Explorer HEV RWD 6cyl 3.3L Automatic 10-spd Hybrid

4.3.2.3. State E SUVs & Minivans

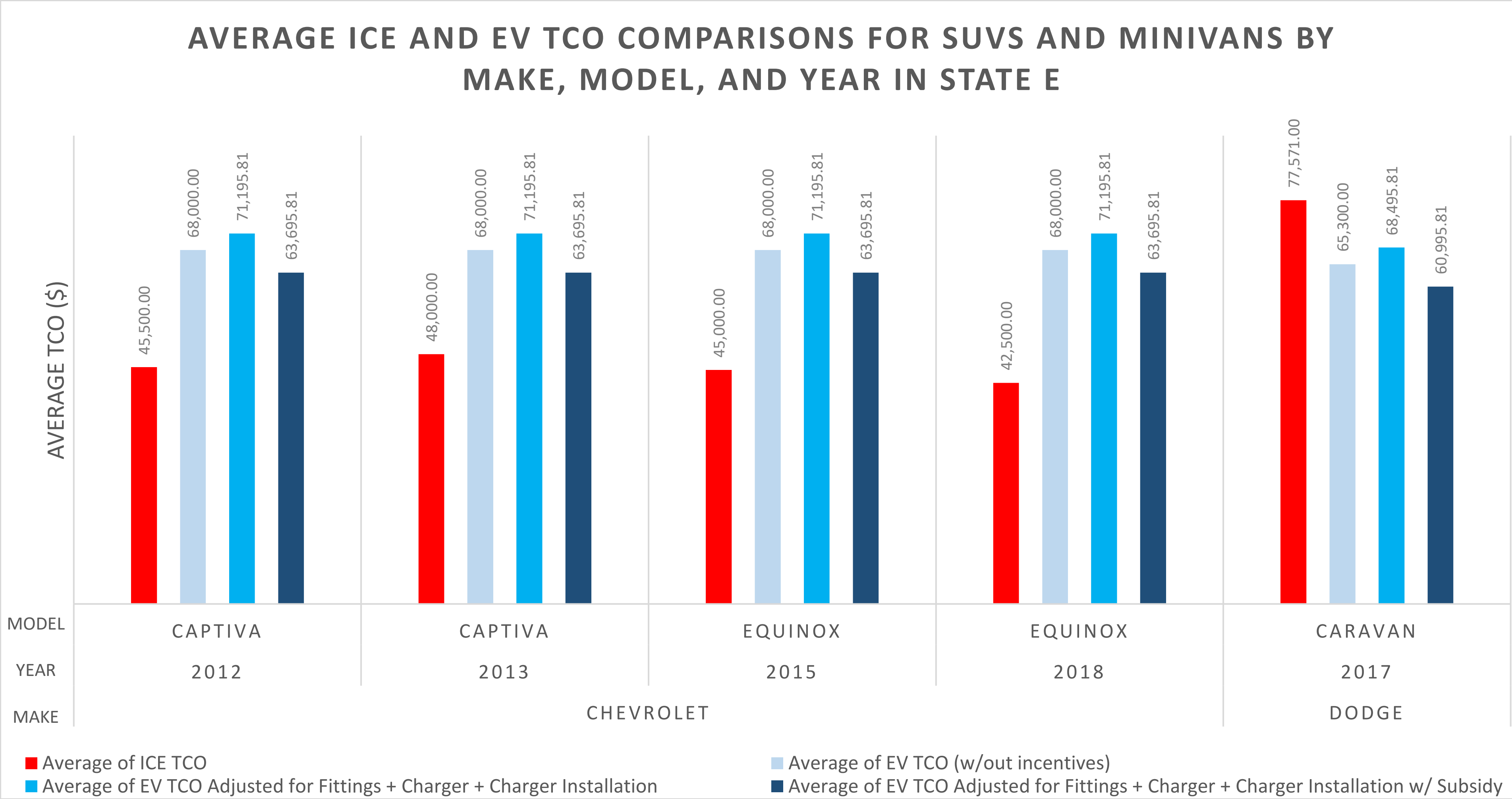

Figure 5: Average ICE and EV TCO Comparisons for SUVs and Minivans by Make, Model, and Year in State E

The primary interpretation of the value of this graph is that all the models are expensive to replace with an equivalent EV model. This increase can be attributed to the initial high MSRP (Manufacturer's Suggested Retail Price) of the equivalent EV and the upfitting cost to the EV TCO and the purchase and installation cost of the charger. Even though upfront costs may be higher for EVs, they generally have cheaper TCOs over their lifetime compared to their ICE vehicles counterparts. This is due to fewer operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts resulting in savings. Thus, when choosing EV equivalents, the IRA Tax Credit can help decrease the TCO as observed in Figure 5, but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 11 contains a list of recommended EVs for the company regarding this analysis.

Table 11: List of EV equivalents for ICE Cars Referenced in Figure 5

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Chevrolet Captiva (2012 – 2013)	2023 Ford Mustang Mach-E AWD Automatic (A1) EV
Chevrolet Equinox (2015, 2018)	2023 Ford Mustang Mach-E AWD Automatic (A1) EV
Dodge Caravan (2017)	2023 Chrysler Pacifica Hybrid (6cyl 2.6L Automatic Plug-in Hybrid)

4.3.3. TCO Trends in States A, B, & E: Light-Duty Bucket Trucks

4.3.3.1. State A Light Duty Bucket Trucks

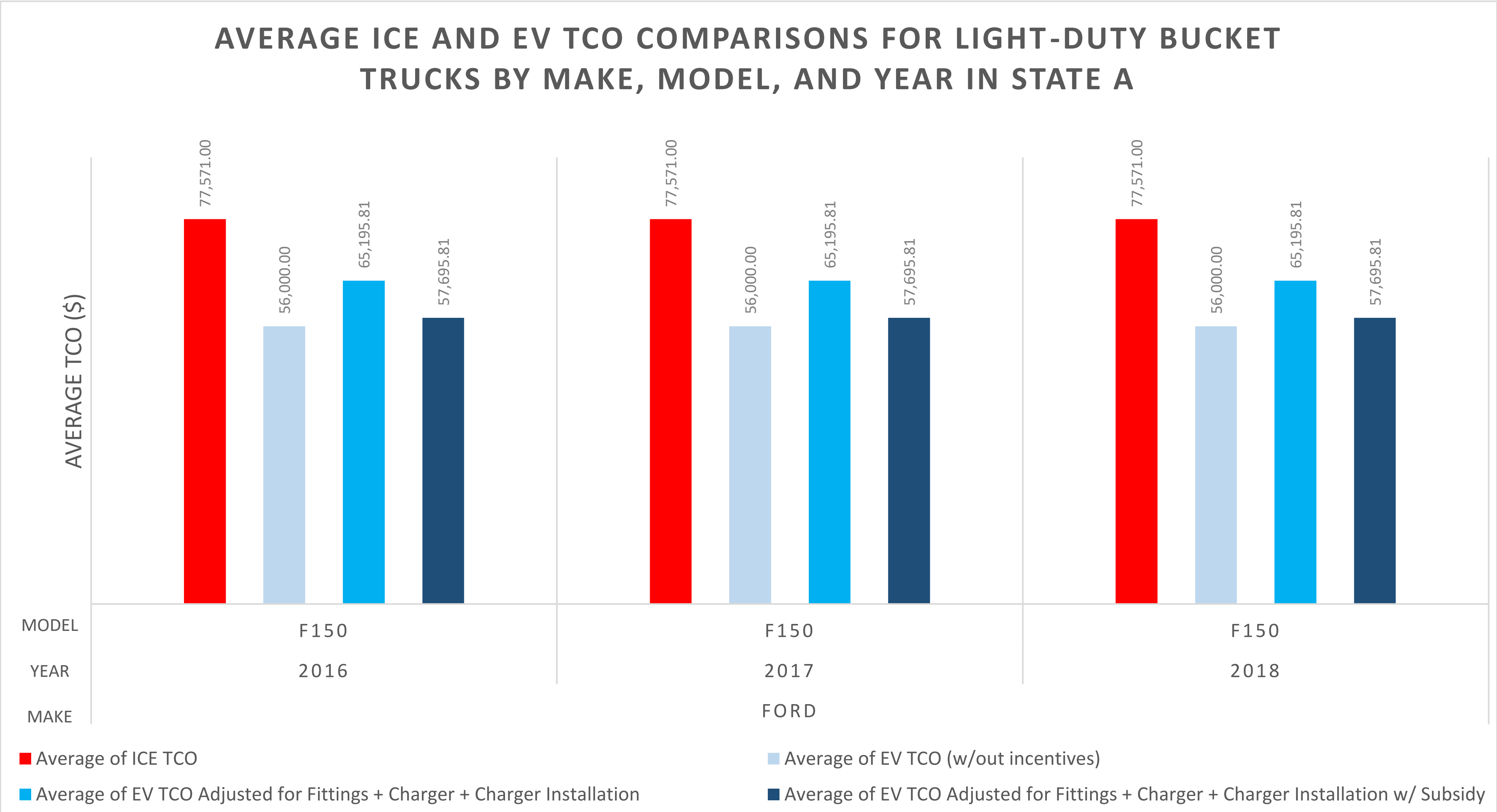

Figure 6: Average ICE and EV TCO Comparisons for Light-Duty Trucks by Make, Model, and Year in State A

The primary interpretation of the value of the Figure 6 graph is that all the models are less expensive to replace with an equivalent EV model. Even though the EV TCO obtained for this analysis is less than that of the ICE car, the EV TCO will further decrease over its lifetime making it a cheaper alternative. This is due to fewer operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts, resulting in savings. Thus, when choosing EV equivalent, the IRA Tax Credit can help decrease the TCO as observed in Figure 6, but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 12 contains a list of recommended EVs for the company regarding this analysis.

Table 12: List of EV equivalents for ICE Vehicles Referenced in Figure 6

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Ford 150 (2016 - 2018)	2023 Ford F-150 Lightning 4WD

4.3.3.2. State B Light-Duty Bucket Trucks

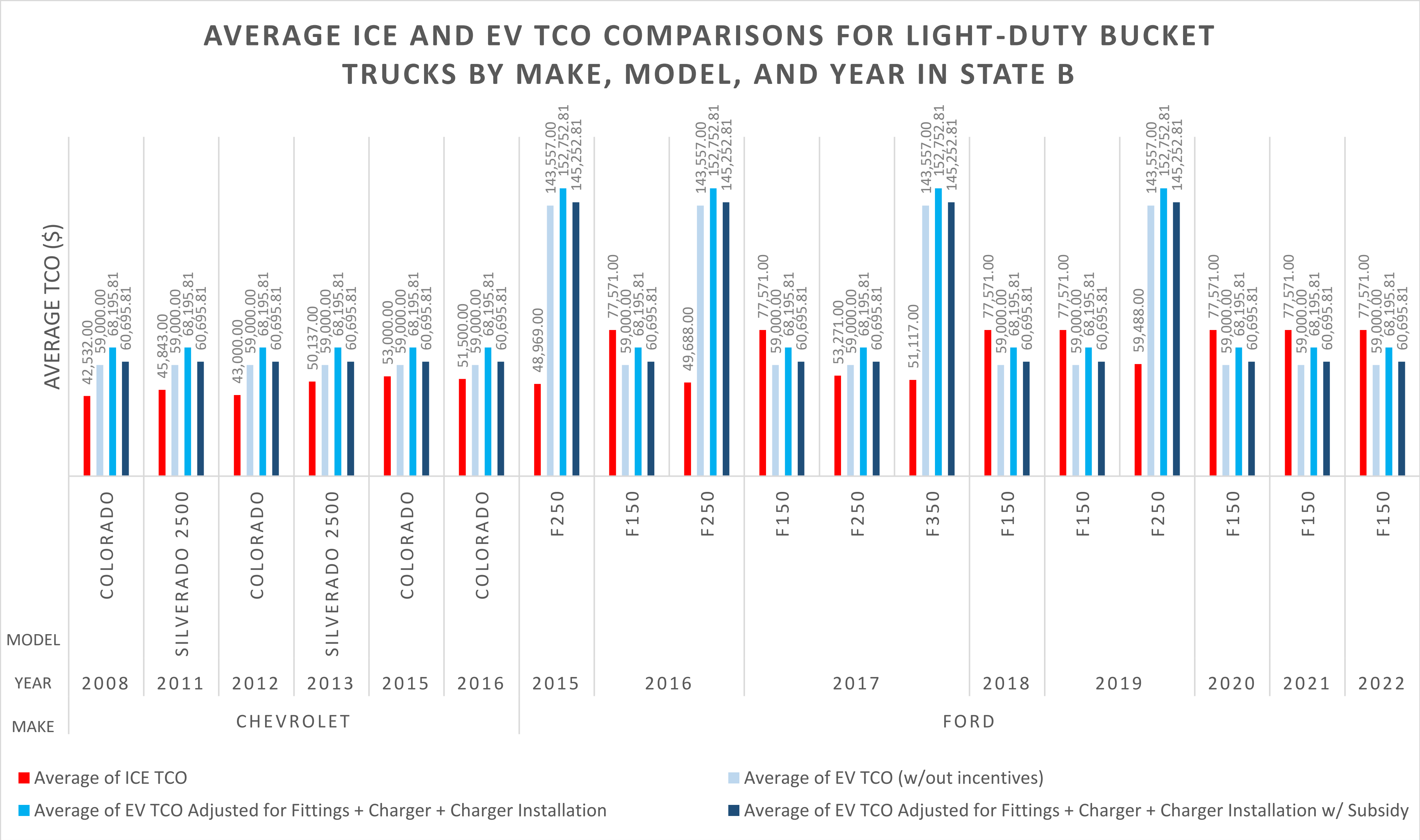

Figure 7: Average ICE and EV TCO Comparisons for Light-Duty Bucket Trucks by Make, Model, and Year in State B

The primary interpretation of the value of the Figure 7 graph is that the F250 and F350 models are more expensive to replace with an equivalent EV model because they are Class 2b and Class 3 vehicles respectively. Their EV equivalents tend to be fewer in the number of available models, and thus, significantly more expensive. For example, the F250s and F350s were placed with the SEA Electric retrofit power trains which cost more. Thus, the best vehicles to prioritize for transition in State E are the Class 1 and 2 vehicles, which are the Chevrolet vehicles and the Ford F150 vehicles.

