# An Innovative Data Driven Approach to Optimize WiFi Performance

A Technical Paper prepared for SCTE by

**Maryam Miri**
Device Technology Specialist
Rogers Communications Inc
8200 Dixie Rd, Brampton, ON L6T0C1
647-203-2375
maryam.miri@rci.rogers.com

**Kevin Esdale**
Sr. Mgr, Data Prod & Automation
Rogers Communications Inc
8200 Dixie Rd, Brampton, ON L6T0C1
647-203-6060
kevin.esdale@rci.rogers.com

# Table of Contents

**Title** **Page Number**



## List of Figures

**Title** **Page Number**



## List of Tables

**Title** **Page Number**

# 1. Introduction

Applying a proactive communication approach with the focus of customers with technical issues is an effective business strategy and a proven method that enhances both customer satisfaction as well as brand reputation. In a proactive program, the organizations initiate communication with customers and by keeping customers informed of feasible technical solutions, they stay ahead of possible complaints.

Leveraging data driven approaches in a proactive communication program can significantly elevate the success rate. By utilizing data analytics tools, different insights, patterns, and correlations can be extracted. This helps in identifying the underlying issues and their general causations and hence, a more goal-oriented communication effort. In this paper, we describe the implementation of an end-to-end solution that by leveraging the analysis on millions of recorded data points, improves the wireless fidelity (WiFi) experience of users.

In other words, by identifying and addressing the underlying in-home network issues that cause video quality degradations, we offer solutions to enhance customers' experience. To achieve this goal, we analyzed reported data from various sources such as set-top boxes (STBs), gateways (GWs), point of deliveries (PODs), and user feedback to identify patterns or trends that indicate issues affecting video quality. Then, by correlating the video quality impairments to the WiFi telemetries such as throughput, response time, and latency we isolate the WiFi degradation root causes such as poor received signal strength index (RSSI), low signal to noise ratio (SNR), and high band utilizations. Finally, by defining the root causes' thresholds and developing a decision tree, we confidently propose educated solutions based on the root causes. By proactively reaching out to more than 5000 customers so far and employing the solutions, the results illustrate a notable improvement in the video quality. The observations of different cohorts depict that the pre-post video quality comparisons sustained greater than 70% improvement post implementations.

# 2. Background

WiFi has introduced a fundamental shift in human lifestyle by becoming the preferred medium of our everyday communications. Over the last 5 years, there has been a significant increase in the total number of connected devices in a household. Dominated in the internet of things (IoT) space, a huge growth in the total number of devices is expected over the coming years. This has increased the demand for connectivity and convenience in various aspects of our lives and the need for devices to be interconnected and able to communicate with each other. Therefore, having access to a reliable WiFi network with a robust infrastructure to support the growing number of devices is a crucial need today. It is worth noting that the reliability of WiFi depends on the performance of both access network and the in-home network.

## 2.1. Data Driven Proactive Schemes

Data mining has become one of the major methods in uncovering hidden insights and trends within large volumes of data in recent years. Identifying patterns, relationships, and insights from large volumes of data allows organizations to develop optimal strategic planning and marketing campaigns. Analyzing operational data enables organizations to identify potential bottlenecks and areas for improvement. This can lead to enhanced cost efficiency, customer satisfaction, and overall stronger customer relationships. Utilizing data to detect patterns and possible impairments in access network has been greatly discussed in [1]-[4-10]. In [1], using an unsupervised model, the authors analyze RF impairments observable by proactive network maintenance (PNM) and combine it with CableLab's spectral impairment detector (SID) observations [2]-[3] to improve SID's impairment classifiers. By transforming the state-of-the-art object detection algorithm into an anomaly detection model in [4], a flexible and high-performance anomaly detection solution is proposed for cable industry. The authors in [4] reach the mean average precision (mAP) of 97.82% in localizing and classifying network anomalies via developing a 1D-Convolutional Neural Network that includes 45 1D-Convolutional layers. In [5], a detection model is proposed that accurately differentiates among RF wave types and successfully detects the network impairment signatures. Also, by narrowing down the origin of the impairments through a network topology graph representation, the problem resolving mechanism has been further improved.

