From Manual to Automated

AI-Driven Network Engineering and Operations

A Technical Paper prepared for SCTE by

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1. Introduction

The hybrid fiber-coax (HFC) networks are rapidly changing as we approach mass deployments of next generation DOCSIS and spectrum expansion. Knowing that HFC networks amalgamate the strengths of optical fiber and coaxial cable technologies, we are faced with a new level of intricacy to their design and maintenance. As the frequencies utilized in these networks continue to climb, the intricacies associated with HFC networks have surged significantly. One of the key factors contributing to this intricacy is the complex interdependencies among the various departments engaged in the design and maintenance process of HFC networks. The alignment of different segments such as network planning, engineering, and operations has become pivotal for the seamless functioning of these networks.

As the demand for higher data speeds and bandwidth increases, the frequency spectrum used in HFC networks expands, leading to enhanced complexity in design. With higher frequencies, challenges such as signal attenuation, interference, and noise become more pronounced. Furthermore, different departments—such as engineering, operations, and maintenance—become increasingly interdependent due to the intricate nature of these networks. Ensuring efficient signal transmission, maintaining signal quality, and minimizing signal degradation are tasks that require a meticulous approach.

This paper delves into how network automation and software defined networks can alleviate a large majority of the concerns, both from plant upgrade and on-going maintenance perspectives. A central focus of this exploration is the transformative potential of artificial intelligence (AI) in reshaping the landscape of end-to-end design and maintenance within the realm of HFC networks. By harnessing the power of AI, it becomes possible to reimagine and revolutionize the conventional methodologies that govern the optimization of nodes, amplifiers, and the overall capacity management. The utilization of AI-driven algorithms and predictive analytics offers a promising avenue for addressing the challenges associated with HFC networks, paving the way for enhanced efficiency, reliability, and adaptability.

This paper interlaces the potential advantages of AI in HFC network design with its impacts across the diverse realm of network management. These benefits span from substantial cost savings via power and resource optimization to informed decision-making enabled by data-driven AI insights. Moreover, the infusion of AI can also increase the plant reliability of HFC networks, enhancing proactive maintenance and anomaly detection algorithms.

2. Modern Day Design Challenge

Historically, operators have predominantly used static parameters to formulate optimal network designs for specific regions. A case in point is the downstream design process, which traditionally unfolds through a series of steps. Initially, operators identify a worst-case or, at the very least, a reasonable worst-case scenario for span loss. Subsequently, they establish a corresponding worst-case or reasonable worst-case situation for drop loss. Following this, the optimal receive level of end devices such as modems and set-top boxes is determined. Finally, operators determine the maximum output power of amplifiers and nodes, a crucial criteria to not exceed. However, this conventional approach, while providing a baseline for network design, lacks the dynamic adaptability and precision that contemporary data-driven techniques can offer.

Furthermore, in the conventional approach, network designers often take the side of caution, designing the network infrastructure to accommodate peak demands and extreme usage scenarios. While this strategy ensures network reliability during spikes in usage, it leads to underutilization of resources during normal operation, resulting in inefficient capacity allocation. This over-provisioning of resources translates to increased costs in terms of both equipment and energy consumption, hindering cost-

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effectiveness and sustainability. Moreover, traditional designs lack the agility to adapt to fluctuating usage patterns, leading to suboptimal performance during off-peak hours.

Contrastingly, emerging data-driven and AI-assisted methodologies for network design introduce a paradigm shift. Instead of relying solely on static worst-case assumptions, these advanced techniques can tap into real-time data streams and predictive algorithms. This empowers operators to tailor their designs more precisely to actual usage patterns and network conditions. The rigid sequence of steps in traditional design gives way to a dynamic and adaptive process, where network adjustments are made in response to fluctuating demand and environmental factors. By leveraging the insights gleaned from data analytics, operators can achieve a level of optimization that transcends the limitations of traditional static approaches. By analyzing historical usage patterns and current network conditions, AI models can optimize capacity allocation dynamically, ensuring that resources are allocated precisely where and when they are needed most. This adaptive approach not only maximizes the utilization of available bandwidth and infrastructure but also reduces the need for excessive over-provisioning. Consequently, this data-driven design methodology leads to substantial cost savings, as operators can efficiently allocate resources based on actual demand rather than hypothetical worst-case scenarios.

