COX CPEONE Suite Now and in the Future!

A technical paper prepared for presentation at SCTE TechExpo24

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1. Introduction

Internal data challenges arose due to a migration to a cloud data service, along with new company policies on data types and retention, these challenges caused many teams across departments to start drafting and pulling their own data which caused a lot of inconsistencies. The need to create one single space where field, operation, supply chain and other departments could pull data from one sole source so that all teams were talking the same language. Cox in 2023 launched an analytical tool to track CPE product performance metrics and device behavior analytics. We called this Tool: CPEONE

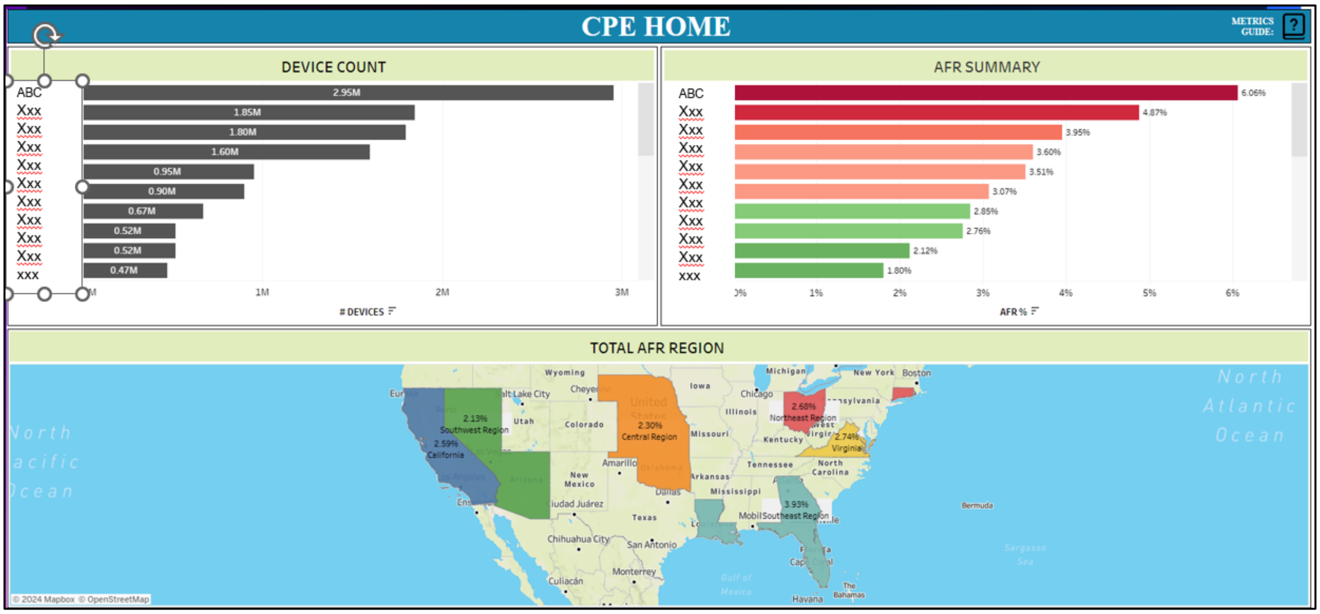

Figure 1 - Main Page, AFR & Repaired Parts

2. Purpose

This article demonstrates some key high-level abilities and features of the tool along with discussing how we were able to measure and trend Reliability and Quality metrics. The main drivers of this tool were the reliability metrics (AFR, MTBF, MTTR, etc.). Having the ability to tie device hardware and software versions, failure modes and network performance back to the actual truck rolls or customer calls and the symptoms of that failure offered significant advantages. Having the ability to analyze hardware lifecycles, show KPI metrics and device behavior that links to our current SLAs, and MSAs also provided useful feedback. Tracking old and new products' contract compliance fostered vendor accountability. This tool allows Cox to alert our vendors to early life failure modes for rapid mitigation which provides Cox the advantage of collaborating with vendors for innovative design specs to make their devices more robust within our network. The decision to add in SPC thresholds allowed Cox clearly to see over time how devices are currently performing inside of our network compared to the performance in prior years. The ability to trend on device returns, hardware and software failure modes, total repairs, and the trouble found rate along with TCO helps teams within Cox make future business decisions based on the data this tool provides. For example, the new analytics from our tool allow for forecasting along with the ability to help lower Opex costs.