### 2.2. In-home WiFi Performance Optimization

Inspired by the above discussions and considering the major effect of WiFi performance on various aspects of modern life, in this paper, we analyze the reported data from controlled devices such as STB, POD, and GW to identify the factors that impact the in-home WiFi performance negatively and determine potential solutions. Figure 1 displays the topology of a WiFi network in a home environment with a streaming device that uses WiFi as the primary connection. As this figure depicts, depending on parameters such as the strength of the received signal from the APs, STB can connect to either GW or the POD. The received power by the receiver $r$ from the transmitter $t$ can be approximated by

$$P_r = P_t G_t G_r (\frac{\lambda}{4\pi d})^2,$$

in which a free space is assumed, and $d$, $P_t$, $G_t$, and $G_r$ represent the distance between the transmitter and the receiver, the transmitted power, the transmitter antenna directivity gain, and the receiver antenna directivity gain, respectively. Also, according to the Shannon capacity theorem, the maximum achievable data transmission rate on a noisy channel is limited by the channel bandwidth and the signal to interference plus noise ratio (SINR) at the receiver [11]. This sheds light on the importance of a proper AP connection as well as frequency band selection.

In other words, the quality of the connection plays a crucial role in determining the selected modulation, error correction techniques and ultimately, the data transmission rates. It is worth noting that the total raw bit rate of a video that needs to be transmitted through IPTV depends on the video resolution as well as multiple other attributes. I.e., for a video stream with the resolution of $n_x \times n_y$pixels per frame, the frame rate of $n_f$, and the total $n_a$ stereo channels of audio, the bit rate can be calculated as

$$R_{b\_total} = 3n_b \times n_x \times n_y \times n_f \times r_{dc} \times r_{cc} + n_a \times R_a,$$

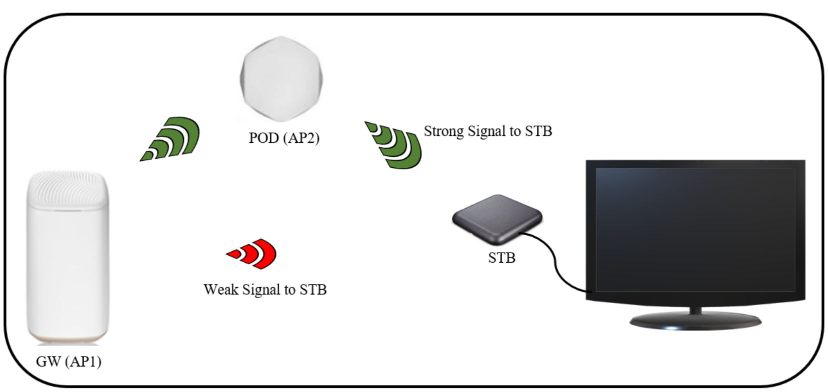



**Figure 1 - WiFi Network Topology**

where $n_b$ is the number of quantization bits per pixel, $r_{dc}$ and $r_{cc}$ show the data compression ratio and colour compression ratio, and $R_a$ represents the audio transmission rate (comprised of audio sampling rate and the number of quantization bits per sample).

In the case of a WiFi connection degradation where a modulation with low transmission rate is selected, the channel profile usually changes to a lower resolution, i.e., from 18.7Mbps to a lower data rate such as 6Mbps for a 4k video. Hence, if the WiFi connection to the STB is in the poor stages, it is impossible to stream a 4k resolution video with a bit rate of 18.7Mbps without observing defects such as automatic bit rate shifting (ABR), black screen, frame freezing and skipping, and pixelation. Furthermore, poor in-home coverage may result in other disturbances such as the video player aborting the manifest file that makes it impossible to recover the video content resulting in onscreen errors.

By tracking the reported profile changes as well as other video events and correlating them to the recorded in-home telemetries such as SNR and WiFi bandwidth, we can detect the video quality degradation events and offer solutions based on the root causes. Table 1 illustrates the events that we track in our data as the video quality degradation fingerprints and a brief description regarding each one of those events.

To verify the accuracy of these fingerprints, we conducted an SINR test experiment with 5 different scenarios by changing the STB AP as well as the location of the interference generator and monitored the reported events and telemetries by GW, STB, and POD. In each one of those scenarios, we ingested a partial interference with the bandwidth of 20MHz into an 80MHz WiFi channel, while streaming a 4k video on IPTV to observe the effects on the perceived quality of the video and the recorded errors. For further analysis and comparisons, two laptops, one streaming a YouTube channel and the other one connected to a Microsoft teams video call were also left in close range of the STB. As Figure 2 shows, once the experiment began the video frames on TV became frozen, the lowest profile alerted, and the manifest failed messages appeared in reported logs by the STB. Also, degradation was observed on both laptops; the YouTube channel streaming stopped, and the teams video call dropped or disrupted during all the scenarios. All in all, our SINR test scenarios not only verified the accuracy of aforementioned fingerprints reported by the STB, but also confirmed these markers can generally represent a degraded experience of other devices that have the same WiFi connection/proximity as the STB.