Data-driven and AI-assisted HFC design revolutionizes network planning by harnessing the power of near-real-time data and predictive analytics. By analyzing historical usage patterns and current network conditions,

Furthermore, the incorporation of AI and data-driven techniques in HFC design addresses another critical aspect: power reduction. Traditional designs tend to overlook energy efficiency, focusing primarily on network stability. This oversight leads to unnecessary power consumption, contributing to higher operational costs and a larger carbon footprint. In contrast, AI-driven designs take into account dynamic power management and predictive algorithms. By optimizing power distribution and consumption across the network, AI-based designs can significantly reduce energy expenditure without compromising network performance or reliability. This dual advantage of cost reduction and environmental sustainability positions data-driven design as a compelling alternative to traditional HFC approaches.

AI-driven design can also further enhance predictive maintenance capabilities, where machine learning algorithms continuously monitor network components and identify early signs of degradation or impending failures. This proactive approach enables network operators to perform targeted maintenance interventions, mitigating the risk of unplanned downtime and enhancing overall plant reliability. This reliability enhancement is crucial in maintaining customer trust and satisfaction, a factor that is often compromised in traditional design approaches.

2.1. HFC Statistics

Manual design and maintenance of HFC networks experiences significant challenges stemming from design, operations, and engineering domains bring heavily intertwined. The traditional approach to HFC network management relies on segregated teams responsible for different stages of the network lifecycle, including initial design, deployment, and ongoing maintenance. However, the high degree of interdependencies between these stages gives rise to a cascade of downfalls that hinder efficiency, scalability, and overall network performance.

The functional isolation of engineering, design and operations impedes the flow of critical information and insights that each domain possesses. Designers might lack real-world operational context, leading to impractical designs that struggle to adapt to the complex realities of network deployment. Conversely, operational teams might find themselves constrained by design choices that do not align with the practical

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constraints they encounter in the field. This lack of synergy perpetuates inefficiencies, maintenance challenges, and suboptimal network performance.

Figure 1 outlines the interdependency of various departments involved in design and maintenance of a network.

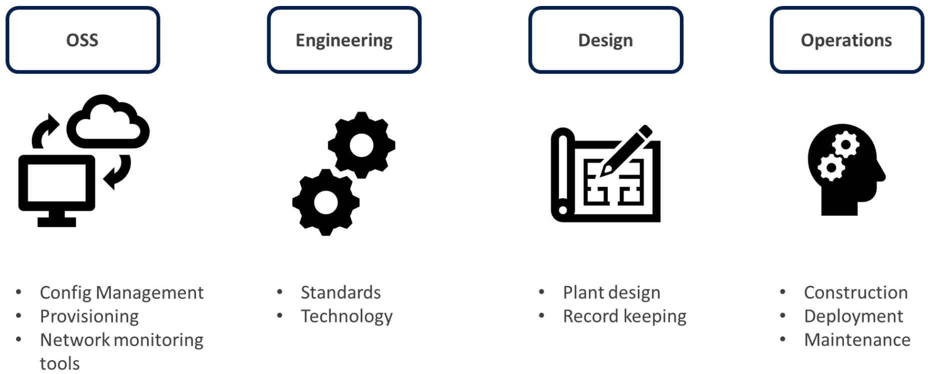

Figure 1 – Various Teams Interfacing with Access Network

Moreover, the manual approach encounters difficulties when confronted with the dynamic nature of modern telecommunication networks. HFC networks are subject to ever-evolving demands, technologies, and environmental factors. Manual design and maintenance processes struggle to keep up with rapid changes, resulting in delayed responses to network issues, prolonged downtimes, and ultimately, reduced customer satisfaction. The interplay between design, operations, and engineering requires adjustments and adaptive strategies that manual processes often struggle to accommodate.