Table 13: List of EV equivalents for ICE Vehicles Referenced in Figure 7

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Chevrolet Silverado 2500 (2011, 2013)	Ford F150 Lightning
Chevrolet Colorado (2008, 2012, 2015,2016)	Ford F150 Lightning
Ford F-150 (2016-2022)	Ford F150 Lightning
Ford F-250 (2015-2017, 2019)	Ford E-350 SEA Electric retrofit power trains
Ford F-350 (2017)	Ford E-350 SEA Electric retrofit power trains

4.3.3.3. State E Light-Duty Bucket Trucks

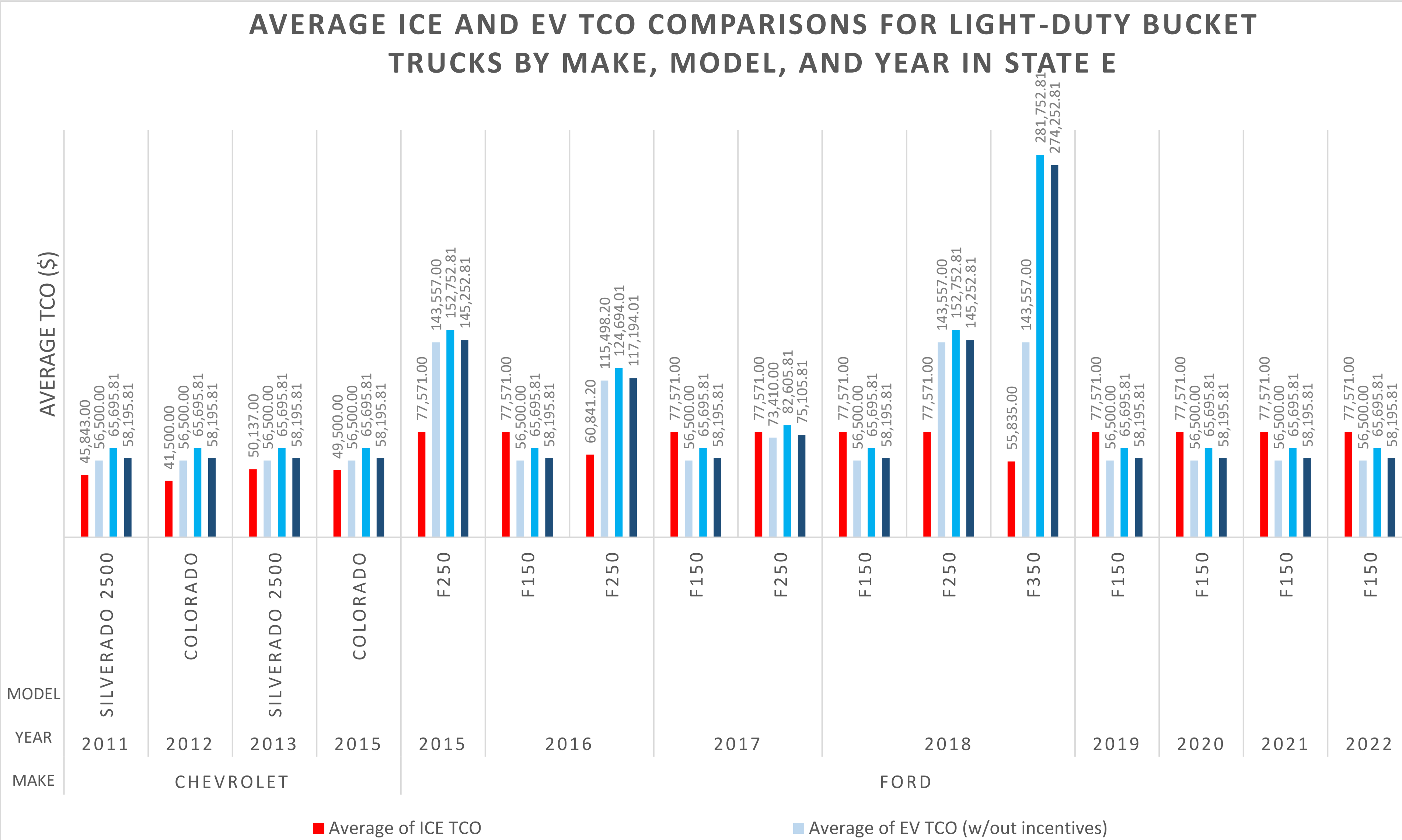

Figure 8: Average ICE and EV TCO Comparisons for Light-Duty Bucket Trucks by Make, Model, and Year in State E

The primary interpretation of the value of Figure 8 is that the F250 and F350 models are more expensive to replace with an equivalent EV model because they are Class 2b and Class 3 vehicles respectively. Their EV Equivalents tend to be fewer in the number of available models, and thus, significantly more expensive. For example, the F250s and F350s were placed with the SEA Electric retrofit power trains which cost more. Thus, the best vehicles to prioritize for transition in State E are the Class 1 and Class 2 vehicles, which are the Chevrolet vehicles and the Ford F150 vehicles.

Table 14: List of EV equivalents for ICE Vehicles Referenced in Figure 8

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Chevrolet Silverado 2500 (2011, 2013)	Ford F150 Lightning
Chevrolet Colorado (2012, 2015)	Ford F150 Lightning
Ford F-150 (2016-2022)	Ford F150 Lightning
Ford F-250 (2015-2018)	Ford E-350 SEA Electric retrofit power trains
Ford F-350 (2018)	Ford E-350 SEA Electric retrofit power trains

4.3.4. TCO Trends in States A, B, & E: Medium-Duty Trucks

4.3.4.1. State A - Medium-Duty Bucket Trucks

There are not any medium duty bucket truck vehicles operated in State A.

4.3.4.2. State B Medium-Duty Bucket Trucks

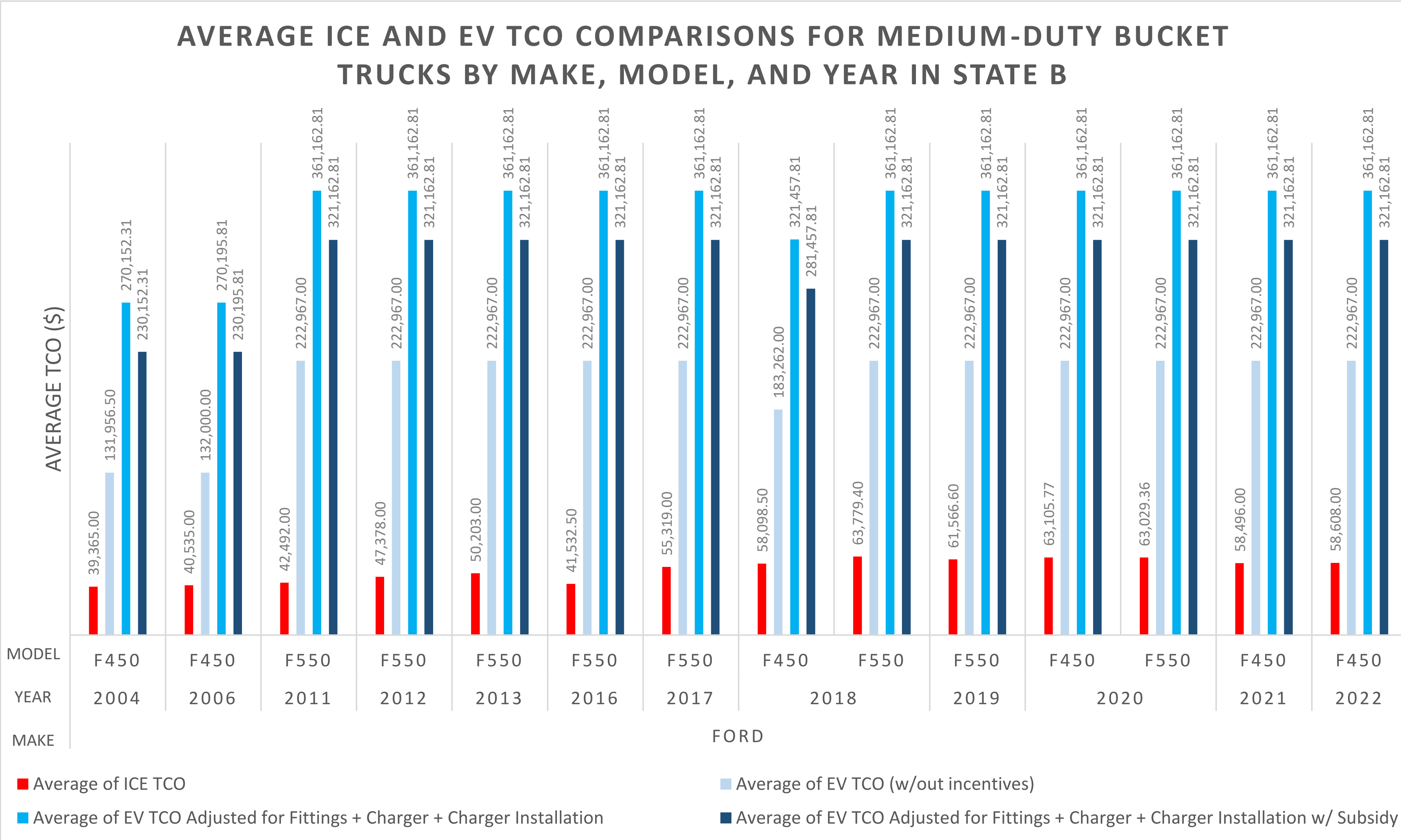

Figure 9: Average ICE and EV TCO Comparisons for Medium-Duty Bucket Trucks by Make, Model, and Year in State B

The primary interpretation of the value of Figure 9 is that the F450 and F550 models are more expensive to replace with an equivalent EV model because they are Class 4 and Class 5 vehicles. Their EV Equivalents tend to be fewer in number of available models, and thus, significantly more expensive. For example, the F450s and F550s are placed with the SEA Ford 450-650 Electric retrofit power trains which cost more. Even though upfront costs may be higher for EVs, they generally have cheaper TCOs over their lifetime compared to their ICE vehicles counterparts. This is due to fewer operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts resulting in savings. Thus, when choosing EV equivalent, the IRA Tax Credit can help decrease the TCO as observed in Figure 9, but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 15 contains a list of recommended EVs for the company regarding this analysis.

Table 15: List of EV equivalents for ICE Vehicles Referenced in Figure 9

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Ford F450 (2004, 2006, 2018, 2020 – 2022)	SEA Ford 450-650 Cutaways
Ford F550 (2011 - 2013, 2016 - 2020)	SEA Ford 450-650 Cutaways

4.3.4.3. State E – Medium-Duty Bucket Trucks

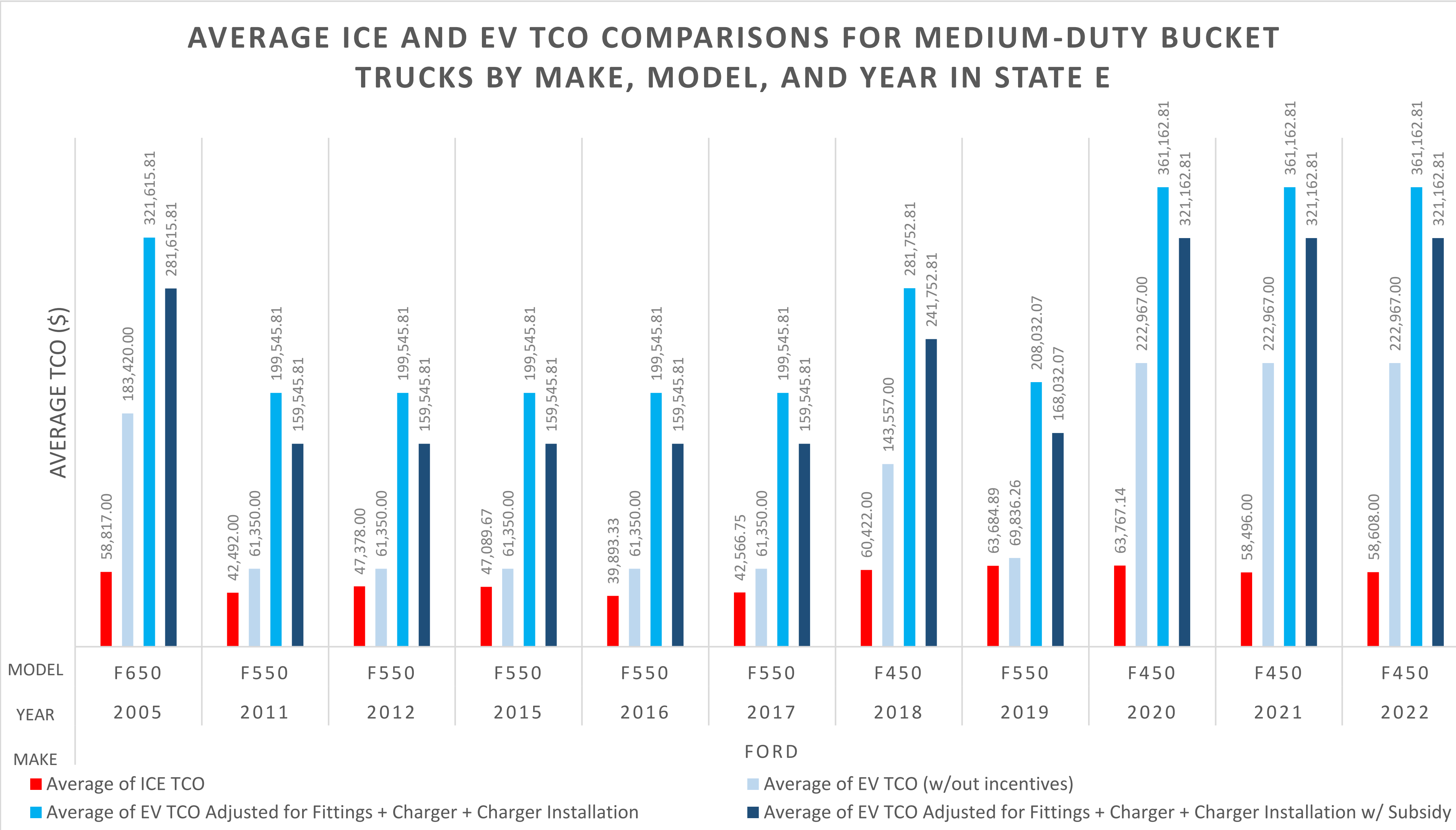

Figure 10: Average ICE and EV TCO Comparisons for Medium-Duty Bucket Trucks by Make, Model, and Year in State E

The primary interpretation of the value of Figure 10 is that the F450 and F550 models are more expensive to replace with an equivalent EV model because they are Class 4 and Class 5 vehicles. Their EV Equivalents tend to be fewer in the number of available models, and thus, significantly more expensive. For example, the F450s and F550s are placed with the SEA Ford 450-650 Electric retrofit power trains which cost more. Even though upfront costs may be higher for EVs, they generally have cheaper TCOs over their lifetime compared to their ICE vehicles counterparts. This is due to fewer operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts, resulting in savings. Thus, when choosing EV equivalents, the IRA Tax Credit can help decrease the TCO as observed in Figure 10, but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 16 contains a list of recommended EVs for the company regarding this analysis.

Table 16: List of EV equivalents for ICE Vehicles Referenced in Figure 10

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Ford F450 (2018, 2020 – 2022)	SEA Ford 450-650 Cutaways
Ford F550 (2011 - 2012, 2015 – 2017, 2019)	SEA Ford 450-650 Cutaways
Ford F550 (2005)	2022 Freightliner

4.3.5. TCO Trends in States A, B, & E: Vans

4.3.5.1. State A Vans

There are not any vans in the fleet that are operated in State A.