3. Anomaly Detection

Let us first discuss ***The Anomaly Detection Framework***. The concept or idea to start tracking and trending on Anomalies is something that most companies would not do. An Anomaly is an abnormal occurrence or something that happens irregularly. You might have heard the synonyms: exception, variation, rarity, phenomenon, oddity. What many people may not realize is that even one or two data anomalies each month may be a cause of something greater that could be happened in your network last week, or the effect of something failing inside of the box due to age, electrical overstress, or a broken part. The intermittent failures could be the signs of a bigger issue inside of your network that does not happen often but occasionally. Either way, these things all affect the customer's experience and our reputation. The CPE devices may hiccup, bounce, overheat or even show signs of signal issues while providing video or Internet to our customers.

"***If it's not a daily occurrence, then how can you measure?***" you ask, see my theory and formula below:

Residual statistical bounds are calculated and overlaid onto the forecast to detect weekly anomalies at each of our PDCs. The anomaly bounds are adaptive in nature and can be adjusted to weaken or strengthen the sensitivity of the bounds along with using the product family's prior history.

SPC controls are used to identify imminent issues with dynamic thresholds using the tool's metrics. Some examples of metrics we have found to be useful are:

Annualized Failure Rate (AFR) = *sum(repairs + scraps)/(sum(days installed/365.25*

Repair Rate = *#repairs monthly /total tested devices*

Testing Failure Rate (TFR) = *(sum code load failure)/sum code loads*

Bounce Rates = # bounces <15 days of installation

BER/Scrap Rates = *# pre-repair scraps + # scraps /# of vendor returns*

The tool uses time series forecasting to predict **Device Testing Failure Rates** and **Device Repair Rates** for all active device populations.

****Key point***: There must be enough historical data with seasonal patterns for the model to learn from so that it can produce accurate predictions. The anomaly thresholds are created by applying statistical bounds (Mu+2sigma, Mu+3sigma) to the model's variance. Cox created residual anomaly detector for all active CPE models across four regional PDCs (warehouses) for two KPIs: 1) **TFR-** Testing Failure Rate, (# failed code loads)/ (#code load tests) and 2) **RR**- Repair Rates. (# repairs) / (#active devices).