In light of these challenges, the shift toward AI-driven solutions is gaining traction. AI has the potential to bridge the gaps between design, operations, and engineering by facilitating continuous data exchange, predictive analytics, and automated adjustments. By leveraging AI's ability to process large volumes of real-time data and optimize network parameters across the entire lifecycle, HFC networks can achieve enhanced efficiency, agility, and resilience, overcoming the pitfalls associated with the traditional manual approach.

In the following sections we will explore why some of the historical and manual design and deployment methodologies can result in suboptimal system performance.

2.2. Histograms and Probability Density Functions

In HFC networks, understanding the distribution of cable modem transmit levels and receive levels is crucial for optimizing network performance. As a matter of fact, modem and set top box levels, both in the upstream and downstream are the core of HFC design. As mentioned in the previous section, the historical approach entails selecting a worst-case scenario or reasonable worst-case scenario to design the access network. Knowing that many probability density functions (PDF) are Gaussian in nature, the historical method of designing the network can be described as designing for $\sim 3\,\sigma$ which can be deemed a worst-case scenario.

Gaussian distributions are commonly used to model these levels due to their prevalence in real-world scenarios. However, a noteworthy observation is that while individual cable modem transmit and receive levels might exhibit Gaussian distributions, the resulting signal-to-noise ratio (SNR) or modulation error

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ratio (MER) might display left-skewed characteristics when considered in aggregate. This phenomenon arises due to the complex interplay of factors within the HFC environment.

Cable modem transmit levels are subject to variations caused by factors like attenuation, noise, and signal degradation. Similarly, receive levels are influenced by various factors including signal attenuation, noise amplification, and interference. The inherent variability in these parameters contributes to the Gaussian nature of their distributions. However, when these variations accumulate and affect the SNR or MER, a left-skewed distribution may emerge. This asymmetry is a result of the impact of unfavorable conditions that can lead to sudden drops in signal quality, producing extended tails on the left side of the distribution.

Mathematically speaking, we can also prove that the sum of two or more Gaussian distributed histograms does not necessarily result in a Gaussian distributed result and can exhibit skewness. Let us consider the sum of two Gaussian distributions.

Let X be a random variable following a Gaussian distribution with mean μ_1 and variance σ_1^2, and Y be another random variable following a Gaussian distribution with mean μ_2 and variance σ_2^2. The probability density function (PDF) of a Gaussian distribution is given by:

$$f(x) = (1 / (\sigma * \sqrt{(2\pi)})) * e^{(-((x-\mu)^{\wedge}2) / (2\sigma^{\wedge}2))}$$

Now, let us consider the sum Z = X + Y. The mean of Z is $\mu z = \mu x + \mu y$, and the variance of Z is $\sigma_z^2 = \sigma_x^2 + \sigma_y^2$ due to the independence of X and Y.

The PDF of Z can be obtained by convolution of the PDFs of X and Y:

$$fz(z) = \int [f(x) * f(y)]\, dx$$

This convolution operation makes the result more complex, and in general, it does not yield a Gaussian distribution. When $\mu x \neq \mu y$ and/or $\sigma x \neq \sigma y$, the convolution may lead to skewness in the resulting distribution. The convolution of two Gaussian distributions may result in a distribution that is broader or skewed, rather than being perfectly Gaussian.

Another phenomenon that can be observed as a result of this is the fact that there is typically a low amount of correlation between transmit and receive levels in comparison to downstream and upstream SNR/MER.

In the context of Gaussian distributions, the correlation between X and Y can be expressed as:

$$\rho(X, Y) = \mathrm{cov}(X, Y) / (\sigma_1 * \sigma_2)$$

Where:

- $\mathrm{cov}(X, Y)$ is the covariance between X and Y,
- and $\sigma_1 * \sigma_2$ is the product of their standard deviations.