**Table 1 – Video Quality Degradation Events**

| Channel Resolution | Tracked Event | Description |
|---|---|---|
| 4k resolution video | Fog_Warn_Lowest_Profile_set | The bit rate shifts to 6.3Mbps |
| | Fog_Info_LowProfile | The bit rate shifts to a lower rate such as 12.8Mbps. |
| UHD resolution video | Fog_Warn_Lowest_Profile_set | The bit rate shifts to 3.8Mbps |
| | Fog_Info_LowProfile | The bit rate shifts to a lower rate such as 4.6Mbps. |
| 4k and UHD resolution video | Fog_Warn_Mfstdwnld_Failed | Manifest file failed to download or Aborted |
| | Fog_ERR_NoUpdatePlaylist | No Update for the last playlist file |
| | Fog_Info_CDNTimeout | Timeout occurred reaching the URL for the next video file |

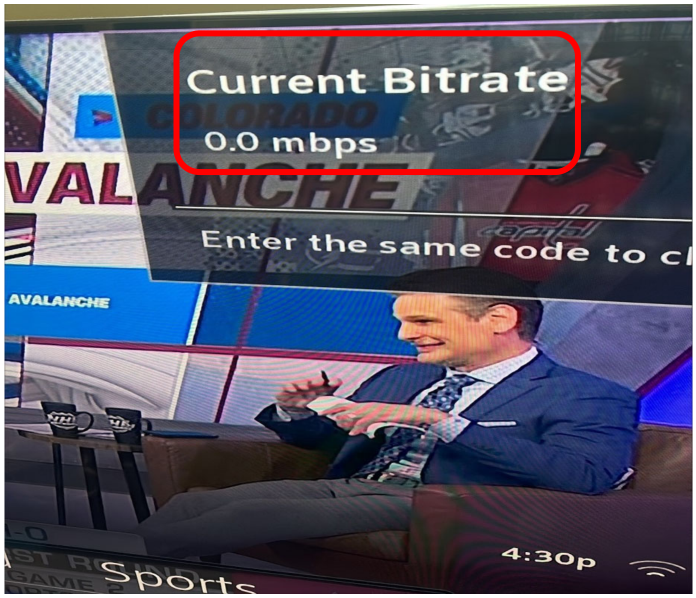



**Figure 2 – Video Quality Degradation by Interference Injection**

## 3. System Model Architecture

This section begins with a discussion on the root cause analysis conducted in our model, employing a data-driven approach. Next, we present the development of a decision tree that provides diverse solutions derived from the root cause analysis. Finally, we elaborate an illustrative use case of this study, demonstrating the practical implementation of an algorithm called clean-home.

### 3.1. Video Quality Degradation Root Cause Analysis

To perform the root cause analysis for customers encountering the fingerprint issues mentioned above, we employ the hourly collected values reported by GW, POD, and STB. In order to eliminate any video quality degradations resulting from factors outside the home environment, we exclude all degraded RF network telemetry data that could contribute to poor video experience.  Put differently, we employ the filters outlined in Table 2 on hourly data of customers with degraded video quality to define appropriate thresholds for various WiFi parameters, such as RSSI and channel utilization.

**Table 2 – Specific Filters to Avoid External Effects**

| Hourly Parameter | Value |
|---|---|
| # of GW/STB reboots | 0 |
| # of GW re-registrations | 0 |
| STB connection type | WiFi |
| # of WiFi crashes and WiFi disconnects | 0 |
| # of upStream/downStream docsis errors | 0 |
| ODM_score | <200 |
| Node_score | <25 |
| Area Congestion (upstream_score+downstream_score>1000) | No |

Also, considering the varying performances of different GW models (XB6, XB7, and XB8), we categorize the hourly data points that satisfy all the filters mentioned above based on the respective GW models. Due to the distinct channel bandwidth and supported standards of different operational WiFi bands (such as 2G, 5G, and 6G bands), it is necessary to further classify the data based on the STB connection band as well. Subsequently, to identify the root causes behind video quality degradations and establish degradation thresholds for parameters such as RSSI and channel utilization, we utilize diverse correlation graphs corresponding to each classified data group. Figure 3 shows the number of hourly fingerprints versus the reported achievable rate for STBs connected to 2.4GHz bandwidth of an XB6 GW. Figure 4 displays response time versus the achievable bit rate for the same STB connection. As depicted in Figure 3, for achievable bit rates of 150 Mb/s and higher, it is evident that not only are there no instances of more than 4 fingerprints, but the occurrences of fingerprints also become infrequent and scattered. Therefore, the 150 Mb/s bit rate can be regarded as one of the thresholds that determines the quality of IPTV signals for STBs connected to the 2.4 GHz band of an XB6. The noticeable deterioration of response time in Figure 4 when the bit rates are below 150 Mb/s further validates the reliability of this threshold.