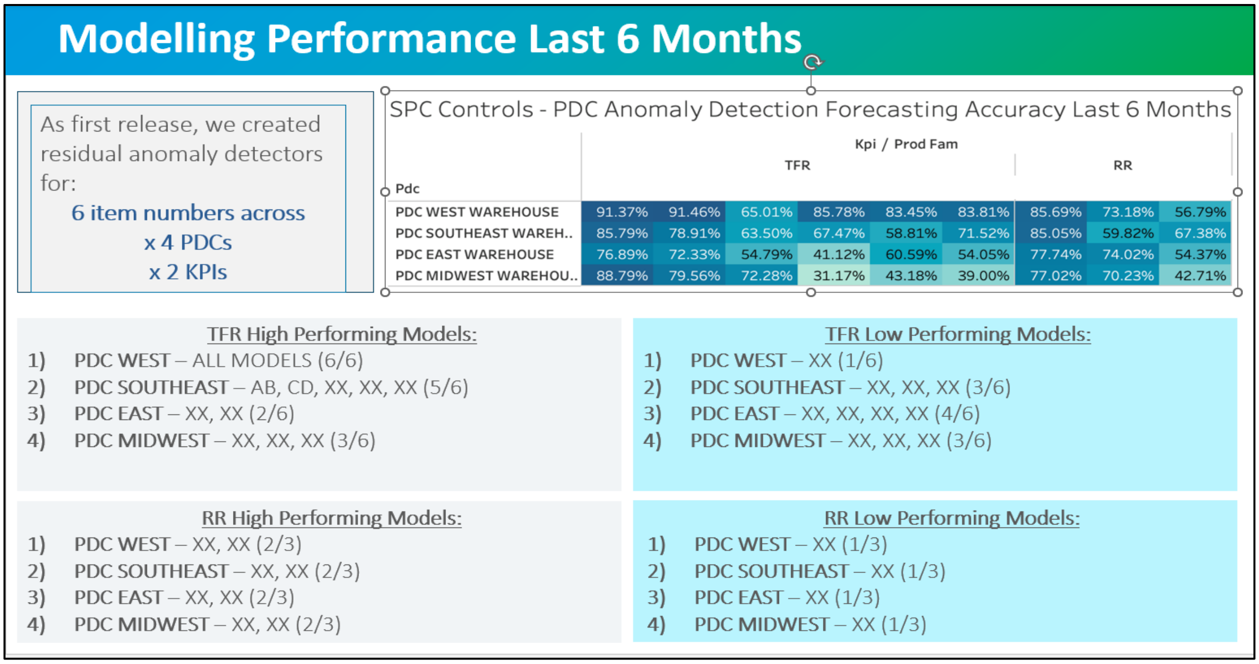

Figure 2 - SPC

When a predicted value falls outside of the anomaly threshold bounds, a flag is raised, and the issue is brought to a Bi-weekly Reliability meeting. In this Bi-weekly report, the team discusses raised anomalies. The team then determines if the issue is actionable, or if it is something we want to monitor.

This is an iterative way to monitor possible incoming performance related issues. The ability to constantly monitor device performance is required to prevent small issues or uncommon failure modes from reaching catastrophic or epidemic levels. This model can be utilized for new products as well as older models. The model can be utilized for new products during their first year of life to create an 'Early-Life Detection' analysis. For a new product, plotting anomaly bounds can show any early life hardware or software failure modes sooner than expected based on derived models on a weekly basis. With this newfound information Cox can work with repair vendors and manufacturers on CARS (Corrective Action Request) or SCARS (Supplier Corrective Action Request) or 3PL (third Party Logistics) request if needed.

Anomoly Dectection

Date Opened	Product	KPI	Type	Region	Auto	Observation	Decision	RACI	Next Step	Closeout Date	Remediation
3/5/2024	xxx	AFR SCRAP AFR	Lifetime	Southeast	N	AFR > 7%; SCRAP AFR > 1%	Monitor	Judy Brown (R)	Dig into CPE One for components driving high AFRs Consult whats out of norm - Kinney Bacon (Product) Potentially Open a CAR (Design, Normal Wear, End of Life) PW7/8 Power Supply Performance Analysis Georgia vs. Florida Repair Rates		Expected outcome 1: swap rates go down because techs are swapping power supply instead of entire devices. Expected outcome 2: power supply inventory on trucks will decline. *possible work order solution code added to track technician power supply changes
3/5/2024	xxx	SCRAP AFR	Lifetime	Northeast	N	SCRAP AFR > 1%	Monitor				
3/5/2024	xxx	Out Warr Repair %	Lifetime	ALL	N	99.07% of CiOne repairs are out of warranty	Next Meeting				
4/1/2024	xxx	AFR %	Lifetime	Southwest, California	N	easing YTD (3.38% to 3.7%); Southwest AFR increasing	Monitor		Post Putty Repair Bounce Analysis		
4/1/2024	xxx	AFR %	Lifetime	Southeast	N	AFR over 3% SLA	Monitor		1) Ask CTDI: Why do some regions not have repairs in a given querter? 2) Ask CTDI: Send CTDI batch of software repair orders to determine repair done 3) Matan: look at repair level of software repairs		
4/17/2024	xxx	AFR %	Lifetime	Virgina and Northeast	N	Virginia and Northeast regions have 80/20 software/hardware repair ratio while other regions have 25/75 software/hardware repair ratio.	Monitor		1) Ask CTDI: send CTDI batch of software repair orders to determine repair done 2) Matan: look at repair levels of software repairs		

Figure 3 - B-Weekly Anomaly Detection Report

An example of the model detecting a **TFR** anomaly for our model-X is shown above. These models were repaired at the West PDC on January 24th, 2024. On 1/1/24, our model predicted a **<u>TFR of 39.8%</u>** while the **actual <u>TFR was 52.9%.</u>** The delta between the prediction and actual outcome on this date falls outside our anomaly bounds, thus kickstarting the anomaly tracking process. The issue was raised in our Bi-Weekly Reliability meetings and the team concluded that the issue needed to be investigated further. The team used the tool to perform a deep-dive analysis on the repairs done in the following weeks to isolate which repaired part was driving this failure mode. The analysis concluded that over 50% of repairs being done at the PDC were driven by a specific failed part. We knew that the model-X devices were showing signs of high node ingress in the west region, potentially due to hardware issues. A decision was made by the business to have a sample sent for further testing.