When the convolution of X and Y leads to a skewed or non-Gaussian distribution, the relationship between the original Gaussian PDFs and the resulting PDF becomes nonlinear. This nonlinearity can result in a lower covariance (cov(X, Y)) and consequently a lower correlation (ρ(X, Y)) between the original Gaussian variables and the resulting variable.

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Graphically the derivation above can be shown as:

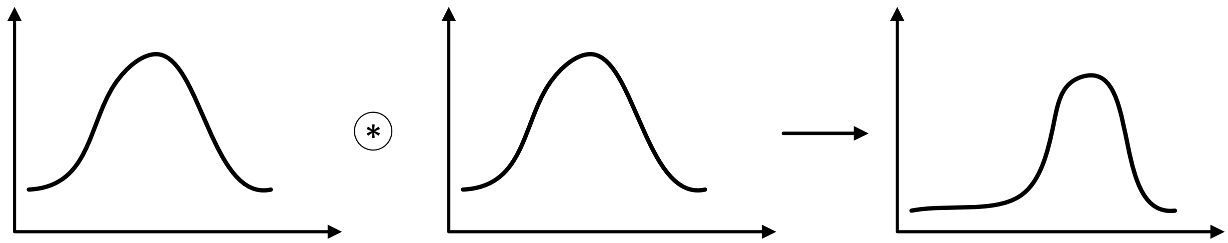

Figure 2 – Convolution of Two Normally Distributed Variables

From an RF perspective, we will explore this non-linearity in the section below.

2.3. Non-Linearities in HFC

In this section we will explain the phenomenon laid out in section 2.2, from a noise and distortion accumulation perspective.

We know that the carrier-to-noise ratio (CNR) of a single amplifier can be derived from the following formula:

$$C/_N\,(dB) = \; C_i(dBmV) + 57.1 - NF(dB)$$

Where:

- C_i: input signal
- NF: Noise figure of the amplifier

The number 57.1 is the minimum thermal noise at ~16.7 °c expressed in dBmV/6.4MHz.

Note: the minimum thermal noise power for different temperatures can be calculated using the following formula:

$$n_p = kTB$$

where:

- n_p = noise power in watts
- k = Boltzmann's constant (1.34×10^{-23} joules/K)
- T = absolute temperature in K
- B = bandwidth of the measurement in Hz

Knowing the noise products accumulate in 10log fashion due to the non-coherent nature of noise, the overall cascade C/N for amplifiers operating at different output levels can be derived from the following equation:

$$C/_{N_{total}}\,(dB) = -10log\left\{10^{\frac{-C/_{N1}}{10}} + \; 10^{\frac{-C/_{N2}}{10}} + \cdots + \; 10^{\frac{-C/_{Nn}}{10}}\right\}$$

Where, $C_{/N_x}$ is the carrier to noise of each amplifier calculated independently.

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Distortion products from an amplifier or series or amplifiers historically have been characterized by measuring composite second order (CSO) and composite triple beat (CTB) on analog carriers. These distortion products are harmonics of the primary signal. Today on the other hand, cable operators primarily use digital carriers. Digital carriers' distortion products do not appear similar to the analog carriers. Instead, they appear very similar to a raised noise. For this reason, composite intermodulation noise (CIN) is the best way to characterize the distortion performance of amplifiers today. The rate of accumulation of CIN products is dependent on whether the distortion products are coherent or non-coherent. The range of CIN accumulation can range between [10-20]log.