4.3.5.2. *State B Vans*

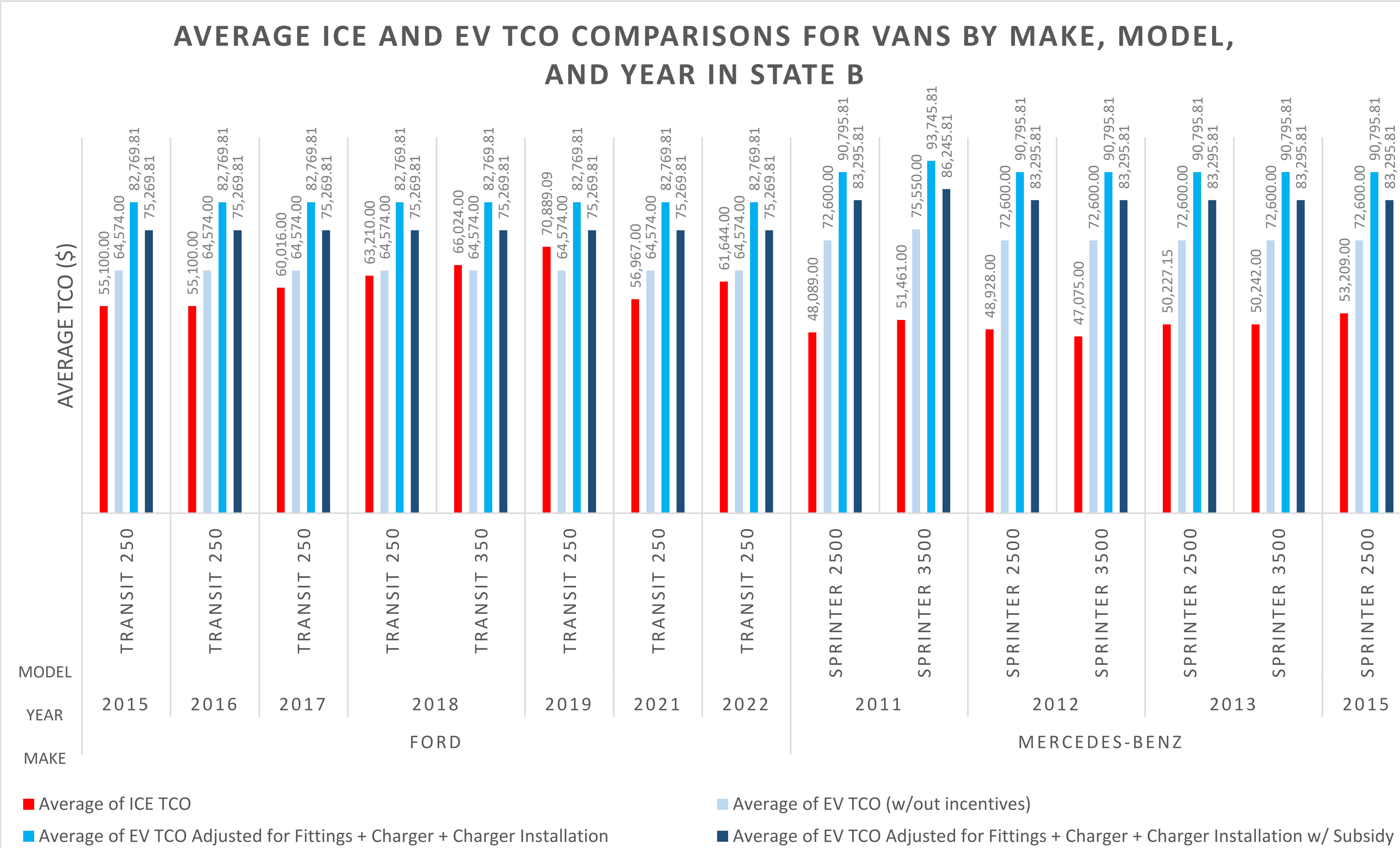

Figure 11: Average ICE and EV TCO Comparisons for Vans by Make, Model, and Year in State B

The primary interpretation of the value of the Figure 11 graph is that all the models are expensive to replace with an equivalent EV model. This increase can be attributed to the initial high MSRP (Manufacturer's Suggested Retail Price) of the equivalent EV, the upfitting cost to the EV TCO, and the purchase and installation cost of the charger. Even though upfront costs may be higher for EVs, they generally have cheaper TCOs over their lifetime compared to their ICE vehicles counterparts. This is due to fewer operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts, resulting in savings. Thus, when choosing EV equivalents, the IRA Tax Credit can help decrease the TCO as observed in Figure 11, but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 17 contains a list of recommended EVs for the company regarding this analysis.

Table 17: List of EV equivalents for ICE Vehicles Referenced in Figure 11

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Ford Transit 250 (2015 – 2019, 2021 - 2022)	Ford E-Transit Cargo Van
Ford Transit 350 (2018)	Ford E-Transit Cargo Van
Mercedes-Benz Sprinter 2500 (2011-2013, 2015)	E-Transit - Passenger Van XL, E-Transit (T350) Chassis Cab (350 High Roof 3dr Van w/148" WB), E-Transit Cargo Van (350 High Roof 3dr Ext Van w/ 148" WB (electric DD))
Mercedes-Benz Sprinter 3500 (2011-2013)	E-Transit (T350) Chassis Cab (350 High Roof 3dr Van w/148" WB), E-Transit Cargo Van (350 High Roof 3dr Ext Van w/ 148" WB (electric DD))

4.3.5.3. State E Vans

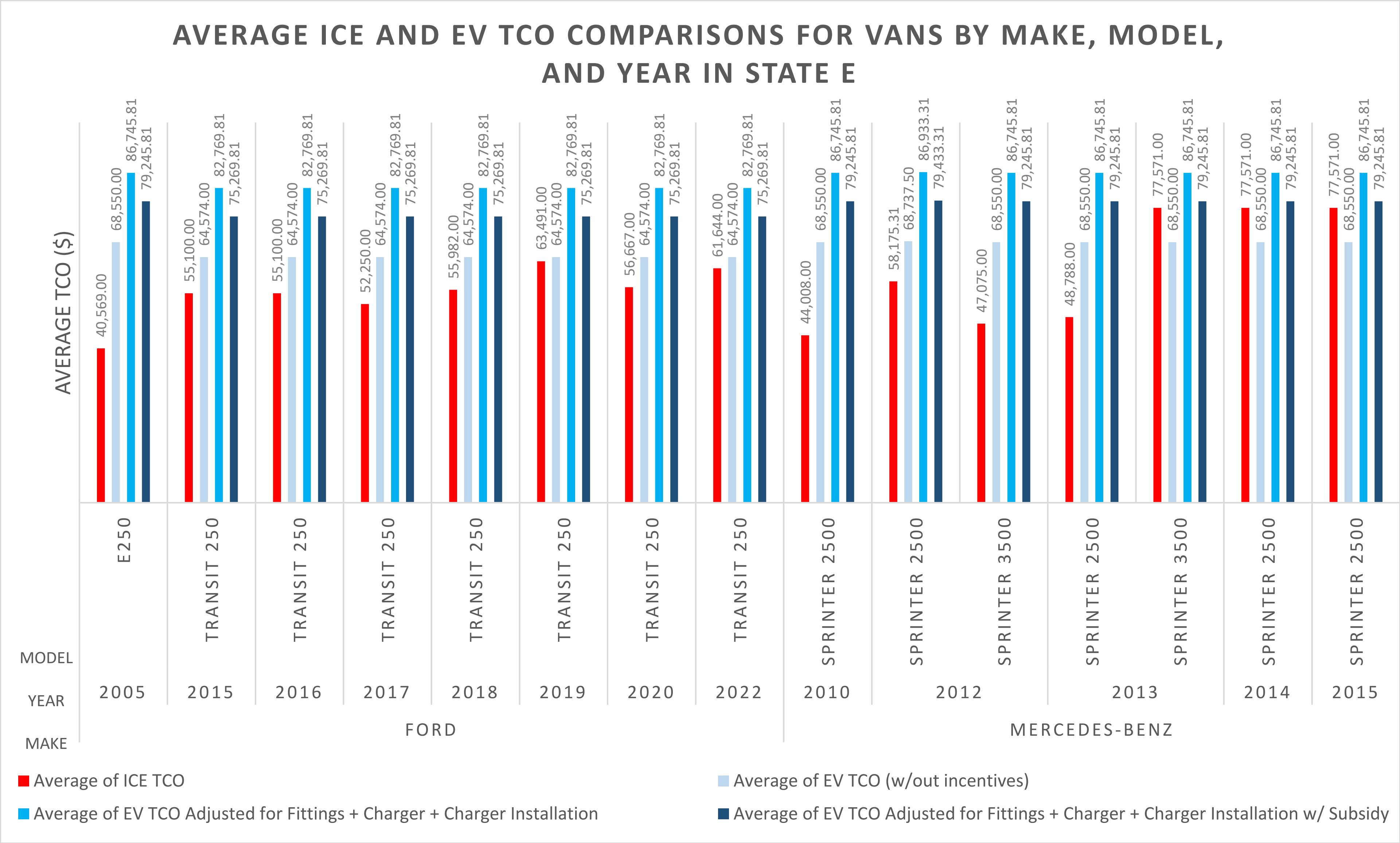

Figure 12: Average ICE and EV TCO Comparisons for Vans by Make, Model, Year in State E

The primary interpretation of the value of the Figure 12 graph is that all the models are expensive to replace with an equivalent EV model. This increase can be attributed to the initial high MSRP (Manufacturer's Suggested Retail Price) of the equivalent EV and the upfitting cost to the EV TCO and the purchase and installation cost of the charger. Even though upfront costs may be higher for EVs, they generally have cheaper TCOs over their lifetime compared to their ICE vehicles counterparts. This is due to fewer operations and maintenance requirements such as oil changes or new air filters because of fewer moving parts, resulting in savings. Thus, when choosing EV equivalents, the IRA Tax Credit can help decrease the TCO as observed in Figure 12, but it is possible to further decrease the EV TCO by considering state, utility, and private incentives for EVs and charging infrastructures. Table 18 contains a list of recommended EVs for the company regarding this analysis.

Table 18: List of EV equivalents for ICE Vehicles Referenced in Figure 12

ICE Vehicle from Original Fleet	EV Equivalent considered for TCO calculation
Ford Transit 250 (2015 – 2020, 2022)	Ford E-Transit Cargo Van
Ford E250 (2005)	E-Transit Cargo Van (350 High Roof 3dr Ext Van w/ 148" WB (electric DD))
Mercedes-Benz Sprinter 2500 (2010, 2012 - 2015)	E-Transit - Passenger Van XL, E-Transit (T350) Chassis Cab (350 High Roof 3dr Van w/148" WB), E-Transit Cargo Van (350 High Roof 3dr Ext Van w/ 148" WB (electric DD))
Mercedes-Benz Sprinter 3500 (2012-2013)	E-Transit (T350) Chassis Cab (350 High Roof 3dr Van w/148" WB)

4.4. Carbon Shadow-Pricing Scenario Analysis

With the subset of data available, an analysis of both carbon pricing scenarios was done for the following classes of vehicles: cars, SUVs and minivans, and light-duty bucket trucks. As mentioned in the Methodology section, the analysis was not completed for vans and medium-duty trucks due the absence of one or more of the following data points: the ICE vehicle TCO; the ICE vehicle's annual emissions; the EV vehicle's TCO; and/or the EV vehicle's emissions. The two scenarios evaluated are internal carbon pricing scenarios evaluated at the Biden Administration's latest price of $51/ton carbon emissions [10] and again at the EPA's recommended price of $190/ton of carbon emissions [10]. As previously mentioned, the largest sources of emissions are light-duty trucks, according to the EPA. Furthermore, of the three classes of vehicles within this subset, only the light-duty bucket trucks have upfitting costs in addition to charger purchasing and installation costs to consider. For these two reasons, in this section, the carbon pricing scenarios are shown below for light-duty bucket trucks in states A, B, and E. The equivalent graphs for the cars, as well as the SUVs and minivans, are included in Appendix A {Section 7.1} for reference.

4.4.1. State A – Light-Duty Bucket Trucks

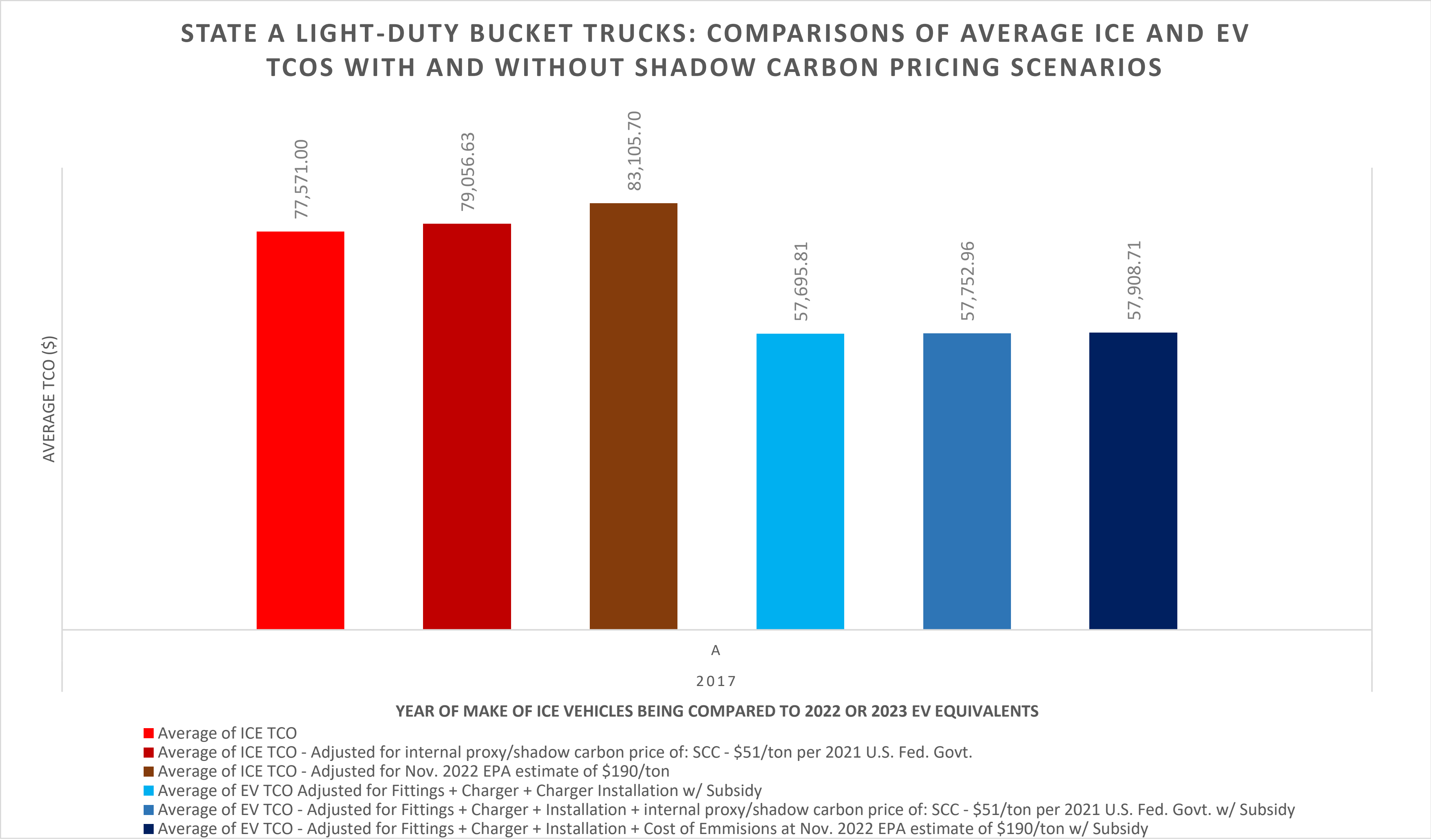

Figure 13: State A Light-Duty Bucket Trucks: Comparisons of Average ICE and EV TCOs with and without Carbon Shadow Pricing Scenarios

In Figure 13, there is a comparison of six average TCOs. As seen from the horizontal axis, for light-duty bucket trucks operated in State A, the TCOs are averaged for ICE models from the same year; the TCOs of the corresponding EV models for those vehicles are also averaged. The ICE TCOs are represented in various shades of red. They represent the average of ICE light-duty bucket truck TCOs, the adjusted ICE TCO in a shadow carbon price scenario of $51/ton of carbon emissions, and the adjusted ICE TCO in a shadow carbon price scenario of $190/ton of carbon from left to right respectively. The EV TCOs are represented in various shades of blue. They represent the average EV TCO price with all the additional costs of upfitting, charger purchase, and charger installation, as well as with the savings from the IRA tax credit; the EV TCO including all additional costs and tax credit in a carbon shadow price scenario of $51/ton; and the EV TCO including all additional costs and tax credit in a carbon shadow price scenario of $190/ton of carbon emissions from left to right respectively.

In the scenario in which the company adopts the Biden Administration's carbon price of $51/ton or in which it is externally mandated, the average ICE TCO increases by nearly $1,500, while the average EV TCO -with all additional costs included- increases by less than $100. In a scenario where the EPA's recommended price of $190/ton is adopted internally and/or is externally mandated, the average ICE TCO increases by approximately $5,500 while the average cost of EVs increases only slightly over $213 over a five-year period. Not only is the financial risk and impact of EV adoption less in the face of carbon regulations, with all costs and the IRA tax credit considered, but the average TCO is less as well. Without carbon shadow pricing, the ICE light-duty bucket truck average TCOs in this state are nearly $20,000 more expensive than that of the EV equivalent. With carbon pricing, that gap only expands, reaching over $21,000 in a $51/ton scenario, and over $25,000 in a $190/ton scenario.