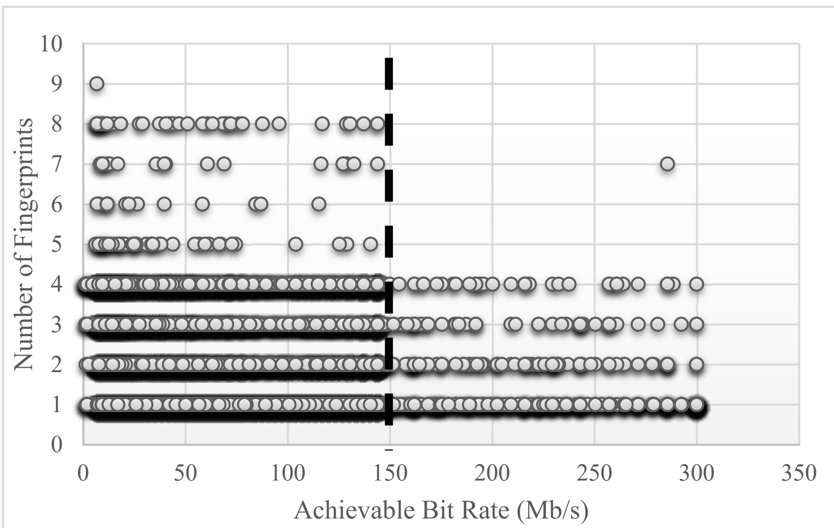



**Figure 3 – Number of Hourly Fingerprints versus Achievable Bit Rate (2.4GHz of XB6s)**

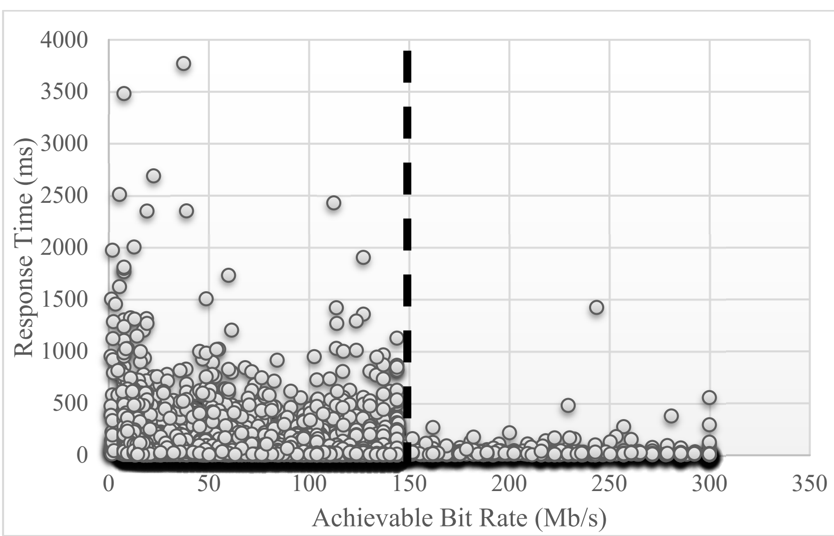



**Figure 4 – Response Time versus Achievable Bit Rate (2.4GHz of XB6s)**

In Figure 5, the relationship between the achievable bit rate and the STB RSSI is illustrated for the connection type mentioned above. As depicted in the figure, when the RSSIs are below -62 dBm, the achievable bit rate rarely exceeds 150 Mb/s. Therefore, we can designate -62 dBm as the threshold for the RSSI values that indicates service degradation. To summarize, it can be concluded that RSSIs below -62 dBm lead to achievable bit rates lower than 150 Mb/s, increased response times, and overall degradation in video quality. Consequently, a low RSSI below the threshold of -62 dBm is identified as one of the root causes incorporated into our decision tree specifically for 2.4GHz bandwidth connections on XB6 GWs. It's important to note that employing a similar analytical approach reveals that a bit rate of 866 Mb/s serves as the critical threshold for ensuring optimal service quality for STBs operating on the 5GHz band of an XB7 device. Figure 6 underscores the essential requirement that the RSSI must surpass the -68 dBm threshold to attain this desired bit rate. Hence, we can designate the RSSI of -68 dBm as one of the thresholds indicatives of service degradation for STBs connected to the 5GHz band of an XB7.