Carrier-to-composite noise (CCN) in this paper has been used as the primary method of determining signal quality. Although SNR and MER can be measured using meters and measurement equipment, there are inconsistencies in these types of measurements, especially when considering different measuring equipment. For this reason, we will consider carrier-to-composite noise (CCN) as the true measure of performance in a cascade. Summing noise and distortion products in a cascade, CCN can be derived from the following formula:

$$CCN(dB) = -10log\left\{10^{\frac{-CCN_i}{10}} + 10^{\frac{-CTN_{Total}}{10}} + 10^{\frac{-CIN_{Total}}{10}}\right\}$$

Where CCN_i is the starting CCN. In essence, the starting CCN (MER) of the modem in the upstream or the CCN (MER) of the node/remote PHY device (RPD) in the downstream.

2.4. SNR/MER Convergence

Based on the formulas laid out in the previous section, Figure 3 demonstrates how CCN can converge into a very predictable number based on the depth of the cascade.

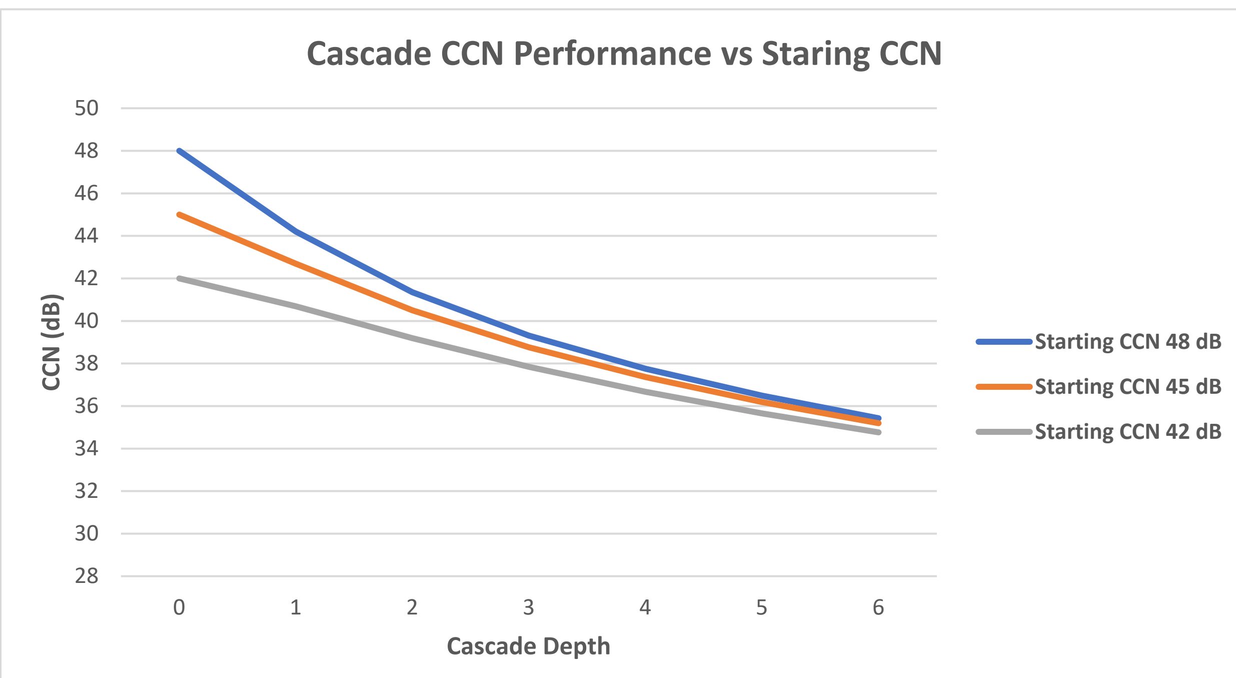

Figure 3 – Cascade CCN vs Starting CCN

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Figure 3 serves as an illustration for what was discussed in section 2.2, the emergence of skewed SNR and MER distributions, despite the Gaussian nature of cable modem transmit and receive levels. This intriguing occurrence can be the main reason behind many complexities observed in the HFC plant.