4.4.2. *State B – Light-Duty Bucket Trucks*

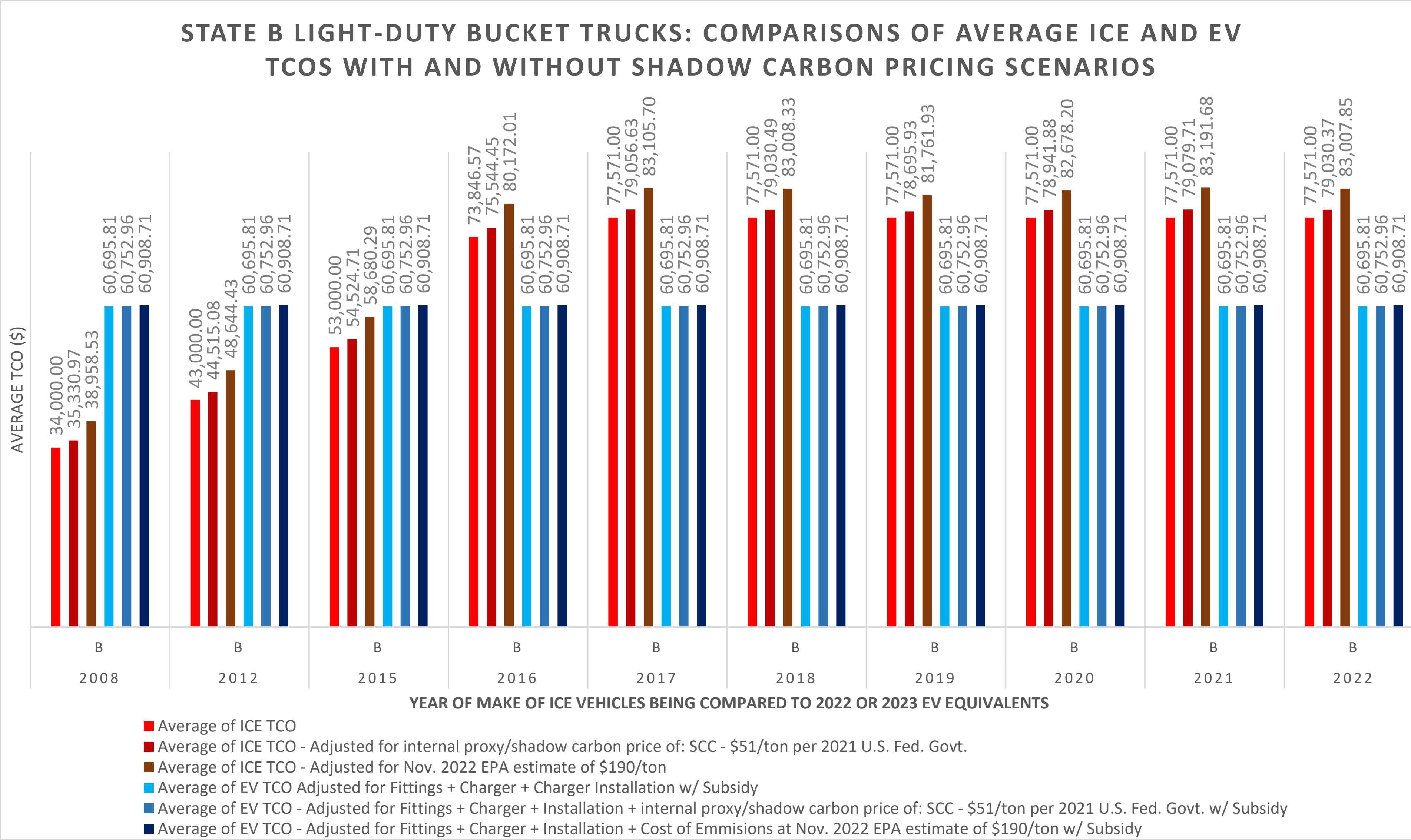

Figure 14: State B Light-Duty Bucket Trucks: Comparisons of Average ICE and EV TCOs with and without Shadow Carbon Pricing

In Figure 14, there is a comparison of six average TCOs for years ranging from 2008 to 2022. As seen from the horizontal axis, for light-duty bucket trucks operated in State B, the TCOs are averaged for ICE models from the same year and the TCOs of the corresponding EV models for those vehicles are also averaged. The ICE TCOs are represented in various shades of red. They represent the average of ICE light-duty bucket truck TCOs, the adjusted ICE TCO in a shadow carbon price scenario of $51/ton of carbon emissions, and the adjusted ICE TCO in a shadow carbon price scenario of $190/ton of carbon from left to right respectively for each year. The EV TCOs are represented in various shades of blue. They represent the average EV TCO price with all the additional costs of upfitting, charger purchase, and charger installation, as well as with the savings from the IRA tax credit; the EV TCO including all additional costs and tax credit in a carbon shadow price scenario of $51/ton; and the EV TCO including all additional costs and tax credit in a carbon shadow price scenario of $190/ton of carbon emissions from left to right respectively for each year.

In both scenarios, the EV TCOs (which are all based on 2023 Ford F-150 Lightning EVs), including additional costs and the IRA tax credit, are not always exceeded by ICE TCOs, such as seen in the average TCOs of the models in 2008, 2012 and 2015, despite the fact that the average ICE TCOs increase by over $1,000 in the $51/ton scenario, and by over $4,000 in the $190/ton scenario in these years. For 2008, the average TCOs are only based on one vehicle in that year from the dataset due to previously mentioned data gaps for ICE and EV TCOs and emissions. Thus, it is possible that the comparison may differ with a larger sample set of light-duty bucket truck vehicles from 2008 models in the fleet. The 2012 average is based on the conversion of twelve of the same make and model vehicles from that year, and thus, the gap may simply be due to the age of the vehicles, which likely are not experiencing significant depreciation losses. Ultimately, the reason(s) is/are an area of further exploration to be considered in future research. The 2015 average is based on six vehicles of the same make and model as those of the 2012 vehicles and is less than the average EV TCOs in all scenarios, though to a much lesser extent, such that, especially in the $190/ton scenario, the prices are nearly the same based on conversion.

For the average TCOs for models in 2016 and onward, the trend shifts. In 2016, there are 24 Ford F150s and four Chevy Colorado vehicles. The remaining years consists of averages of varying numbers of Ford F150 vehicles in the original fleet, with 33 in 2017, 51 in 2018, 17 in 2019, eight in 2020, 21 in 2021, and two in 2022.

The average EV TCOs are significantly less than those of the ICE vehicles in the original fleet – approximately $13,000 vs. approximately $18,000 in a carbon pricing scenario of $0/ton.

In the scenario in which the company adopts the Biden Administration's carbon price of $51/ton or in which it is externally mandated, the average EV TCO is approximately $15,000 less than the average ICE TCO in 2016 and is approximately $18,000 less than the average ICE TCOs of the remaining years through 2022.

In a scenario where the EPA's recommended price of $190/ton is adopted internally and/or externally mandated, the average EV TCO is approximately $19,000 less than the average ICE TCO in 2016 and is approximately $21,000 or $22,000 less in the remaining years through 2022.

Again, overall, not only is the financial risk and impact of EV adoption less in the face of carbon regulations, with all costs and the IRA tax credit considered, the average TCO is less as well, as observed in State A.

4.4.3. State E – Light-Duty Bucket Trucks

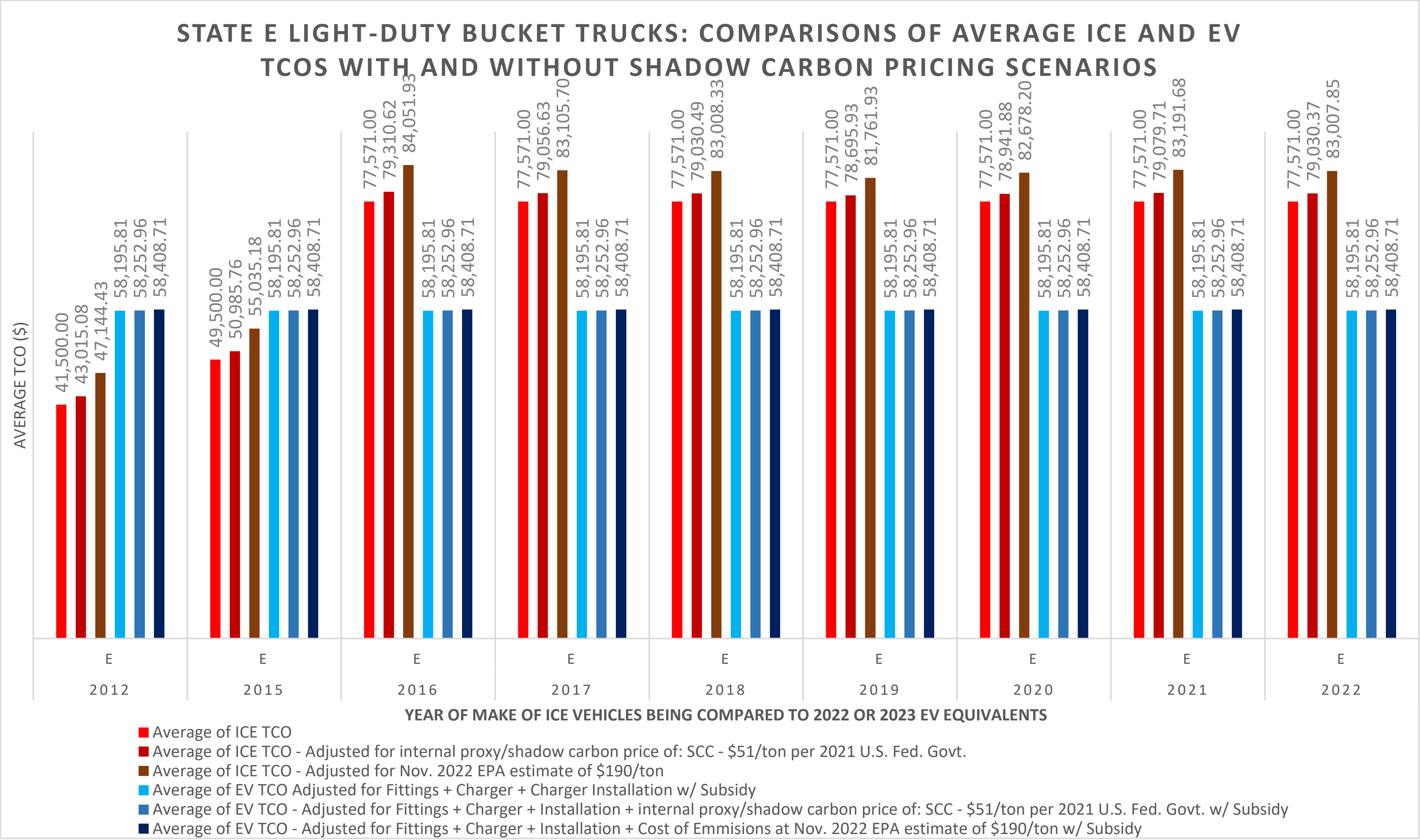

Figure 15: State E Light-Duty Bucket Trucks: Comparisons of Average ICE and EV TCOs with and without Shadow Carbon Pricing Scenarios

In Figure 15, there is a comparison of six average TCOs for years ranging from 2012 to 2022. As seen from the horizontal axis, for light-duty bucket trucks operated in State B, the TCOs are averaged for ICE models from the same year and the TCOs of the corresponding EV models are also averaged. The ICE TCOs are represented in various shades of red. They represent the average of ICE light-duty bucket truck TCOs, the adjusted ICE TCO in a shadow carbon price scenario of $51/ton of carbon emissions, and the adjusted ICE TCO in a shadow carbon price scenario of $190/ton of carbon from left to right respectively for each year. The EV TCOs are represented in various shades of blue. They represent the average EV TCO price with all the additional costs of upfitting, charger purchase, and charger installation, as well as with the savings from the IRA tax credit; the EV TCO including all additional costs and tax credit in a carbon shadow price scenario of $51/ton; and the EV TCO including all additional costs and tax credit in a carbon shadow price scenario of $190/ton of carbon emissions from left to right respectively for each year. All the EV equivalent vehicles considered for these ICE light-duty bucket trucks are 2023 Ford F150 Lightning vehicles.

In both scenarios, as observed for State B, the EV TCOs, including additional costs and the IRA tax credit, are not always exceeded by ICE TCOs. This is apparent for the average TCOs of the models from 2012 and 2015. The 2012 average ICE TCO is based on 34 Chevy Colorado and the 2015 average ICE TCO is based on 18 Chevy Colorado vehicles. As in the case of ICE light-duty trucks in States A and B, these average EV TCOs are based on switching these vehicles to Ford F-150 Lightning EVs. As mentioned in the State B analysis, the average ICE TCO for the 2012 models is around $16,700 less expensive than that of the average EV TCO, and even in the more expensive carbon pricing scenario of $190/ton of carbon emissions, the average ICE TCO is still over $11,000 less than that of the average EV TCO with all additional expenses and the IRA tax credit in this scenario. In the 2015, the difference is less, with average ICE TCOs ranging from $8700 less expensive than the average EV TCOs in a $0/ton of carbon emissions price to approximately $3,400 less expensive in a carbon pricing scenario of $190/ton/ton of carbon emissions. Again, the reasons for this difference should be further explored to determine their significance to vehicle prioritization in each state.

For the average TCOs for models in 2016 and onward, just as observed with vehicles in State B, the trend shifts. There are 17 vehicles from 2016, 19 from 2017, 61 from 2018, 11 from 2019, two from 2020, three from 2021, and two from 2022. The average EV TCOs are always significantly less than those of the ICE vehicles in the original fleet.

In the carbon pricing scenario of $0/ton of carbon emissions, the average EV TCO is approximately$19,300 less than the average ICE TCO for vehicles manufactured in the 2015-2022 range.

In the scenario in which the company adopts the Biden Administration’s carbon price of $51/ton or in which it is externally mandated, the average EV TCO is approximately $20,000-$21,000 less than the average ICE TCO in 2016 through 2022.

In a scenario where the EPA’s recommended price of $190/ton is adopted internally and/or externally mandated, the average EV TCO is approximately $24,000 to over $25,000 less than the average ICE TCO in 2016 through 2022.

Again, overall, not only is the financial risk and impact of EV adoption less in the face of carbon regulations, with all costs and the IRA tax credit considered, the average TCO is less as well, as observed in State A.

4.4.4. Summary

Overall, light-duty bucket trucks, which represent about a quarter of the fleet's vehicles in States A, B, & E, are a significant opportunity to reduce emissions through electrification, due to being one of the highest emitting vehicle types in the transportation sector according to the EPA [1]; they bring significant economic savings for each ICE vehicle replaced in most cases, particularly for those vehicles manufactured in 2016 and onward. Using shadow carbon pricing scenarios of $51/ton of carbon emissions and $190/emissions provide insight into how this can bring EV price parity with ICE vehicle TCOs and can show that the EV TCOs become less than that of the ICE TCOs. As regulations develop and advance, it is possible that the TCO trends observed from the carbon pricing scenarios no longer remain hypothetical.

5. Conclusion

5.1. Electrification Strategy and Research Process Considerations

The key takeaways from this project touch every phase of fleet vehicle procurement. The state of the data was foundational to this project, as publicly available tools were relied upon to make informed decisions on vehicle replacements. The team found that, overall, the data across the identified TCO calculators is robust, with recorded data for true cost of ownership (TCO), and sometimes for annual emissions and cost per mile. Uniformity across calculators, however, is a bit trickier, with similar fundamentals of TCO calculation for each tool, but different assumptions. These differences manifest in assumed depreciation, fuel spend, etc., and can be adjusted in the data processing phase, but it highlights the need for more clearly stated assumptions with TCO calculators and use of consistent assumptions across all calculations.

Vehicle availability is another factor significant to this analysis. The electric vehicle market is actively developing as technology improves and demand increases, and more new options for fleet electrification are being rolled out year after year. With that said, it can be difficult to project future availability of electric vehicles, and working only with existing information is useful, but can lead to unavoidable differences in projections against reality. For example, while there is a developed consumer market for electric sedans, SUVs, and pickup trucks, with a variety of identified alternatives from large OEM's, any vehicles above a Class 2 GVWR, like medium- and heavy-duty trucks and full-size vans, have limited replacement options, and few, if any, are produced by OEMs with large service and maintenance networks. Some OEMs have begun to announce short-term deadlines for electrification of larger vehicles [12], but cost and widespread availability cannot be assumed and, as such, it is difficult to predict required investment for transitioning vehicles without a large existing market.