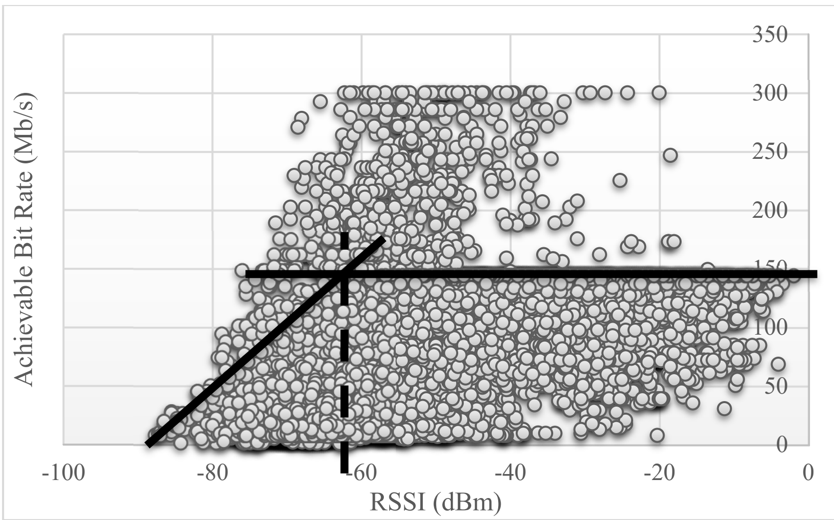



**Figure 5 – Achievable Bit Rate versus RSSI (2.4GHz of XB6s)**

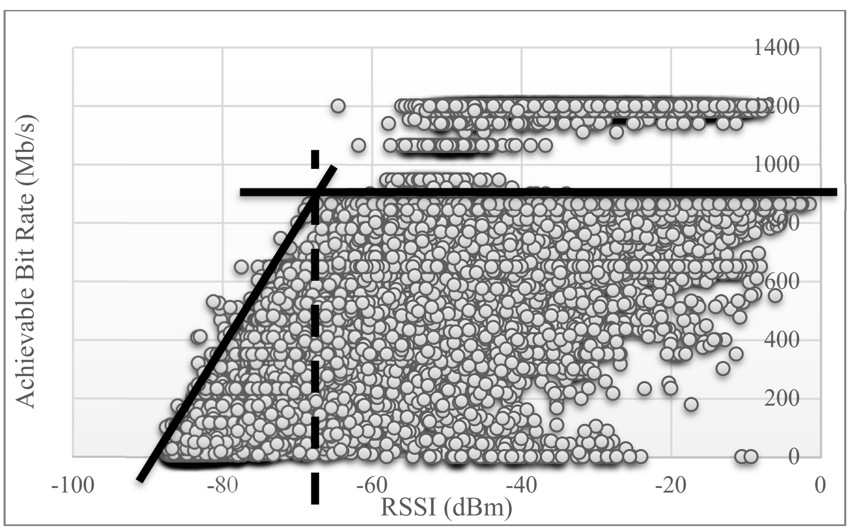



**Figure 6 – Achievable Bit Rate versus RSSI (5GHz of XB7s)**

As mentioned earlier, channel utilization also has a major effect on the video quality and overall service performance. Figure 7 displays the achievable bit rate versus the channel utilization for STBs connected to 2.4GHz bandwidth of an XB7 GW. As depicted in this figure, for utilization below 70% there is a notable concentration of samples with achievable bit rates of more than 150 Mb/s as opposed to greater than 70%. Based on this analysis, 70% can be considered the threshold for the WiFi band congestion in the decision tree.