As discussed in the previous section, the Gaussian distribution, characterized by its bell-shaped curve, often characterizes the individual transmit and receive levels of cable modems within HFC networks. However, the amalgamation of these individual Gaussian distributions into aggregate SNR and MER distributions reveals a fascinating skewness. The key insight that Figure 2 demonstrates is the manifestation of left-skewed tendencies, where the distribution's tail extends towards the lower values of SNR and MER.

This observation holds significance for HFC network design and management. Ensuring consistent and reliable network performance requires not only a comprehensive understanding of individual distributions but also an awareness of how these parameters interact and shape the overall quality of signal transmission. By considering the left-skewed tendencies in aggregated SNR/MER distributions, HFC network operators can implement strategies that address the challenges posed by such asymmetries. Advanced data-driven techniques and AI-driven algorithms can be employed to dynamically adjust network parameters and mitigate the impact of left-skewed distributions, leading to improved overall performance and end-user experiences in HFC systems.

This peculiar left-skewed behavior is attributable to the intricate dynamics at play within the HFC plant. Various factors, including attenuation, noise amplification, and distortions, contribute to the variations in both upstream and downstream signal quality. When these variations culminate and impact the SNR and MER, unfavorable conditions can lead to pronounced declines in signal quality. As a result, the left-skewed extension becomes pronounced, highlighting the critical role of understanding not only the characteristics of individual parameters but also their collective impact on the overall network performance.

In the context of HFC network management and optimization, the insights gleaned from Figure 2 are invaluable. By discerning the underlying causes of skewed SNR and MER distributions, network operators can tailor strategies to address and alleviate the asymmetries. Leveraging advanced analytical techniques and AI-driven algorithms, HFC systems can be dynamically adjusted to counteract the adverse effects of cumulative noise and distortions, ultimately resulting in enhanced signal quality and increased reliability in the access networks.

3. AI-Driven Design

So far in the paper we have explored the non-linear relationships between output power, signal quality and other factors. Network design has proven to be incredibly complex due to the sheer number of parameters that one has to take into consideration, especially taking the non-linear nature of these parameters. The integration of AI presents a revolutionary shift from traditional approaches. The limitations of static worst-case scenario planning have become evident, particularly when examining the results of the analyses in the previous sections.

AI-driven design offers a transformative solution to this challenge. By leveraging near-real-time data and predictive analytics, AI models can dynamically optimize network parameters. This data-driven methodology not only maximizes capacity utilization but also can mitigate the skewed SNR and MER distributions. Unlike traditional worst-case scenario planning, AI adapts to fluctuating network conditions, responding to variations in transmit and receive levels and thereby preventing the accumulation of noise and distortions leading to sub-optimal results.

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The significance of AI-driven design extends beyond signal quality. Traditional methods involve manual intervention and static assumptions for capacity planning and channel loading, resulting in inefficiencies and underutilized resources. In contrast, AI optimizes node placement, amplifier output power, and capacity management, resulting in substantial cost savings and improved reliability.

The primary method explored in this paper is gradient optimization in any typical machine learning algorithm to optimize for an end objective. Due to the vast number of areas that the gradient optimization can be applied to, for the purpose of this paper, we have only considered the optimization of output power for signal quality and power consumption in the access networks.

3.1. Gradient Optimization

AI-driven HFC design can be framed as a gradient optimization problem, knowing that HFC design and optimization are differentiable functions in nature. In this context, the goal is to find the set of parameters that minimizes or maximizes an objective function, reflecting the desired outcome. The process involves iteratively adjusting network variables based on the calculated gradient of the objective function with respect to these parameters. This iterative refinement is guided by the general gradient optimization formula:

$$\theta_{\mathrm{k+1}} = \theta_{\mathrm{k}} - \alpha * \nabla J(\theta_{\mathrm{k}})$$

Where:

- θ: the parameters being optimized
- α: the learning rate determining the step size in each iteration
- $\nabla J(\theta_k)$: the gradient of the objective function J with respect to θ at the current iteration k.