To ensure continuous development of low-carbon solutions for fleet vehicles, several supply chain impacts must be explored. Electric vehicle sales have increased significantly over the past several years, comprising close to 10% of all vehicles sold globally [13]. The manufacturing of batteries relies on several critical materials and metals, such as lithium, cobalt, and graphite, that are found in a few mineral-rich countries, and over half of the global supply of these minerals are processed and manufactured in China [14]. The commodities are subject to price fluctuation based on geopolitical factors, as evidenced by price increases observed globally because of the Russia-Ukraine war. While these materials do not contribute as heavily to global GHG emissions as traditional fossil fuel extraction and use, they are still exhaustible resources, and continued unabated extraction can further exacerbate supply chain issues. As such, technologies that reduce the use of critical materials, such as manganese or sodium iron cathodes, as well as hydrogen powered batteries, should continue to be developed and explored. Beyond material criticality, the construction and deployment of charging infrastructure is crucial to the success of widespread vehicle electrification. The states prioritized in this project have the highest concentration of charging infrastructure, but with many companies moving Net-Zero goals up to 2035 from 2050, nationwide infrastructure will have to improve to achieve electrification across stateside operations.

5.2. Vehicle Prioritization Recommendations for Replacement with EVs

Through this process, a robust understanding of the company's fleet was achieved. This understanding includes an abundance of information regarding the complexion of the fleet, i.e., make, model, year, function, TCO, emissions, state of operation, vehicle class, etc. These details inform conclusions regarding which vehicles have a variety of readily available alternatives and, as such, are the easiest to replace, and which vehicles may not have electric alternatives from large OEMs on the market today. An understanding of which vehicles also present the best economic case for replacement with EV equivalents (including additional costs for upfitting, charger purchase, and charger installation, as well as the IRA tax credit) resulted from this work with respect to TCOs evaluated over a five-year period.

For cars, it is recommended that all the Chevrolet Malibu vehicles in both States B and E and the 2013 Ford Taurus vehicles be prioritized for replacement first from this vehicle type category because of the emissions and IRA incentives resulting in TCO savings. Replacing the Malibu vehicles with EV equivalents may save anywhere from $5,300-$9,800 per vehicle while replacing the Taurus vehicles may save approximately $12,000 per vehicle.

For SUVs and minivans, again, found only in States B and E from the company fleet data provided, it is recommended that all the Dodge Caravan and the 2016 Ford Explorer vehicles be prioritized for replacement first from this vehicle type category because of the emissions and TCO savings that may result. It is estimated that replacing the Caravans will save anywhere from over $13,800 to over $16,500 per vehicle and replacing the 2016 Ford Explorer vehicles may save over $4,200 per vehicle.

Light-duty bucket trucks are found in States A, B, and E from the company fleet data provided. It is recommended that all Ford F150 vehicles in all three states and the Ford F250 vehicles in State B be prioritized for replacement first in this vehicle type category because of the combination of the emissions and TCO savings that may result. In State A, replacing Ford F150s could save approximately $19,800 per vehicle. In State B, replacing Ford F150 vehicles is estimated to save approximately $16,800 per vehicle and replacing the 2017 Ford F250 vehicles is expected to save approximately $2,400 per vehicle. Finally, in State E, replacing the Ford F150 vehicles may save over $19,000 per vehicle.

Medium-duty bucket trucks are found in States B and E according to the company fleet data provided. Due to the limited number of medium-duty electric trucks available on the market, it is not recommended to prioritize replacing these vehicles without conducting more research and exploring options, such as retrofitting electric power systems into vehicles. Though replacement of these vehicles will have a positive impact on emissions reductions, the EVO TCOs determined in this analysis, even with the IRA tax credit factored in, range from two to over five times the amount of the average ICE TCOs. It was not possible to evaluate the impacts of carbon pricing on the relative ICE and EV TCOs due to the lack of emissions data availability for this class of vehicles.

Vans, found in States B and E, represent a little over 40% of the overall company-provided fleet data for States A, B, and E. When only factoring the IRA tax credit, it is not recommended to prioritize replacement of any of the vans in any of the states due to the EV TCOs being significantly higher than the ICE TCOs. With the help of additional incentives, such as other state, utility and private rebates or tax credits, the 2013 Sprinter 3500, the 2014 Sprinter 2500, and the 2015 Sprinter 2500 vehicles may be able to achieve parity with the ICE TCOs or even become less than them especially when considering the vehicle's lifetime. Currently, their EV equivalent TCOs are approximately $1,600 more expensive. Should emissions estimates be available in the future through the tools used to determine TCO, or should calculations be carried out for these vehicles, whether shadow carbon pricing may further reduce the EV TCOs may also be verified.

These vehicle prioritization recommendations may be confirmed through ongoing research, especially as TCO and annual emissions estimates' data availability increases, as carbon pricing regulations advance, as eligibility for state and local incentives are specifically applied to vehicles in the dataset, and as the EV market expands to offer more options, especially for medium and heavy-duty electric vehicles. Related recommendations are explored in the next section.

In summary, it is recommended that any company should follow the same process to transition its ICE fleet to EVs with the following seven step listed below:

- Determine a transportation emission baseline for your company and establish an emission reduction goal with identification reduction on Scope 1 or 3.
- Establish a yearly budget for EV transition.
- Research and develop a hierarchy of priorities for determining which states receive priority in scale rollout.
- Review ICE fleet inventory for selected states: Identify vehicle leases that are nearing end of term of contract and existing procurement contracts.
- Identify electric vehicle candidates for ICE replacement using available online tools.
- Compare TCO, cost/mile, and, if possible, annual emissions of ICE and EV fleet.
- Transition vehicles at end of lease first before transitioning ICEs with the highest TCOs and emissions.

6. Recommendations

For future projects, it is recommended that the company verifies the respective state, utility and/or private subsidies/incentives that are available down to the local/district level in addition to the IRA subsidies from the Commercial EV and FCEV Tax Credit. It is necessary that the company also verifies that the selected EVs meet the minimum battery capacity requirements for the federal tax credit. For vehicle types or classes that have limited EV equivalent options, the company is encouraged to explore other OEMs and retrofitting options that switch ICE vehicles to electric ones, such as through companies like SEA Electric, though these options may come at an additional cost. It is also advised that the company explore the possibility of setting a shadow carbon price. This can demonstrate to investors that the company understands its exposure to future regulation, as well as make the economic case for pursuing sustainability-driven projects internally. The company can also explore emissions evaluations including other GHGs and factor and update its TCO evaluation accordingly, especially in carbon-pricing scenarios. Ultimately, the conclusions drawn in this study are based on limited data. Thus, the final recommendation is that the company verifies the validity of these conclusions by filling TCO and annual emissions data gaps with its own internal data. It is possible that the trends discovered in this analysis will parallel those of this study, but it is also possible that new insights may be discovered as well.

7. Appendices

7.1. Appendix A – Carbon Pricing Analysis

7.1.1. Cars

There are a total of 79 fleet cars in this analysis with TCO and annual emissions data available for both the ICE vehicle and the researched EV equivalent.

7.1.1.1. State A – Cars

There are not any cars in the subset of the fleet sample set that are operated in State A.

7.1.1.2. State B - Cars

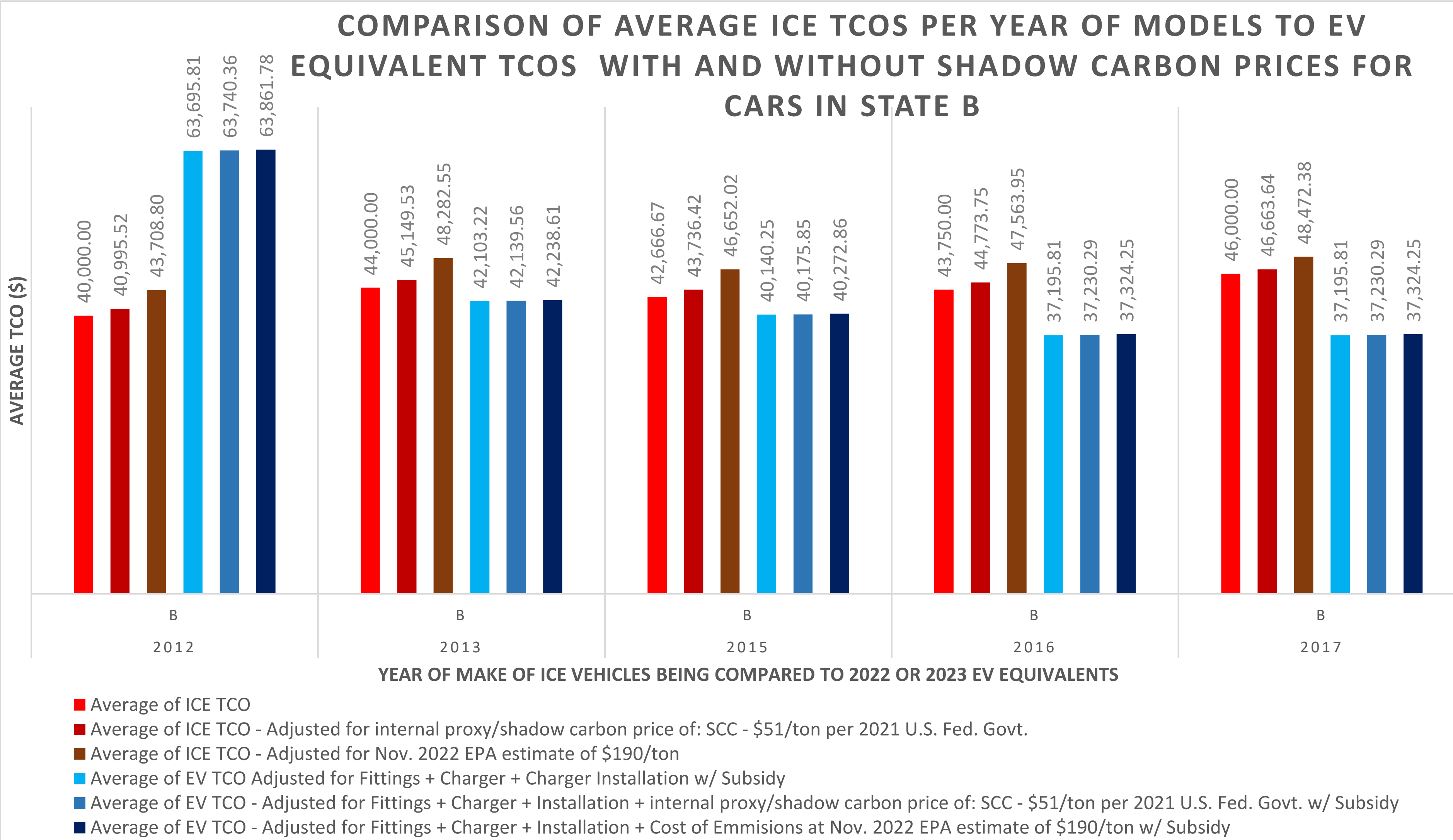

Figure 16: Comparison of Average ICE TCOs per Year of Models to EV Equivalent TCOs with and without Shadow Carbon Pricing for Cars Operated in State B

7.1.1.3. State E - Cars

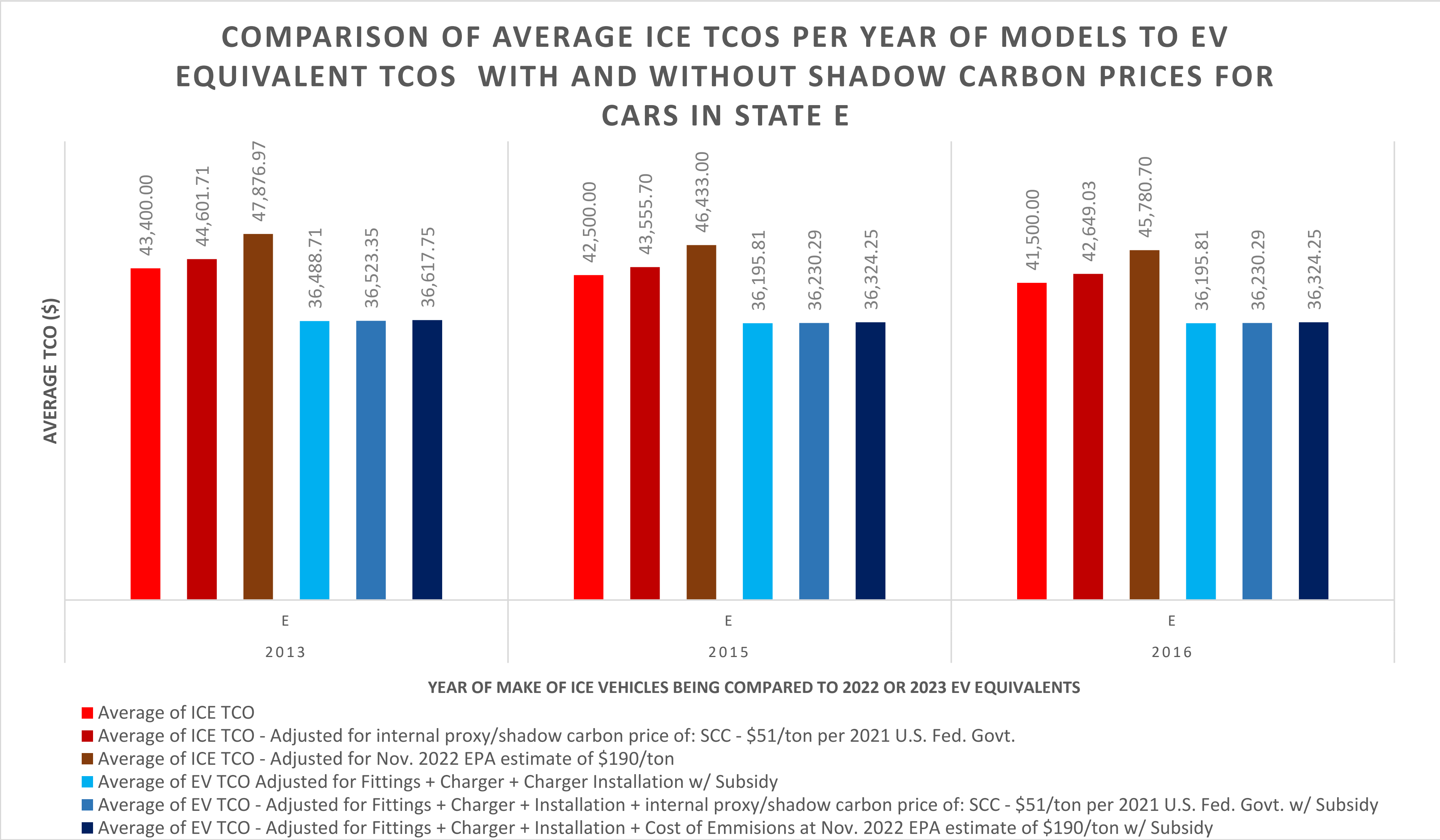

Figure 17: Comparison of Average ICE TCOs per Year of Models to EV Equivalent TCOs with and without Shadow Carbon Pricing for Cars Operated in State E

7.1.2. SUVs & Minivans

There are 46 vehicles of this type in this data subset, 37 of which are SUVs and nine of which are minivans.

7.1.2.1. State A – SUVs & Minivans

There are not any SUVs and minivans in this data subset that are operated in State A.