A sample of fifteen devices were sent back from the field for extensive vendor testing to determine root cause, and mitigation of this issue. The testing concluded that the issues were not enterprise wide but an isolated incident. For some reason, a particular batch or run of model-X units was causing ingress issues on nodes in the West region only. No additional action was needed.

This example shows how the tool helped us successfully detect an issue, provide an analysis, and get a sound decision made quickly. That ability for all teams to work together (field ops, repair vendor, product owners) enabled the coordination necessary to send and evaluate samples of devices within a couple of days. Ability for repair to isolate and address the field issues swiftly instead of the team waiting for a bigger population or waiting for issue to show in other regions which would take weeks if not months provided significant business value.

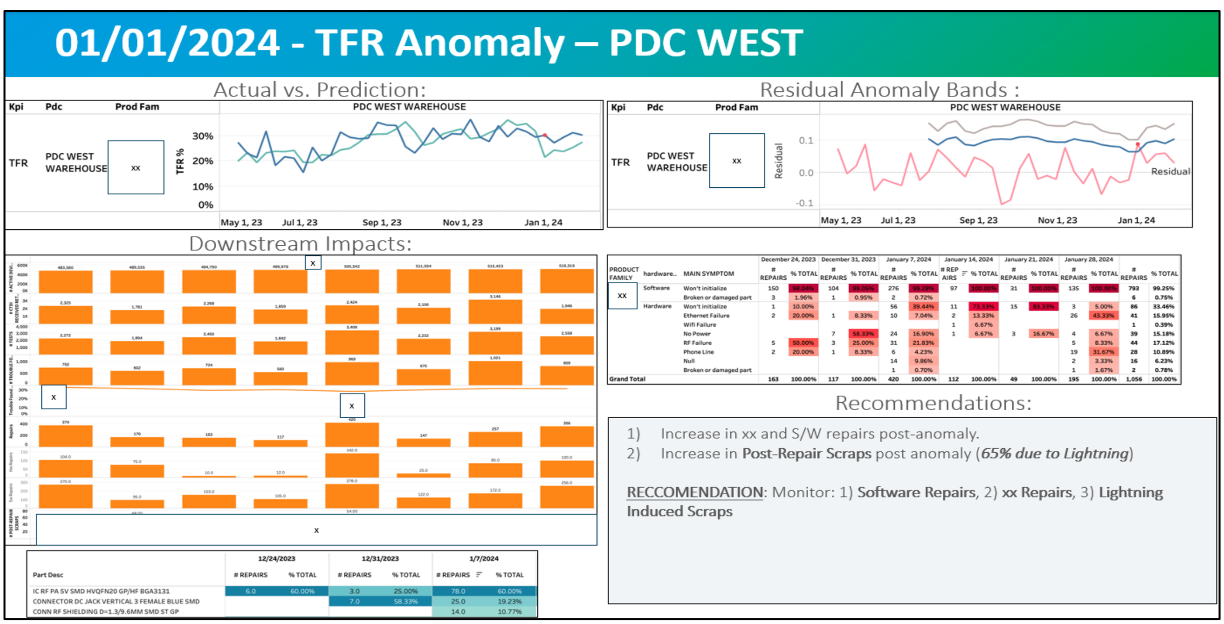

Figure 4 - TFR Anomaly Report

3.1. Total Cost of Ownership Total Cost of Ownership

Another ability inside this tool is ***<u>Total Cost of Ownership</u>*** which combines the complete cost history (i.e., install cost/counts, call cost/counts, truck roll cost/counts, outbound/inbound handling cost, repair cycle cost/counts) of a device into one actionable view. This allows Cox to determine totals cost for each individual serialized device, as well as overall cost of a product family over a span of time.