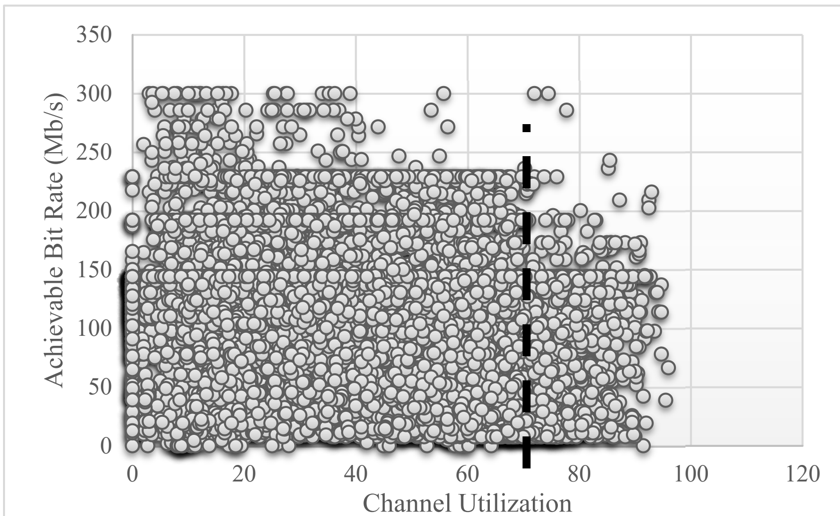



**Figure 7 – Achievable Bit Rate versus Channel Utilization (2.4GHz of XB7s)**

### 3.2. Decision Tree Development

Combining the individual filters, models, WiFi Band and WiFi parameters thresholds allows us to begin structuring the branches within our decision tree. Figure 8 elegantly navigates a specific branch (shown by the red box) for a particular model, traversing Band, RSSI and Utilization ultimately leading to a definitive resolution. This figure clearly demonstrates that the customer's needs can be met by incorporating a POD, effectively expanding the optimal WiFi coverage throughout the house. This, in turn, ensures that the STB in question is directed towards a suitable Access Point (AP) operating on a broader bandwidth and resulting in an enhanced RSSI.

**Resolution**

Pods = 0 → 2G Utilization < 70 → Offer Pod

XB6 → 2.4 Band → RSSI≤-62 → AP=1

⋮

⋮

Pods≥1 → 2G Utilization≥70 → 5G Utilization < 80 → Upgrade Modem

**Figure 8 – Example Branches of Developed Decision Tree (AP=1 depicts that the STB in question never changed its connection)**

### 3.3. Clean Home Development

Ultimately, the output resolutions obtained from the decision tree discussed above, combined with additional KPIs, are fed into another algorithm known as clean-home. This process allows for an extensive analysis and optimization of various factors, contributing to an overall improvement in home network performance and video streaming quality. Table 3 presents a comprehensive list of all KPIs, accompanied by concise explanations, which constitute essential components of the clean-home algorithm. Implementing this algorithm helps us to enhance the efficiency of our proactive program. In simpler terms, each customer has a daily report from the clean-home algorithm, highlighting all detected KPIs and issues. Hence, as we contact the customer, we can address all the identified problems simultaneously, streamlining the resolution process and optimizing our interactions with customers.

It is essential to highlight that our actions concerning customers are prioritized according to the KPIs as well as the number of days the KPI is being degraded. For each customer that appears in the clean-home list, we look at a seven-day window and calculate a normalized score using the following formula

$$customer\ score = \frac{\sum_{i=KPI} w_i d_i}{7\sum_{i=KPI} w_i},$$

where $w_i$ represents the allocated weight for each KPI and $d_i$ represents the number of days that the KPI has been identified as degraded during the last 7 days. By utilizing this formula, we can objectively prioritize actions and allocate resources more efficiently, ensuring an optimal proactive approach that resolves customer issues. The subsequent section delves into the comprehensive results obtained thus far from the clean-home algorithm, providing detailed insights on the observed improvements.

**Table 3 – Clean-Home KPIs**

| KPI | Explanation |
|---|---|
| Video quality, upgrade GW to a higher model | Video quality degradation event observed for three consecutive days; solution: upgrade GW |
| Video quality, add pod for better coverage | Video quality degradation event observed for three consecutive days; solution: offer POD |
| Video quality, customer equipment | Video quality degradation event observed for three consecutive days, customer is using a third-party device; solution: offer pod |
| ODM Impaired | In-home RF issue, when ODM_score>200 and node_score<25 |
| GW re-registration | If the modem goes offline (checking all offline events) at the same time the IPTV customer is using the service for three consecutive days |
| Daisy chained POD | Multiple PODs are interconnected in a serial structure |
| Poor POD backhaul | 90% of the reported backhaul RSSI of the POD is less than -75 dBm for three consecutive days |
| Poor coverage, add pod | Low normalized home score calculated according to STB parameters such as RSSI, packet loss, number of errors, phyrate,…; solution: offer POD |

## 4. Results and discussion

In this section, we will discuss the improvement results obtained from the clean-home algorithm. Through the utilization of the clean-home algorithm, we have proactively engaged with over 5000 customers, implementing various tailored solutions to enhance their experience. These solutions include providing PODs to improve coverage, recommending POD relocation for better backhaul signal, upgrading customer GWs or PODs to newer versions with advanced technologies, especially when multiple PODs are interconnected in a serial structure.