7.1.2.2. State B – SUVs & Minivans

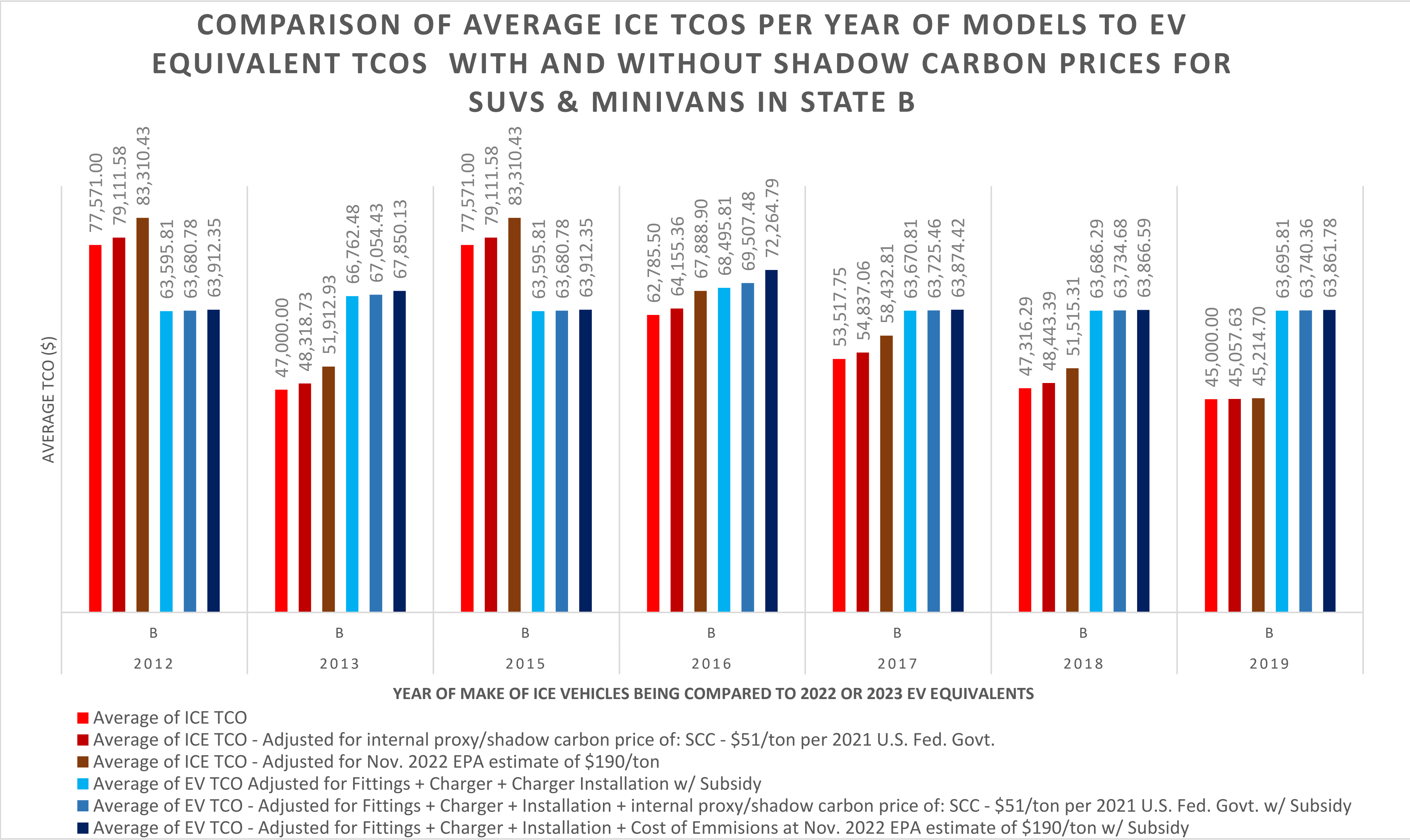

Figure 18: Comparison of Average ICE TCOs per Year of Models to EV Equivalent TCOs with and without Shadow Carbon Pricing for SUVs and Minivans Operated in State B

7.1.2.3. State E – SUVs & Minivans

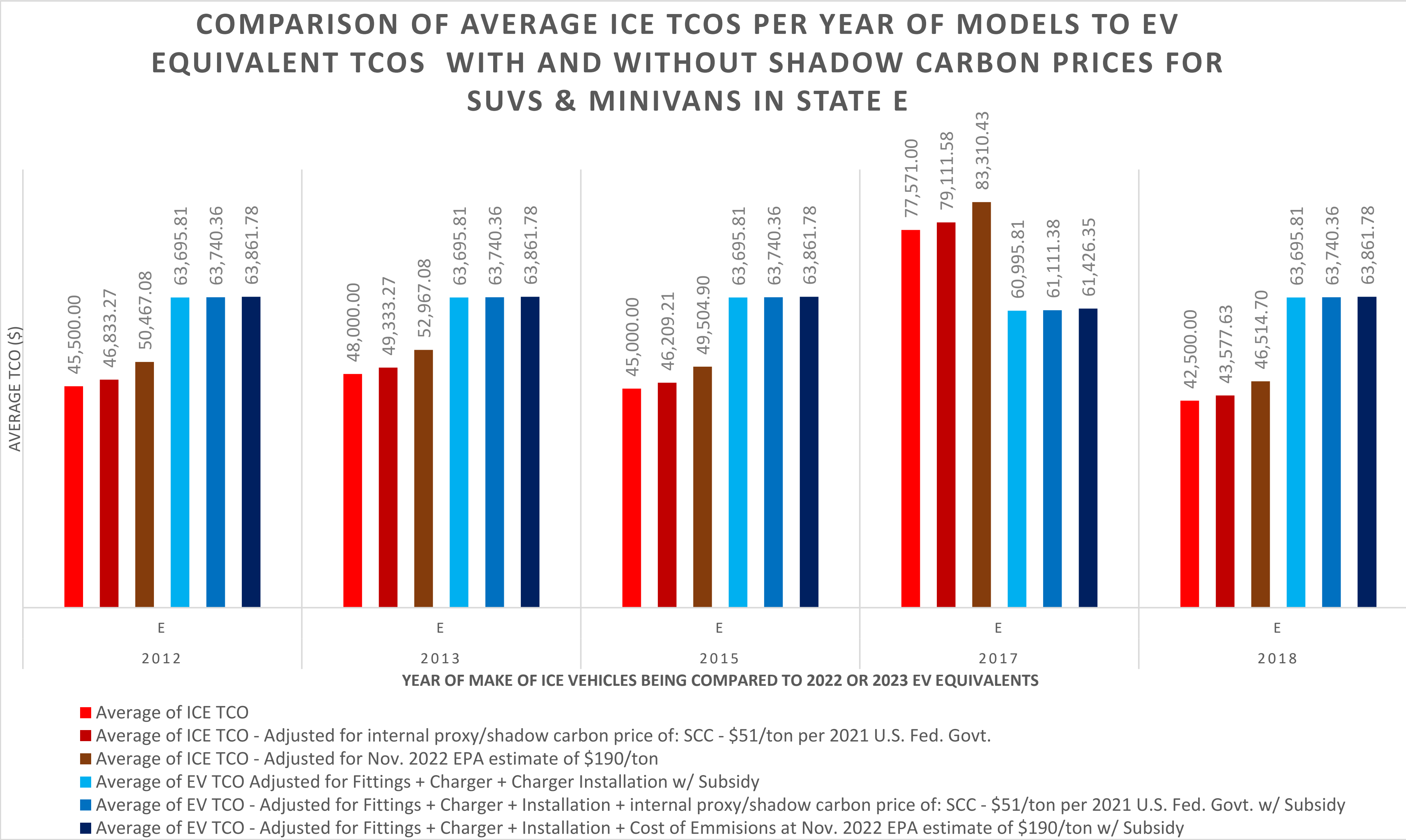

Figure 19: Comparison of Average ICE TCOs per Year of Models to EV Equivalent TCOs with and without Shadow Carbon Pricing for SUVs and Minivans Operated in State E

8. Acknowledgment

The Villanova student team would like to again acknowledge all the guidance and support from SCTE on this RISE project over the course of the Spring 2023 semester. We would especially like to thank Derek DiGiacomo, Margaret Bernroth, and Sam Khola. This RISE project in partnership with SCTE has really complemented the classroom learnings from Villanova's MSSE and MBA by providing a real-world example. The Villanova team is grateful for the opportunity to have worked on this project for SCTE and very thankful for all their support.

9. Abbreviations and Definitions

9.1. Abbreviations

AFDC	alternative fuel data center vehicle cost calculator*
DOE	Department of Energy
EV	electric vehicle
GHG	greenhouse gas
GVWR	gross vehicle weight rating
ICE	internal combustion engine
IEA	International Energy Agency
IRA	Inflation Reduction Act
KPI	key performance indicators
MSRP	manufacturer's suggested retail price
MSSE	Master of Science in Sustainable Engineering
OEM	original equipment manufacturer
RISE	Resilient Innovation through Sustainable Engineering
SCTE	Society of Cable Telecommunications Engineers
TCO	total cost of ownership
ZETI	zero-emission technology inventory
AP	access point
bps	bits per second
FEC	forward error correction
HFC	hybrid fiber-coax
HD	high definition
Hz	hertz
SCTE	Society of Cable Telecommunications Engineers

9.2. Definitions

None applicable to this document.

10. Bibliography and References

[1] O. US EPA, "Sources of Greenhouse Gas Emissions," Dec. 29, 2015. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions (accessed May 12, 2023).

[2] "Trends and developments in electric vehicle markets – Global EV Outlook 2021 – Analysis," *IEA*. https://www.iea.org/reports/global-ev-outlook-2021/trends-and-developments-in-electric-vehicle-markets (accessed May 12, 2023).

[3] "Alternative Fuels Data Center: Vehicle Cost Calculator Assumptions and Methodology." https://afdc.energy.gov/calc/cost_calculator_methodology.html (accessed May 16, 2023).

[4] "Cost of Car Ownership - 5-Year Cost Calculator | Edmunds.com," *Edmunds*. https://www.edmunds.com/tco.html (accessed May 16, 2023).

[5] "Truck Classification Explained | Light vs. Medium vs. Heavy Duty," *Badger Truck & Auto Group*. https://www.badgertruck.com/heavy-truck-information/truck-classification/ (accessed May 14, 2023).

[6] "Alternative Fuels Data Center: Commercial Electric Vehicle (EV) and Fuel Cell Electric Vehicle (FCEV) Tax Credit." https://afdc.energy.gov/laws/13039 (accessed May 14, 2023).

[7] "II. What are the instruments for pricing carbon?," *Second Nature*. https://secondnature.org/climate-action-guidance/ii-what-are-the-instruments-for-pricing-carbon/ (accessed May 16, 2023).

[8] B. J. Parker and D. A. R. Barron, "What is a Proxy Price on Carbon?".

[9] J. L, "Internal Carbon Pricing Guide for Companies 2023," *Carbon Credits*, Dec. 23, 2022. https://carboncredits.com/internal-carbon-pricing-guide-for-companies-2023/ (accessed May 18, 2023).

[10] E. A. and D. Wessel, "What is the social cost of carbon?," *Brookings*, Mar. 14, 2023. https://www.brookings.edu/2023/03/14/what-is-the-social-cost-of-carbon/ (accessed May 14, 2023).

[11] "Alternative Fuels Data Center: Federal Laws and Incentives." https://afdc.energy.gov/laws/fed_summary (accessed May 17, 2023).

[12] "GM Will Replace Chevrolet Express, GMC Savana with EVs in 2026." https://www.autoweek.com/news/a40435740/gm-will-replace-chevrolet-express-gmc-savana-with-evs-2026/ (accessed May 17, 2023).

[13] J. Zinkula, "Electric vehicles accounted for 10% of global auto sales last year — this could quadruple by 2030," *Business Insider*. https://www.businessinsider.com/electric-vehicles-accounted-global-auto-sales-could-quadruple-2030-report-2023-1 (accessed May 17, 2023).

[14] "Global Supply Chains of EV Batteries".

SCTE STANDARDS JOURNAL

Worker Safety: A Robust On-Premise & Cloud Based AI Solution

A Technical Paper prepared for SCTE by

Rohith Kumar Punithavel, Software Engineer, Emerging Technology R&D
Charter Communications
6399 S Fiddlers Green Circle, Greenwood Village, CO 80111
RohithKumar.Punithavel@charter.com
+1 480-241-3019

Vishal Chopade, Sr. Software Engineer, Emerging Technology R&D
Charter Communications
6399 S Fiddlers Green Circle, Greenwood Village, CO 80111
Vishal.Chopade@charter.com
+1 646-215-1036

Charles Hubbard, Network Engineer II, Emerging Technology R&D
Charter Communications
6399 S Fiddlers Green Circle, Greenwood Village, CO 80111
Charles.Hubbard@charter.com
+1 432-212-4801

Mohamed Daoud, Director, Emerging Technology R&D
Charter Communications
6399 S Fiddlers Green Circle, Greenwood Village, CO 80111
Mohamed.Daoud@charter.com
+1 720-699-5077

Table of Contents

List of Figures

1. Abstract

Businesses and their requirements have evolved over the years. Businesses have begun to rely heavily on artificial intelligence (AI) to solve their problem statements due to the low cost and competitive availability of compute-intensive solutions. The primary ingredient in using AI solutions is quality data, and its collection is made easier due to the implications of digital transformation. Businesses usually not only target solutions that are cost-effective and accurate, but also rely on how the solution can address real-time data traffic, recovery, and reliability.

Charter Communications developed a Proof of Concept (PoC) for an industrial application that monitors the safety of drill press workers. Safety related applications are often scrutinized for latency and reliability. In this paper, we briefly discuss the role of AI in businesses and the need for on-premise solutions in safety applications. Second, we discuss Machine Learning (ML) model development and deployment. Then, we describe in detail the evolution of the worker safety application, addressing software, hardware, and both wired and wireless links. Third, we understand the latency and resource utilization. Finally, we demonstrate this application in lab test conditions and discuss current plans to scale the solution from running on-premise to running in a centralized data center on different hardware types.

2. Introduction

AI has revolutionized businesses by automating and streamlining processes. The latest AI tools help provide valuable insights into customer behavior, market trends, and internal operations, guiding strategic decision-making and enhancing profits. The evolution of chatbots and recommender systems has helped deliver precise and personalized content to customers, thus improving customer service and marketing sectors. In supply chain management, AI has optimized inventory management, demand forecasting, and logistics planning, thus reducing operating costs and improving delivery times. Predictive maintenance in manufacturing industries aids in improving equipment efficiency and minimizing costly downtime. AI will continue to enable greater automation, predictive analytics in financial sectors, and efficient diagnosis, treatment, and better outcomes in healthcare industries.

Industry 4.0 is driven by AI, which has significantly improved manufacturing efficiency. The data gathered from smart sensors and AI algorithms have optimized manufacturing processes, minimized waste, and enhanced quality control. The development of AI-powered industrial robots and automation has not only boosted productivity but also reduced the involvement of humans in repetitive and hazardous tasks. Big data analytics is another critical component of Industry 4.0, allowing manufacturers to identify trends, predict demand, and optimize their supply chains. Nonetheless, implementing Industry 4.0 technologies necessitates substantial investments and expertise, while organizations must overcome challenges such as data security and privacy concerns and upskilling the workforce.

The safety and well-being of employees are paramount concerns for responsible businesses. Safety monitoring applications enhance workplace safety by monitoring potential hazards that could lead to accidents or injuries. In industrial settings where heavy machinery is utilized, these applications can monitor machinery performance, workplace hazards, natural disasters, etc., to alert workers and facilitate quick and effective emergency responses. Without safety monitoring applications, workers in industrial settings face increased risks of accidents and injuries from various hazards. Improperly maintained or operated machinery and exposure to hazardous chemicals or substances can cause burns, cuts, or other worker injuries. In severe cases, accidents may result in permanent disability or loss of life. Implementing safety monitoring applications allows businesses to proactively prevent accidents and safeguard employees while avoiding code violations, workstation stoppages, costly fines, and legal liabilities. Investing in safety monitoring applications creates a secure and safe workplace, enhancing productivity and employee satisfaction and reducing accidents and injuries.