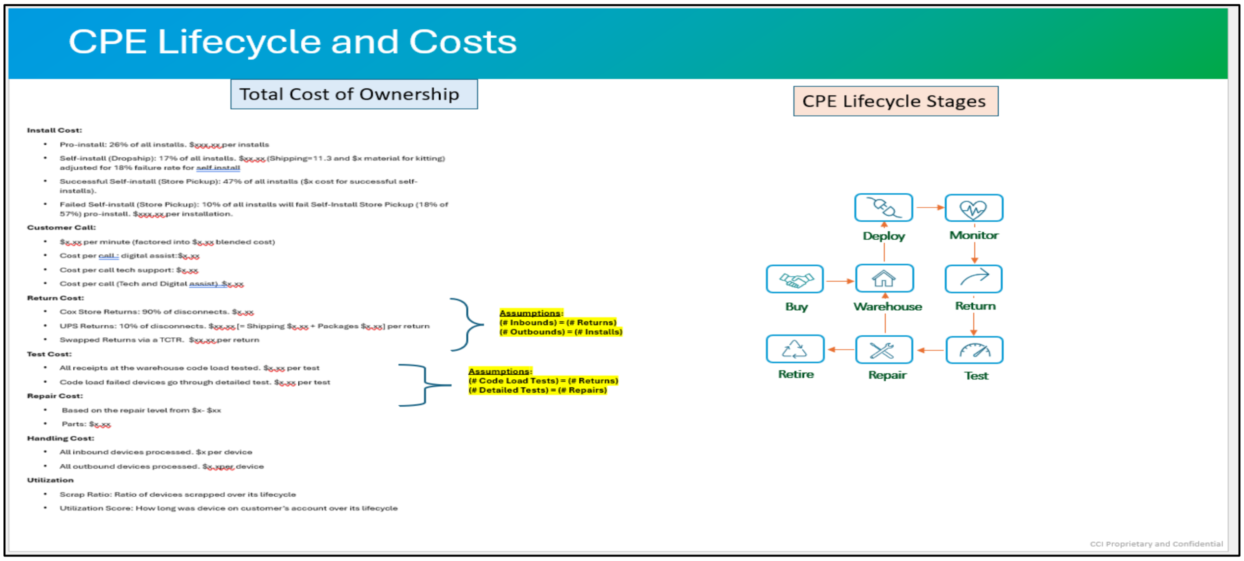

Figure 5 - TCO

The tool utilizes AI/machine learning to assist tracking and trending on other CPE/device attributes such software or hardware versioning and the effects it has on trouble calls and truck rolls as well as the utilization of repair parts across each of PDC's. To deliver this information, we created the ***Smart Watchlist***. This is a serialized model list based on repair cycles and TCO for each serialized device with performance problems.

1) Whitelist (serialized devices that have failed once with a level 3 or 4 repair level category) A device on this list is now flagged in repair system with continuing monitoring and cost tracking

2) Greylist (Serialized devices that failed more than twice for a level 3 or 4 repair category) This is a report that needs to be approved by Business Operations and Product owners. If the device cost is twice the original cost, they must approve to remove out of the network.

3) Blacklist (serialized devices failed three or more times with a level 3 or 4 repair level) A device in this category has an accumulated cost that is more than three times its original capex cost. These devices need to be removed ASAP from their network based on TCO deficient performance.

Segment devices based on the number of returns, TCTRs, repairs and OPEX cost to identify obsolescence optimization opportunities

Return Count	TCTR Count	OPEX	OPEX Level
Return <= 1	TCTR = 0	$55 - $107	Low
	TCTR = 1	$140 - $187	
1 < Return <= 3	TCTR <=1	$136 - $350	Moderate Low
	TCTR >1	$275 - $535	
3 < Return <= 4	TCTR<=2	$203 - $498	Moderate High
	TCTR > 2	$442 - $644	
Return = 5	TCTR<=2	$340-$610	High
	TCTR>2	$575-$776	
5 < Return <= 7	TCTR <= 3	$423 - $771	
	TCTR > 3	$702 - $1007	
Return > 7	TCTR <= 4	$475 - $967	
	TCTR > 4	$827 - $1304	

Figure 6 - Truck Roll/Trouble Call spend categorization.