Figure 9 illustrates the cumulative improvements for each clean-home list to date. To calculate the improvement percentages, we compare the WiFi performance of customers one week before contacting them with their WiFi performance three weeks after the solution is provided. Also, to ensure a fair comparison, we carefully select a control group that we don’t do any actions on; By comparing the progress of customers who received specific actions with those who didn't receive any interventions, we effectively assess the impact of our actions. As shown in this figure, for all the clean-home lists, the improvements achieved for customers who received specific actions are nearly double when compared to the control group. This observation highlights the significant impact of the interventions in enhancing the WiFi performance and indicates the effectiveness of the actions taken.

Figure 10 illustrates the distribution of improvement percentages. As Figure 10-a depicts, for the majority of the customers all the issues are being resolved. Figure 10-b emphasizes that more than 72% of the customers that we did an action on are experiencing 80-100% improvement. Finally, in Figure 11, we present a specific comparison of the total number of video quality degradation events that occurred one

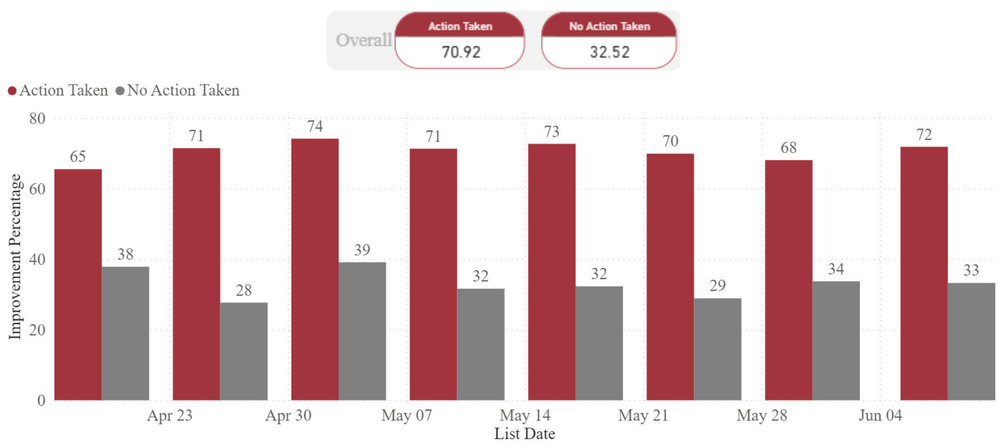
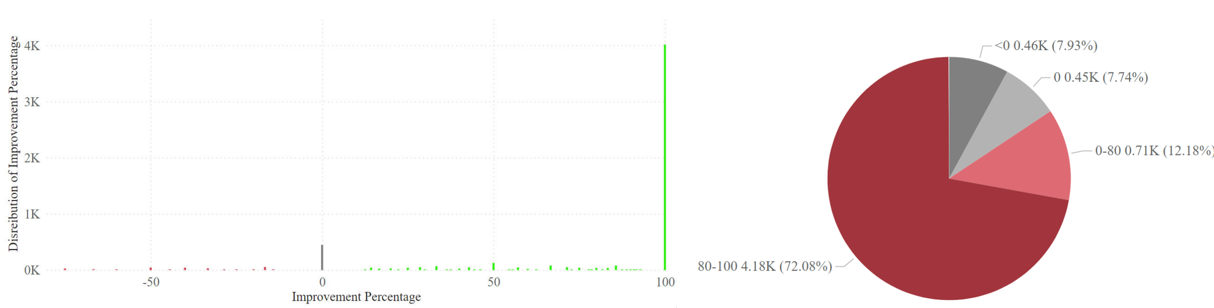
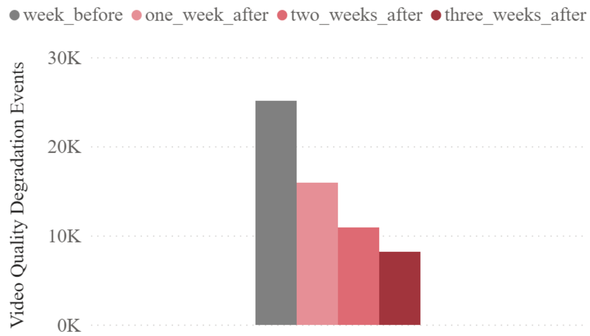