3. Worker Safety Use Case

3.1. Connected Safety in Work Environments

Workplaces are often described as interactions between electric equipment and worker(s). In industrial sectors, workers are exposed constantly to occupational risks, while a range of human behavioral factors causes most workplace accidents. In most cases, labor shortages due to accidents impact the organization's productivity, making it difficult to meet financial goals. Over the years, network connectivity and infrastructure have evolved, and industries have shifted towards reliable mobile digital infrastructure, the backbone of Industry 4.0. During this evolution, the industries started initiatives to formulate a plan to incorporate manufacturing equipment, Internet of Things (IoT) sensors, cameras, and a network to connect all components into an ecosystem. This ecosystem will allow an organization to monitor, control, and enhance safety and productivity anytime and anywhere globally.

The solution discussed in this paper will provide a notable example of a workplace that uses drill presses. The designed solution minimizes the number of accidents caused to workers using the drill press and provides an ecosystem for the organization to monitor and control its workplace remotely. This application will rely on many sensors that work around the clock to build a thriving ecosystem.

3.2. How the Use Case Works?

The worker safety PoC setup is an excellent example of connecting various technologies for a single application. This use case detects the worker and checks if the worker is wearing necessary safety gear such as a hard hat, safety vest, gloves, and goggles. If the worker is wearing all the safety gear, he is classified as a green worker and can operate the drill press; otherwise, he is classified as a red worker and will not be permitted to run the drill press. This use case shuts off the machine when a red worker approaches a green worker while operating the drill press. In addition, this use case also prevents the green worker from injuring his hands when working the drill press.

3.3. Components

3.3.1. Drill Press

The drill press is a stationary tool used to drill holes for household or industrial purposes. The drill hole sizes vary depending on the size of the drill bit, and the goal determines the type of drill press used.

Figure 1 - Drill Press

3.3.2. Camera

The camera is the eye of this application. The camera sensor functions to capture the visual scene within its focal range and uses a Real Time Streaming Protocol (RTSP) to stream the video over the network. A Power over Ethernet (PoE) port or injector powers the camera. For this application, the camera runs with a resolution of 1280x720 at 60 frames per second (FPS) and each frame is encoded using the H.264 standard. The sensor size contributes to the dynamic behavior of the camera. Some cameras require an external lens to focus and adjust the light in the field of view; the measurement of the lens used for this testing is 1/1.8 inch.

Figure 2 - Camera and Lens

3.3.3. Graphics Processing Unit (GPU)

GPUs are specialized computer cores capable of parallel processing/computation. The main advantages of using GPUs are higher memory bandwidth and shared memory; this significantly helps in processing higher resolution images or enabling shorter training duration for ML models trained over large datasets. For ML model training a NVIDIA V100 GPU was used, which has 5120 CUDA cores. The first test iteration of this application used Volta Xavier GPU, which has 384 Nvidia CUDA cores. For further tests, Tesla T4, and GeForce RTX 2080Ti were used. The Tesla T4 has 2560 CUDA cores, and the 2080Ti has 4352 CUDA.

Figure 3 - GPU

3.3.4. Raspberry Pi

Raspberry Pi is a tiny, affordable single-board computer and an integral IoT device. Raspberry Pi 4 has a 64-bit Cortex-A72 processor and supports 1/2/4/8G of RAM. It has 40 general-purpose input/output (GPIO) pins that can provide 5V maximum voltage. They can operate over a range of temperatures between 0°C and 50°C.

3.3.5. Light Emitting Diode (LED)

LEDs are semiconductor devices that emit light due to the current flow. These are utilized primarily for visual representation in the workplace.

3.3.6. Buzzer

A buzzer is an audio signaling device. The buzzer sends audio signals in intervals when an accident or non-compliant scenario occurs in the workplace.

3.3.7. IoT Relay

Relays are switches that are operated based on electrical signals. The GPIO ports of embedded IoT devices can control IoT relays, and based on the signal from the ports, the relay is either switched on or off. This relay acts as a switch for the drill press.

Figure 4 - Raspberry Pi, LED Strip, Buzzer, IoT Relay

3.3.8. Ethernet Cables

An ethernet cable is a medium through which components are connected in a network.

3.3.9. PoE Injector/Port

A PoE injector is an adapter that provides power to PoE devices. In our case, we use a PoE injector to power IP cameras present in the network. In some cases, routers themselves will have a PoE port that can power PoE devices.

3.3.10. Multi-Access Edge Computing (MEC)

Multi-access edge compute assists in moving the compute traffic and services from a centralized cloud to the edge of the network and closer to the customer. Instead of transmitting data to the cloud, MECs can store, analyze, and process data on premises. Using MECs, data collection and processing can now be achieved with lower latency, bringing real-time performance to high-bandwidth applications.

Figure 5 - MEC Unit

3.3.11. Network

The network acts as a bridge between all components of this application. The network allows all the components to communicate and share data. The worker safety application was tested over a local, private, and edge network.

3.4. Machine Learning Model

Artificial Intelligence (AI) applications have taken over our everyday activities in recent years. These activities include using facial recognition on phones, text prediction in messages/search engines, stock market prediction, weather forecasting, road traffic prediction, and beyond. The abundant availability of data and model development resources in a physical or virtual medium contribute to this significant growth. This factor influenced us to develop a custom AI solution to help mitigate accidents in a drill press station. ML and computer vision are the essential subsets of AI. Deep Learning is a subset of ML that consists of combinations of neurons termed artificial neural networks (ANN). The PoC addressed in this paper is a classic example of combining deep learning and computer vision.

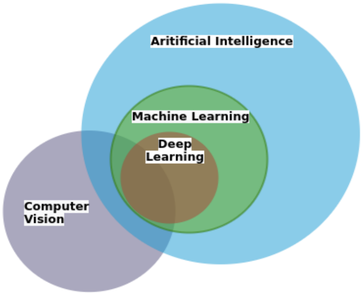

Figure 6 - Specialization Subset Diagram

3.4.1. Neural Networks

The neural network is inspired by how the human brain works and is considered one of the most significant breakthroughs in AI. This innovation provided the world a pathway to turn imagination into algorithms. A neural network consists of several layers, and each layer can have any number of nodes/neurons interconnected between layers. These interconnections may or may not exist between every neuron. The first layer is called the input layer, and the last is called the output layer. The layers between input and output are called hidden layers. The input layer accepts input for the model. The hidden layer is either a single layer or a combination of layers that perform transformations with the help of a non-linear activation function. The application determines the number of neurons and output function in the output layer.

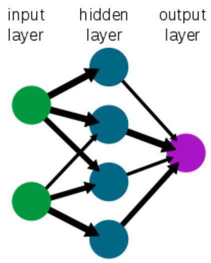

Figure 7 - Simple Neural Network

3.4.2. Choice of Machine Learning Model

In this PoC, the ML model must recognize and classify objects for five classes: worker, safety vest, hard hat, gloves, and goggles. The input video stream may contain multiple objects, which doesn't give any idea of where the things are. Hence our model should not only perform object classification but also localize where those detections are. This localization task helps the algorithm determine if each worker detected wears all the safety equipment. Since this task is associated with images, convolutional neural networks (CNN) is a better choice. CNNs are used predominantly in applications involving images. Some of the applications of CNNs are image classification, image and video recognition, image segmentation, etc. In CNN, the hidden layer performs convolution and pooling accompanied by non-linear activation functions. The other hidden layers in CNNs are fully connected layers, a collection of neuron units followed by a non-linear activation function. The output is a Softmax layer with units equal to the number of classification classes.

There are several open-source CNN models present. You Only Look Once version 4 (YOLOv4) is chosen based on existing research [4].

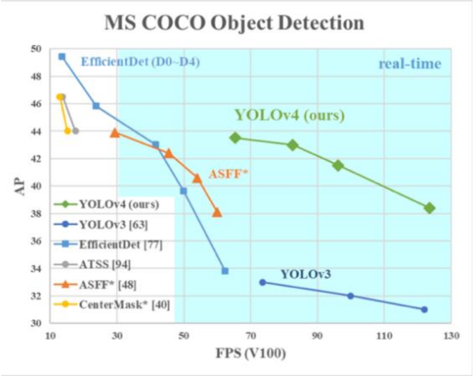

Figure 8 - AP vs FPS for Models

From the above figure, EfficientDet achieves higher average precision (AP) but runs at a lower FPS. You Only Look Once version 4 (YOLOv4) also achieves good and consistent AP at higher FPS, thus making it real-time. Object detection models consist of two main components: backbone and head. The backbone does the feature extraction in any task to detect objects, and the head classifies the objects and gives its bounding box coordinates. In the YOLO model, the backbone is one stage detector, while in other models, they are either two or more stage detectors, thus making them slower. The previous YOLO model generates a feature pyramid network for an image and performs detection in each of the small units in a top-bottom fashion. YOLOv4 additionally utilized two methods to improve the detector's accuracy: Bag of Freebies (BoF) and Bag of Specials (BoS).

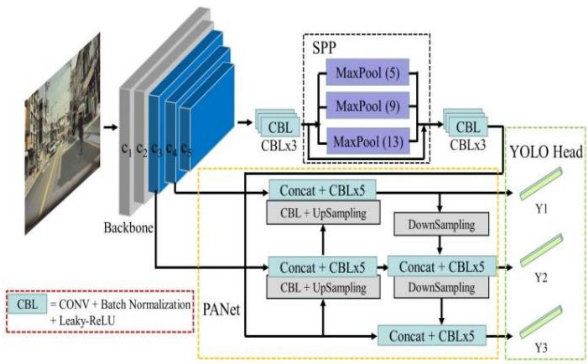

Figure 9 - YOLOv4 Architecture [5]

The BoF method affects the training cost (time) but not the inference cost. This method alters the training methodology. The popular way to modify the training data is using augmentation, but other methods are applied here: CutOut and Random Erasion. In CutOut, areas of pixels are masked randomly, and in Random Erasion, the areas of the pixels are randomly erased. Two network regularization methods are applied to avoid overfitting while training: DropOut and DropBlock. The mean squared error function is not a suitable evaluation metric for dropout regularization, and the model used the Intersection over Union (IoU) loss metric to improve detection accuracy.

$$IoU = \frac{Area\ of\ Intersection\ of\ two\ boxes}{Area\ of\ Union\ of\ two\ boxes}$$

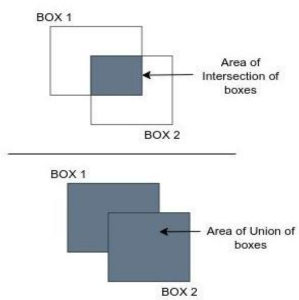

Figure 10 - IoU Diagram

The BoS method slightly increases the inference cost and helps improve the detection accuracy. YOLOv4 uses spatial pyramid pooling (SPP) - this removes the dependency on fixed input size and performs robust pooling to images of different sizes, keeping the pooling output as a fixed-length representation. YOLOv4 also uses the Path Aggregation Network (PAN): once the feature pyramid is generated for detection, each pyramid level is concatenated to the next level to account for feature predictions. Non-max suppression

(NMS) – DIoU-NMS removes multiple detections for a single object. Distance Intersection over Union non-max suppression, or DIoU-NMS is a loss function to reduce the distance between the central points of the detected and ground truth bounding boxes. YOLOv4 uses rectified linear unit ReLU, leaky-ReLU, parametric-ReLU, and Mish activation functions.

ReLU activation function

$$f(y_i) = \max(0, y_i) + a_i \times \min(0, y_i)$$

$a_i = 0$, it becomes ReLU

$a_i > 0$, it becomes leaky ReLU

If a_i is a learnable parameter, it becomes parametric-ReLU

Mish activation function,

$$f(x) = xtanh(ln(1 + e^x))$$

Loss Function is given as,

$$LOSS = L_{ciou} + L_{conf} + L_{class}$$

L_{ciou} is Boundary loss function – IoU for bounding boxes.

L_{conf} is Confidence loss function.

L_{class} is Classified loss function.

$$L_{ciou=}\sum_{i=0}^{S^2}\sum_{J=0}^{B} I_{i,j}^{obj}\left[1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + av\right]$$

$$a = \frac{4}{\pi^2}(\arctan\frac{w^{gt}}{h^{gt}} - \arctan\frac{w}{h})^2$$

$$v = \frac{v}{(1 - IoU) + v}$$

$$L_{conf} = -\sum_{i=0}^{S^2}\sum_{J=0}^{B} I_{i,j}^{obj}\left[\hat{C}_i^j \log(C_i^j) + (1 - \hat{C}_i^j)\log(1 - C_i^j) - \lambda_{noobj}\sum_{i=0}^{S^2}\sum_{J=0}^{B} I_{i,j}^{noobj}\, \hat{C}_i^j \log(C_i^j) + (1 - \hat{C}_i^j)\log(1 - C_i^j)\right]$$

$$L_{class} = -\sum_{i=0}^{S^2} I_{i,j}^{obj} \sum_{c \in classes}\left[\hat{P}_i^j \log(P_i^j) + (1 - \hat{P}_i^j)\log(1 - P_i^j)\right]$$

Figure 11 - Loss Function [10]

For worker safety, transfer learning is predominantly used where the YOLOv4 model architecture is retained, and a few layers are modified based on the number of output units. ML model development follows a cycle where a set of events flow between the development and deployment of the model.

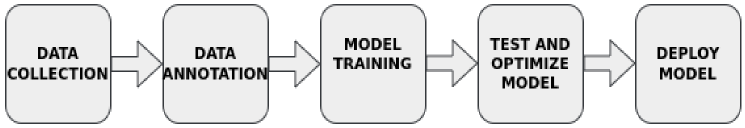

Figure 12 - ML Process Flow Diagram

3.4.3. Data Collection

The data collection is an integral part of the development as it will help decide the quality of the model. In our case, we collected data from a public dataset and captured frames around the workspace to generate our custom dataset. Data collection is balanced to overcome model bias. Around 10,000 images were captured.

3.4.4. Data Annotation

Data annotation is an underestimated task in ML development. Data annotation helps teach the model what and how to learn and to draw bounding boxes for the detected objects. The majority of time spent in the model development cycle is for data collection and annotation. For annotating images, well-defined rules are established based on the problem statement. We used a cloud service and online annotation tools for our dataset. The image size in our dataset may vary, and the annotated bounding box dimensions are normalized to the image size to keep them uniform (see Figure 13).

Figure 13 - Worker, Annotated Worker, Classes, and YOLO Coordinates

3.4.5. Training

Training of an ML model requires bigger GPUs to reduce the total training time. In our case, we utilized a cloud platform to create an Ubuntu-based virtual machine. The training for the proposed model has over 60 million parameters to train. The training is completed by randomly selecting 85% of images from the dataset, with the following parameters: batch size = 64, input size = 416x416, and number of epochs = 25000 on V100 GPU. The rest 15% of the images were used to test and validate the model. The training used backpropagation to optimize the loss function and tune the parameters. The average loss is estimated to be 1.5387.

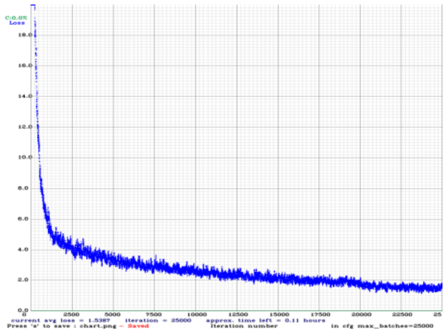

Figure 14 - Loss Curve

Because of batch training, the plot of loss vs. iterations is not a smooth curve; instead, the loss curve's trend is considered to determine model underfitting. The above figure shows that the curve dips as we train for longer epochs; hence the model is not overfitting. This trained model is then accelerated using an open-source framework called TensorRT.

3.4.6. Result Metrics

After training, the weight files are checked and validated. Two metrics are considered to understand the model's behavior: mean average precision (mAP) and frame rate benchmark. The frame rate benchmark tells us how many frames our model can handle per second, which will help set FPS on the stream. Precision gives us the quality of positive predictions made. Precision is the number of true positives divided by the total number of positive detections.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

For object recognition and localization tasks, the precision is estimated based on the accuracy of the detected class and IoU of the detected bounding box against ground truth. There are five classes in our case, so average precision (AP) is calculated for all the detections grouped for each class against the ground truth value. The mAP value is obtained by taking the average AP for each class. For the trained model with input size 416x416, the benchmarked FPS is 72 FPS, and the mAP @ IoU = 0.75 is 0.7238 or 72.38%. We also observed from the benchmarked results that with a change in the input size, there is an increase in mAP and a reduction in the frame rate.