An Example:

- For both Model-D and Model-A repaired in this sample - level 2 repaired devices **had worse cost metrics (including some amount of** Bounces per Device, Repairs per Device, Trouble Calls or Truck Rolls per Device) than level 3 and 4.
    - Suggests that smaller, less serious repairs and failure modes may cause more customer disruption than heavier and more costly repairs.
- Higher age (since 1st Install) is a good indicator of diminishing performance and higher costs for both Model- D and Model-A.
    - Suggestion is to update logic and add Level 2 repair categories into the Smart Watchlist category and determine if each repair meets level 2.
- Level 2 repaired Model-A had **31%** higher average Cost of Ownership than level 4 and **11.6%** higher than level 3 repaired Model-A.
- Older device age is a good indicator of diminishing performance and higher costs for both Model-D and Model-A.
    - 9 Model- D devices have a lifetime cost over $1,000 so need to be end-of-lives, so those serial numbers were added into a Blacklist.

Lifetime Cost of Ownership - Model D & Model A Devices Repaired Jan. 24 - Level 2,3,4 - Counts by Age Bins

Product	Repair Level	Age Since 1st Install Bins	# Devices	# Installs	Installs / Device	# Returns	Returns / Device	# Bounces (30day)	# Bounces (30day) / Device	# Calls	Calls/Device	# TCTRs	TCTRs/Device	# Service Disconnects	Service Disconnects / Device	# Repairs	Repairs / Device
mm	Four	0-1 Yrs	214	325	1.52	243	1.14	107	0.50	119	0.56	26	0.12	217	1.01	218	1.02
		1-2 Yrs	126	268	2.13	160	1.27	45	0.36	92	0.73	12	0.10	148	1.17	128	1.02
		Total	**340**	**593**	**1.74**	**403**	**1.19**	**152**	**0.45**	**211**	**0.62**	**38**	**0.11**	**365**	**1.07**	**346**	**1.02**
	Three	0-1 Yrs	831	1,437	1.73	1,034	1.24	444	0.53	596	0.72	99	0.12	935	1.13	986	1.19
		1-2 Yrs	967	2,123	2.20	1,490	1.54	404	0.42	770	0.80	109	0.11	1,381	1.43	1,203	1.24
		2-3 Yrs	676	1,713	2.53	1,156	1.71	318	0.47	485	0.72	74	0.11	1,082	1.60	861	1.27
		Total	**2,474**	**5,273**	**2.13**	**3,680**	**1.49**	**1,166**	**0.47**	**1,851**	**0.75**	**282**	**0.11**	**3,398**	**1.37**	**3,050**	**1.23**
	Two	0-1 Yrs	195	373	1.91	242	1.24	121	0.62	167	0.86	18	0.09	224	1.15	255	1.31
		1-2 Yrs	251	652	2.60	470	1.87	190	0.76	270	1.08	44	0.18	426	1.70	389	1.55
		2-3 Yrs	255	701	2.75	480	1.88	159	0.62	202	0.79	27	0.11	453	1.78	360	1.41
		Total	**701**	**1,726**	**2.46**	**1,192**	**1.70**	**470**	**0.67**	**639**	**0.91**	**89**	**0.13**	**1,103**	**1.57**	**1,004**	**1.43**
	Total		**3,515**	**7,592**	**2.16**	**5,275**	**1.50**	**1,788**	**0.51**	**2,701**	**0.77**	**409**	**0.12**	**4,866**	**1.38**	**4,400**	**1.25**
mm	Three	0-1 Yrs	28	30	1.07	7	0.25	3	0.11	0	0.00	0	0.00	7	0.25	35	1.25
		1-2 Yrs	54	119	2.20	90	1.67	17	0.31	23	0.43	2	0.04	88	1.63	59	1.09
		2-3 Yrs	65	140	2.15	109	1.68	22	0.34	44	0.68	8	0.12	101	1.55	76	1.17
		3-4 Yrs	210	487	2.32	342	1.63	71	0.34	114	0.54	23	0.11	319	1.52	231	1.10
		4-5 Yrs	236	672	2.85	498	2.11	95	0.40	190	0.81	33	0.14	465	1.97	287	1.22
		5-6 Yrs	111	366	3.30	247	2.23	46	0.41	87	0.78	12	0.11	235	2.12	140	1.26
		Total	**704**	**1,814**	**2.58**	**1,293**	**1.84**	**254**	**0.36**	**458**	**0.65**	**78**	**0.11**	**1,215**	**1.73**	**828**	**1.18**
	Two	0-1 Yrs	488	543	1.11	142	0.29	109	0.22	88	0.18	15	0.03	127	0.26	556	1.14
		1-2 Yrs	447	965	2.16	727	1.63	185	0.41	268	0.60	47	0.11	680	1.52	569	1.27
		2-3 Yrs	693	1,574	2.27	1,109	1.60	229	0.33	470	0.68	55	0.08	1,054	1.52	802	1.16
		3-4 Yrs	2,794	7,040	2.52	4,820	1.73	1,038	0.37	1,859	0.67	282	0.10	4,538	1.62	3,333	1.19
		4-5 Yrs	2,913	8,147	2.80	5,801	1.99	1,196	0.41	2,447	0.84	381	0.13	5,420	1.86	3,567	1.22
		5-6 Yrs	1,591	5,182	3.26	3,544	2.23	774	0.49	1,249	0.79	165	0.10	3,379	2.12	1,903	1.20
		Total	**8,926**	**23,451**	**2.63**	**16,143**	**1.81**	**3,531**	**0.40**	**6,381**	**0.71**	**945**	**0.11**	**15,198**	**1.70**	**10,730**	**1.20**
	Total		**9,630**	**25,265**	**2.62**	**17,436**	**1.81**	**3,785**	**0.39**	**6,839**	**0.71**	**1,023**	**0.11**	**16,413**	**1.70**	**11,558**	**1.20**
Grand Total			**13,145**	**32,857**	**2.50**	**22,711**	**1.73**	**5,573**	**0.42**	**9,540**	**0.73**	**1,432**	**0.11**	**21,279**	**1.62**	**15,958**	**1.21**