**Figure 9 – Cumulative Improvement of Clean-Home Lists**

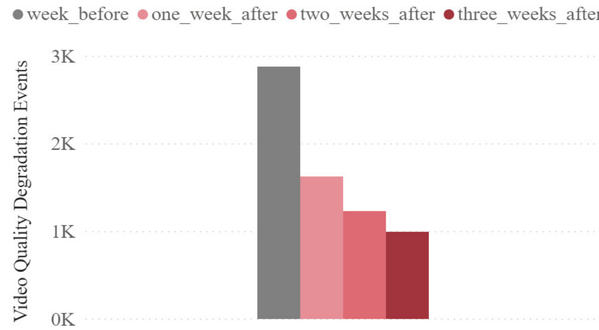



a) All Improvement Percentages b) Bucketized Improvement Percentages

**Figure 10 – Distribution of Improvement Percentage**




a) Offer POD to Customer




b) Upgrade Customer's GW

**Figure 11 – Total Video Quality Degradation Events**

week before the resolution was provided, with those happening one, two, and three weeks after. We explore this comparison across various solutions, including offering POD and upgrading the customer's GW. When comparing the number of video quality degradation events from the week before to the three weeks after, we observe significant improvements at approximately 70% for both solutions. In summary, all the results conclusively demonstrate the effectiveness of our proactive approach and the reliability and success of our strategies in addressing the WiFi in-home challenges.

## 5. Conclusion

In this paper, we have presented a proactive approach that by leveraging data-driven techniques, effectively identifies and addresses in-home network issues. Through extensive experimentation and engagement with over 5000 customers so far, we have demonstrated the remarkable effectiveness of our method in proactively optimizing the performance and stability of in-home networks. The analysis of the results highlights the resounding success of our proactive clean-home algorithm, achieving a 70% improvement overall for the group of customers who received our targeted interventions. Notably, a significant majority of these customers experienced a remarkable 100% enhancement in WiFi performance after implementing the suggested actions.

The results of this work can be extended through the further optimization of our customer scoring method in future work. By delving deeper into the feedback from customers who encountered WiFi problems but chose not to participate in our program, we can establish meaningful correlations and craft a refined scoring method capable of accurately predicting a customer's inclination to engage in our proactive program. This provides a strategic advancement in our resource allocation and by directing our efforts towards customers who are most likely to benefit from, ensures a more targeted and efficient proactive approach.

# Abbreviations

| | |
|---|---|
| AP | access point |
| GW | gateway |
| IoT | Internet of things |
| POD | point of delivery |
| PNM | proactive network maintenance |
| RSSI | received signal strength index |
| SINR | signal to interference plus noise ratio |
| STB | set-top box |
| UHD | ultra high definition |
| WiFi | wireless fidelity |

# Bibliography & References

[1] Volpe, B., Ottlik, B. (2021). Machine Learning and Proactive Network Maintenance: Transforming Today's Plant Operations. *SCTE 2021 Fall Technical Forum.*

[2] Cable Television Laboratories, Inc. (2016). *PNM Best Practices: HFC Networks (DOCSIS 3.0).*

[3] able Television Laboratories, Inc. (2022). *Primer for PNM Best Practices in HFC Networks (DOCSIS 3.1).*

[4] Zhu, J., Sundaresan, K., & Rupe, J. (2020). Proactive Network Maintenance using Fast, Accurate Anomaly Localization and Classification on 1-D Data Series. *2020 IEEE International Conference on Prognostics and Health Management (ICPHM).*

[5] Dugan, K., Evans, J. (2022). A Deep Learning Approach for Detecting RF Spectrum Impairments and Conducting Root Cause Analysis. *SCTE 2022 Fall Technical Forum.*

[6] Volpe, B., & Ottlik, B. (2021). Machine Learning and Proactive Network Maintenance: Transforming Today's Plant Operations. *SCTE 2021 Fall Technical Forum*.

[7] Virang, D., Chari, S., & Kraiman, S. (2021). Machine Learning for RF Impairment Classification. *SCTE 2021 Fall Technical Forum.*

[8] Ferreira, J., Harb, M., Subramanya, K., Santangelo, B., & Rice, D. (2020). Convolutional Neural Networks for Proactive Network Managment. *SCTE 2020 Fall Technical Forum.*

[9] Wolcott, L., Heslip, J., Thomas, B., & Gonsalves, R. (2016). A Comprehensive Case Study of Proactive Network Maintenance, *SCTE/ISBE Cable-Tec Expo 2016.*

[10] Rupe, J., Zhu, J. (2019). Kickstarting Proactive Network Maintenance with the Proactive Operations Platform and Example Application, *SCTE/ISBE 2019 Fall Technical Forum.*

[11] Shannon, C. E. (1949). The Mathematical Theory of Communication. *Urbana, IL: University of Illinois Press.*