3.4.7. Model Deployment

The trained model is converted to Open Neural Network Exchange (ONNX) format. ONNX is a middleware framework that converts models from one framework to another. The ONNX file with weight and model information is then converted to TensorRT format. TensorRT is a highly optimized and accelerated ML framework that helps you achieve faster inferences. TensorRT runs on the CUDA Cores of the GPU. The accelerated model benchmarked at 96 FPS.

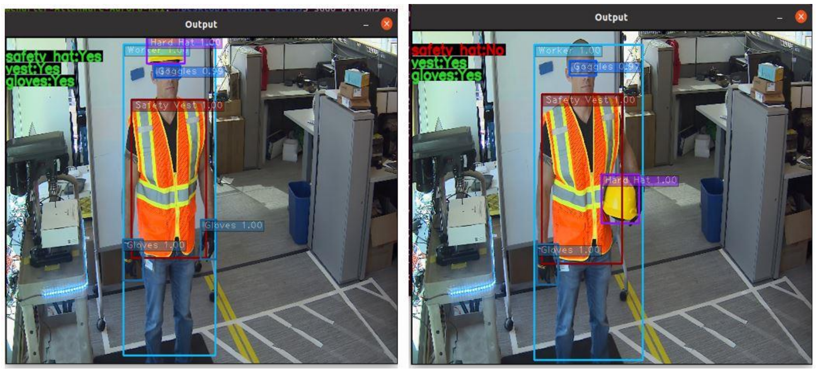

Figure 15 - Model Inference

This trained model performs object detection, and the developed computer vision algorithm checks if the worker is wearing all safety equipment based on the spatial coordinates of detected objects. If a worker wears all safety equipment, the worker is classified as a green worker, otherwise a red worker. In addition, the computer vision algorithm also shuts off the drill press if the worker's glove(s) (hand) is close to the pointed tip of the drill press.

3.5. Evolution of Worker Safety Use Case

3.5.1. Embedded Edge Compute

The first iteration of this application ran on a Volta Xavier GPU-powered single-board computer. The embedded edge device was compact and contained 384 CUDA cores. The board connected the buzzer, LED, and relay through GPIO pins. A network connected the edge device and camera, and the RTSP protocol fetched frames from the camera. The application processed every input frame, making decisions based on the output. This setup was straightforward, and all connections were wired connections.

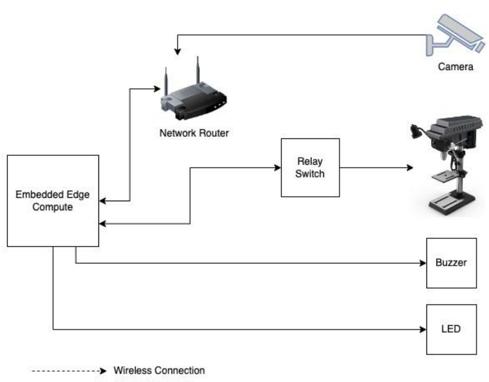

Figure 16 - Architecture with Embedded Edge Compute

3.5.2. High-End GPU Computer

The next iteration ran on a powerful computer. The GPU used was 2080Ti consisting of 4352 CUDA cores. This setup introduced a low-cost Raspberry Pi 4 computer, connecting the buzzer, LED, and relay.

A network connected the GPU server, camera, and Raspberry Pi. The GPU server processed camera frames, and the output was transmitted over a wireless channel to reach the Raspberry Pi to present the outcomes.

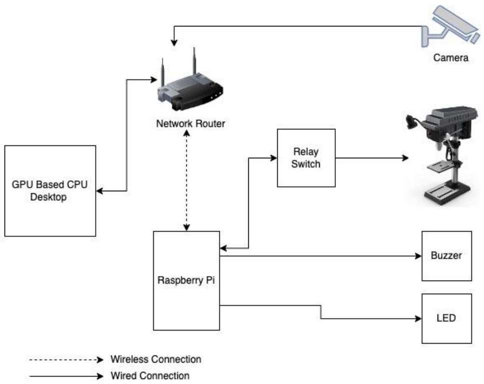

Figure 17 - Architecture with High-End GPU Computer

3.5.3. Multi-Access Edge Compute

The last iteration of the proposed solution ran on edge computing. The choice of edge computing was to tackle response time, latency, security, and scalability. This setup was like the previously referenced High-End GPU computer, except for the computer. The MEC was configurable, and GPU units could be stacked, enabling scaling. Tesla T4, which has 2560 CUDA cores, was used.

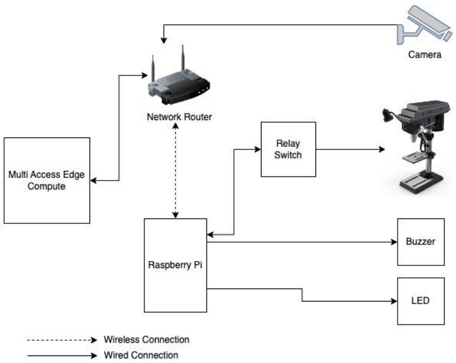

Figure 18 - Architecture with Multi-Access Edge Compute

3.6. Observations and Results

To test this application, a trained worker ran all application use cases in a closed environment. Since the cameras operate at 720p with 60 FPS over the network, it would raise questions regarding congestion and traffic. The cameras used a higher compression performance of the H.264 standard, thus reducing the network throughput by an enormous scale.

Raw video streams usually don’t have a fixed size. It varies with the resolution, frame rate, number of channels, etc. We decided to use 1280x720 resolution at 60 FPS for our application.

Raw video:

$$Bitrate = Resolution \times FPS \times Number\ of\ Channels \times Number\ of\ Bits\ per\ pixel$$

$$= 1280 \times 720 \times 60 \times 3 \times 8 = 1{,}327{,}104{,}000\ bps$$

$$= 1327.104\ Mbps$$

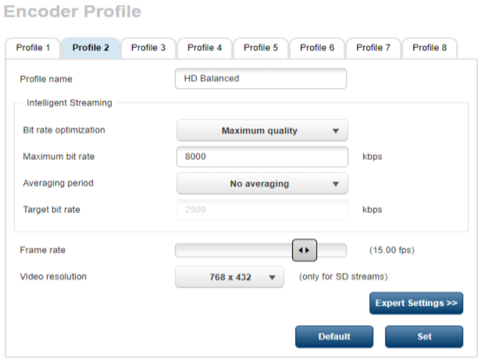

Figure 19 - Camera Software Settings

Profile Two was considered to set the stream output on the camera hardware interface, and it used variable rate H.264 encoding Figure 19. This profile achieved higher resolution and lower bitrate. The maximum bitrate for every reference frame for encoding was limited to 8 Mbps. The settings imply that the earned compression ratio was in the order of 100s.

At maximum bitrate,

$$Compression\ Ratio = \frac{Raw\ Bitrate}{Max\ Compressed\ Bitrate} = \frac{1327.104}{8} = 165.888 \cong 166$$

The camera did not consistently achieve this compression rate, which is variable to facilitate lower bitrate consumption. The camera used intra-coding techniques, and the value of the instantaneous bitrate of the frame decided the compression ratio.

3.6.1. Embedded Edge Compute

On the embedded edge compute, the binary files of the trained ML model ran at 5 FPS, whereas the accelerated model for this application ran at 15 FPS. Due to functional limitations, the hardware setup supported only one drill press up to 15 FPS for the accelerated model. The presence of physical connections minimized output response time. Fewer frames captured the information only for the whole second when the camera was at a lower frame rate. There was still a significant delay between obtaining frames averaging 35ms. The generated output responses were choppy and not consistent with real-time processing. If the solution needed to be scaled, it would require multiple units of embedded edge compute processors and would be challenging to maintain. The overall end-to-end latency was around 700ms.

3.6.2. High-End GPU Computer

The migration to a GPU computer was to enable scaling, allowing it to handle four drill presses simultaneously. The accelerated model supported 15 FPS and above. This setup introduced wireless link delay in addition to camera frame fetch delay. The wireless link delay corresponded to a delay in the transmission of processed output responses from the GPU to Raspberry Pi. The frame fetch delay for this setup was estimated between 7ms and 8ms for 60 FPS. The GPU computer handled the maximum frame rate capacity of the camera available, 60 FPS, and output responses were smooth and looked real-time. The overall end-to-end latency was around 300ms.

3.6.3. Multi-Access Edge Compute

The MEC unit was scalable and could accommodate multiple GPU units. The accelerated model supported 15 FPS and above. This setup also added wireless link delay and camera frame fetch delay. The frame fetch delay for this setup was between 7ms and 8ms for 60 FPS. The MEC unit also handled the video streams at 60 FPS; output responses were smooth and looked real-time. The estimated overall end-to-end latency was 300ms.

4. Conclusions

Our groundbreaking approach to worker safety, utilizing the combined power of AI and embedded systems, yielded exceptional outcomes. By integrating advanced technology into the workplace, we reassured workers operating near machinery and significantly elevated overall safety standards across the work environment. Through AI, our system can analyze real-time data collected from various sensors deployed throughout the workplace. This capability enables us to train AI algorithms to swiftly identify potential hazards and risky situations, empowering us to take proactive measures to prevent accidents and injuries. Also, the embedded systems perfectly harmonize with AI, creating a network of interconnected devices that constantly monitor the work environment. These systems detect abnormalities or deviations from standard safety protocols, triggering immediate responses such as automated machine shutdowns or alerts to nearby workers.

Furthermore, our project can scale up its operations by integrating multiple cameras connected to a centralized server for efficient data processing. This scalability allows us to gather information from various points within the workplace and relay it back to the relevant machines. This approach ensures comprehensive worker safety coverage and provides valuable insights into machine runtime and maintenance records. This newfound capability allows us to proactively identify potential machine issues before they arise, minimizing downtime and optimizing maintenance processes. As a result, our project not only prioritizes worker safety but also contributes to improved machine performance and longevity.

By combining the power of AI and embedded systems, we have not only revolutionized worker safety but also nurtured a culture of awareness and accountability. These advanced technologies instill a sense of responsibility among workers, motivating them to adhere to safety guidelines and remain vigilant.

This solution's impact extends beyond individual workers' safety, creating a ripple effect of safety throughout the workplace. By establishing a safer working environment, we protect the workers directly involved in machinery operation and their colleagues around them. This comprehensive approach to safety fosters a positive work culture, boosts productivity, and saves lives; also, by proactively reducing risk, liability and workmen’s compensation insurance coverage can be minimized.

This solution presented in this paper revolutionizes worker safety by providing real-time monitoring, proactive hazard detection, and immediate response capabilities. Through the fusion of technology and security, we have prioritized the well-being of individual workers and high safety standards throughout the workplace, leading to increased productivity, peace of mind, and prosperity.

5. Abbreviations and Definitions

5.1. Abbreviations

AI	artificial intelligence
ANN	artificial neural networks
AP	average precision
Avg	average
BoF	Bag of Freebies
BoS	Bag of Specials
Bps	bits per second
°C	Celsius
CBRS	Citizens Broadband Radio Service
CNN	convolutional neural network
FPS	frames per second
GPIO	general purpose input/output
GPU	graphics processing unit
IoT	Internet of Things
IoU	Intersection over Union
IP	Internet Protocol
LED	light emitting diode
LTE	long-term evolution
mAP	mean average precision
Max	maximum
Mbps	megabits per second
MEC	multi-access edge computing
Min	minimum
ML	machine learning
ms	millisecond
NA	not applicable
NMS	non-max suppression
ONNX	Open Neural Network Exchange
p	pixels
PAN	Path Aggregation Network
PoC	proof of concept
PoE	Power over Ethernet
RAM	random access memory
ReLU	rectified linear unit
RTSP	Real Time Streaming Protocol
SPP	spatial pyramid pooling
V	voltage
YOLO	You Only Look Once
YOLOv4	You Only Look Once version 4

5.2. Definitions

CUDA	Parallel computing platform and programming model developed by NVIDIA for general computing on GPU
EfficientDet	Machine Learning model that detects and classifies objects within an input image by extracting features and perform feature fusion techniques to build feature pyramid network
Mish	An activation function which is a combination of identity, hyperbolic tangent and softplus. It is defined as $f(x) = x \tanh softplus(x)$, where $softplus(x) = \ln(1 + e^{x})$
ONNX	ONNX is an intermediary machine learning framework used to convert between different machine learning frameworks.
ReLu	A piecewise activation function that will output the input directly if it is positive, otherwise, it will output zero.
Softmax	Mathematical function that converts a vector of numbers into a vector of possibilities, where probabilities of each value are proportional to the relative scale of each value in the vector.
TensorRT	A deep learning inference optimizer and runtime library developed by NVIDIA. It is developed to optimize and accelerate the inference process on NVIDIA GPUs.

6. Bibliography and References

[1] Z.-Q. Zhao, P. Zheng, S.-t. Xu, and X. Wu, “Object detection with deep learning: A review,” IEEE transactions on neural networks and learning systems, vol. 30, no. 11, pp. 3212–3232, 2019.

[2] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” in Proceedings of the IEEE 10 conference on computer vision and pattern recognition, 2016, pp. 779– 788.

[3] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification." In *Proceedings of the IEEE international conference on computer vision*, pp. 1026-1034. 2015.

[4] Bochkovskiy, Alexey, Chien-Yao Wang, and Hong-Yuan Mark Liao. "Yolov4: Optimal speed and accuracy of object detection." *arXiv preprint arXiv:2004.10934* (2020).

[5] Zheng, Zhaohui, Ping Wang, Wei Liu, Jinze Li, Rongguang Ye, and Dongwei Ren. "Distance-IoU loss: Faster and better learning for bounding box regression." In *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, no. 07, pp. 12993-13000. 2020.

[6] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Spatial pyramid pooling in deep convolutional networks for visual recognition." *IEEE transactions on pattern analysis and machine intelligence* 37, no. 9 (2015): 1904-1916.

[7] Huang, Zhanchao, Jianlin Wang, Xuesong Fu, Tao Yu, Yongqi Guo, and Rutong Wang. "DC-SPP-YOLO: Dense connection and spatial pyramid pooling based YOLO for object detection." *Information Sciences* 522 (2020): 241-258.

[8] Wang, Chien-Yao, Alexey Bochkovskiy, and Hong-Yuan Mark Liao. "Scaled-yolov4: Scaling cross stage partial network." In *Proceedings of the IEEE/cvf conference on computer vision and pattern recognition*, pp. 13029-13038. 2021.

[9] Guoliang Zhang, Zexu Du, Weijiang Lu, and Xiaoyan Meng. "Dense Pedestrian Detection Based on YOLO-V4 Network Reconstruction and CIoU Loss Optimization". *Journal of Physics: Conference Series* 2171, no.1 (2022): 012019.

[10] Changhong Wang, Qiang Luo, Xin Chen, Bingliang Yi, and Haibao Wang. "Citrus recognition based on YOLOv4 neural network". *Journal of Physics: Conference Series* 1820, no.1 (2021): 012163.

[11] Camera Browser Interface DINION / FLEXIDOME IP starlight 6000/7000 – Software Manual,https://resources-boschsecurity-cdn.azureedge.net/public/documents/NxN_6300_7300_Operation_Manual_enUS_23634193547.pdf

[12] P1378-Le datasheet, https://www.networkwebcams.co.uk/downloads/axis/axis-p1378-le-data-sheet-new.pdf

[13] Dinion IP Starlight 7000 HD – NBN-73013-BA datasheet, https://resources-boschsecurity-cdn.azureedge.net/public/documents/NBN_7300_Data_sheet_enUS_22455561611.pdf

[14] Dinion IP Starlight 8000 MP – NBN-80052-BA datasheet, https://resources-boschsecurity-cdn.azureedge.net/public/documents/NBN_80052_Data_sheet_enUS_78712137995.pdf

SCTE
a subsidiary of CableLabs®

140 Philips Road, Exton, PA 19341-1318 | 800.542.5040 | **scte.org**