Figure 7 - TCO

3.2. Hardware and Software Revisions

Another innovative feature that was added to the tool was tracking for hardware and software revisions. As a company you need to know if a hardware or software revision was performed and what impact it might have. Does it affect the performance or behavior of the devices we own? What effect does this revision have on our customers?

Hardware revisions are normally done as a corrective measure for an identified problem. Software revisions are normally done to enhance performance of a device or fix a known issue, such as a bug. The question becomes "Does Cox measure the impact of hardware and software revisions?" Yes, we do.

In this tool, we can map hardware revisions back to trouble calls and truck rolls. Having the ability to see the impact on our customers and trend on issues in real time allows the business to make faster decisions. The customer experience is extremely valuable to Cox. Below is an example tracking the effects of three Hardware revisions during the first 3 years (early life) of model delta. As you see in the diagram below that version 2.1 increased subscriber calls and truck roll rates by 50% or more.

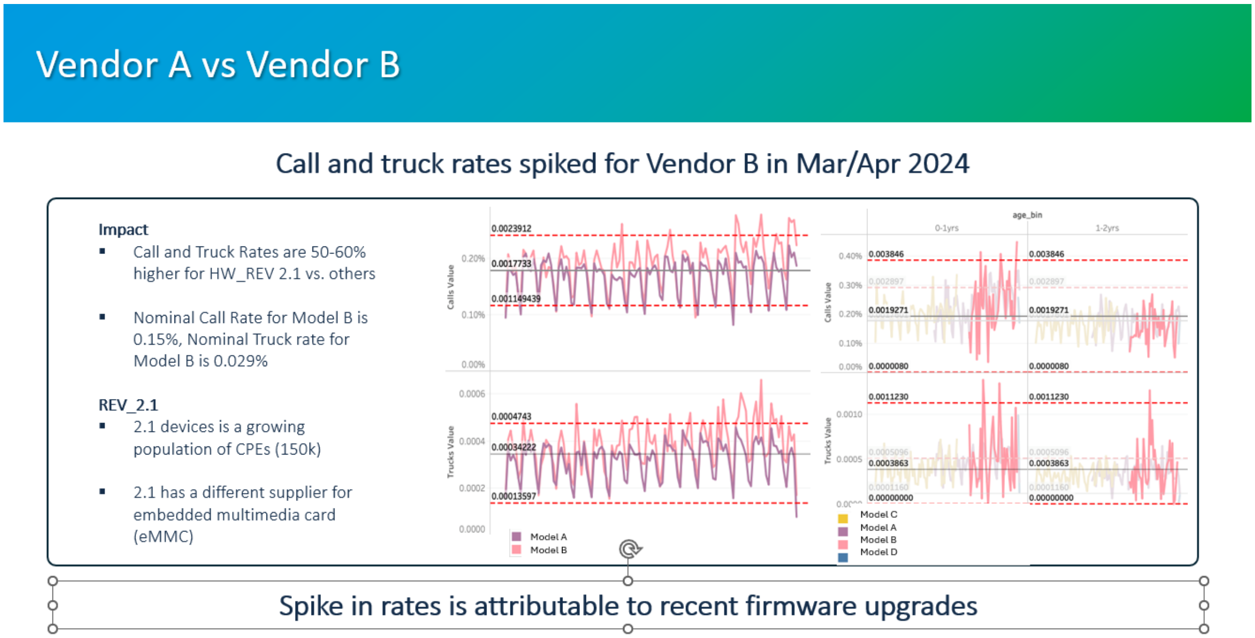

Figure 8 - Software upgrade

We were informed by the vendor that the three revisions accommodated supply chain issues. The next step in this revision analysis would be to start digging into the specific hardware differences and determine their failure modes to provide insight on what types of identified issues is potentially related to the hardware variations. Also, we may need the vendor to compare our reported issues to other MSOs to determine overall potential effects of this change.

HardVer (-h)	Comment
2.000123	Pilot/ Mass Production XX card
2.17563	BB brand Card
2.2022	XY Brand Card

Figure 9 - Hardware Revision

4. Conclusion

When we first designed this tool and engineered its abilities to use for CPE analysis, we wanted to also use reliability and Six Sigma methodologies to drive conservation and decision making. Quality metrics can tie into about anything that needs to be analyzed and measured. Using metrics and data tell the story but the biggest advantage is being able to visualize the masses of available data strategically and see just how failure modes affect customers. We take pride that our work is really driving change and better customer performance. More AI and machine learning needs to be inside of this tool. Using these tools to help make future business choices on hardware based on performance & it's abilities of forecasting and purchasing is our continuing goal.

Creating this tool has provided a clear answer to the age-old questions ***"How are my devices behaving and what are they costing us" and "Should we be spending this much on repairs or buying new products?"*** *and lastly and my favorite* ***"How are we doing against other MSO?"*** I can honestly say that this tool provides all those answers and much, much more.

Abbreviations

3PL	Third party logistics
AFR	Annualized Failure Rate
AI	Artificial Intelligence
AWS	Amazon Web Service
CPE	Customer premise equipment
CTDI	Communications test design Inc.
EOL	End of Life
HDD	Hard disk drives
KPI	Key Performance Indicators
MTBR	Mean Time Between Failures
Mu	avg variance between the forecast vs actual over the past 10 weeks
NPE	New Product Introduction
PDC	Product Data Center
R R	Repair Rate
RR	Return Rate
SCTE	Society of Cable Telecommunications Engineers
SPC	Statistical process controls
T.F. R	Testing found rate
TCO	Total Cost of Ownership
TCTR	Trouble call, truck roll
TFR	Trouble found rate

Table of Formulas:

AFR = (Number of Failures / Total Operational Time)

Example: Number of Failures = 5

Total Operational Time = 10,000 hours

Factor = 1 (as the period is already one year)

Then: *AFR* = 0.0005 × 100 = 0.05%

MTBF = Total uptime / # failures

MTTR= Total time spent on repairs / # of repairs

Availability = MTBF / (MTBF + MTTR)

SPC controls - Identify imminent issues with dynamic thresholds using the tool's metrics.

AFR = sum (repairs + scraps) / (sum (Days install/365.25)

Repair rate = #repairs monthly /Total tested devices

TFRs = (sum code load failure)/sum Code loads

Bounce Rates = # Bounces <15 days of installation

BER/Scrap *rates* = # pre-repair scraps + # Scraps /# of vendor returns

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