The gradient $\nabla J(\theta_k)$ indicates the direction of steepest ascent (for maximization) or descent (for minimization) in the parameter space. By iteratively updating θ based on the gradient, the optimization process converges towards a solution that aligns with the desired network performance outcomes.

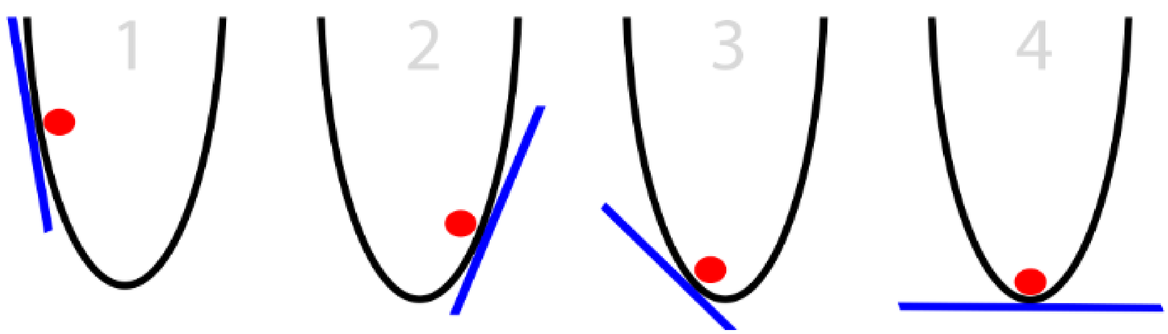

Figure 4 – Simplified Gradient Optimization

In the context of HFC network design, this gradient optimization paradigm enables AI algorithms to dynamically adjust variables such as cable modem transmit levels, amplifier settings, and even node placements. The objective function can encapsulate goals like maximizing data throughput, minimizing power consumption, and increasing signal quality/capacity. By iteratively fine-tuning network parameters based on the calculated gradients, AI-driven HFC design converges towards a configuration that

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optimally balances diverse performance factors, resulting in a network that is efficient, reliable, and tailored to near-real-time demands.

3.2. Application

In the context of this paper, when the outside plant is established and calibrated to ensure adequate signal delivery to cable modems (CMs), an array of factors, including adjustments to outside amplifier settings, can induce fluctuations in CM signal levels. The impact of events such as variations in outside amplifier configurations can potentially disrupt signal consistency for CMs. However, the application of internal control techniques, such as temperature and gain control mechanisms inherent in digital amplifiers, effectively counteracts signal drift attributed to temperature fluctuations and passive component deviations.

Furthermore, network optimization plays a pivotal role in maintaining the stability of the entire network across amplifiers within the access network. This optimization process is designed to comprehensively address network stability concerns by accounting for the relationship of amplifiers and environmental factors. In the context of this paper, four distinct scenarios underscore the importance of network optimization as a control mechanism within the access network:

- Initial Deployment: During the initial network setup, network optimization techniques are employed to fine-tune parameters, ensuring an optimal signal distribution across CMs. This process enhances signal reliability and minimizes potential disparities in signal strength, thereby establishing a robust foundation for network performance.
- Carrier Expansion and Management: As operators expand their carrier offerings or activate/deactivate specific carriers, the dynamic nature of network optimization comes into play. This technique allows operators to precisely manage carrier configuration changes, maintaining equilibrium in signal distribution and preventing disruptions during transitions.
- Split Adjustment: When adjustments to the upstream and downstream splits are needed, network optimization techniques facilitate seamless adaptation. These methods ensure that the alterations are executed smoothly, without causing distortions in signal quality or network stability.
- Plant Element Changes: Plant element changes necessitate recalibration of the network to accommodate the altered load. Network optimization is crucial in this scenario, recalibrating parameters to ensure uniform signal strength and optimal network performance despite changes in the environment.

In order to demonstrate how the methodologies of this paper can be implemented, the design shown in Figure 5 has been taken into consideration.

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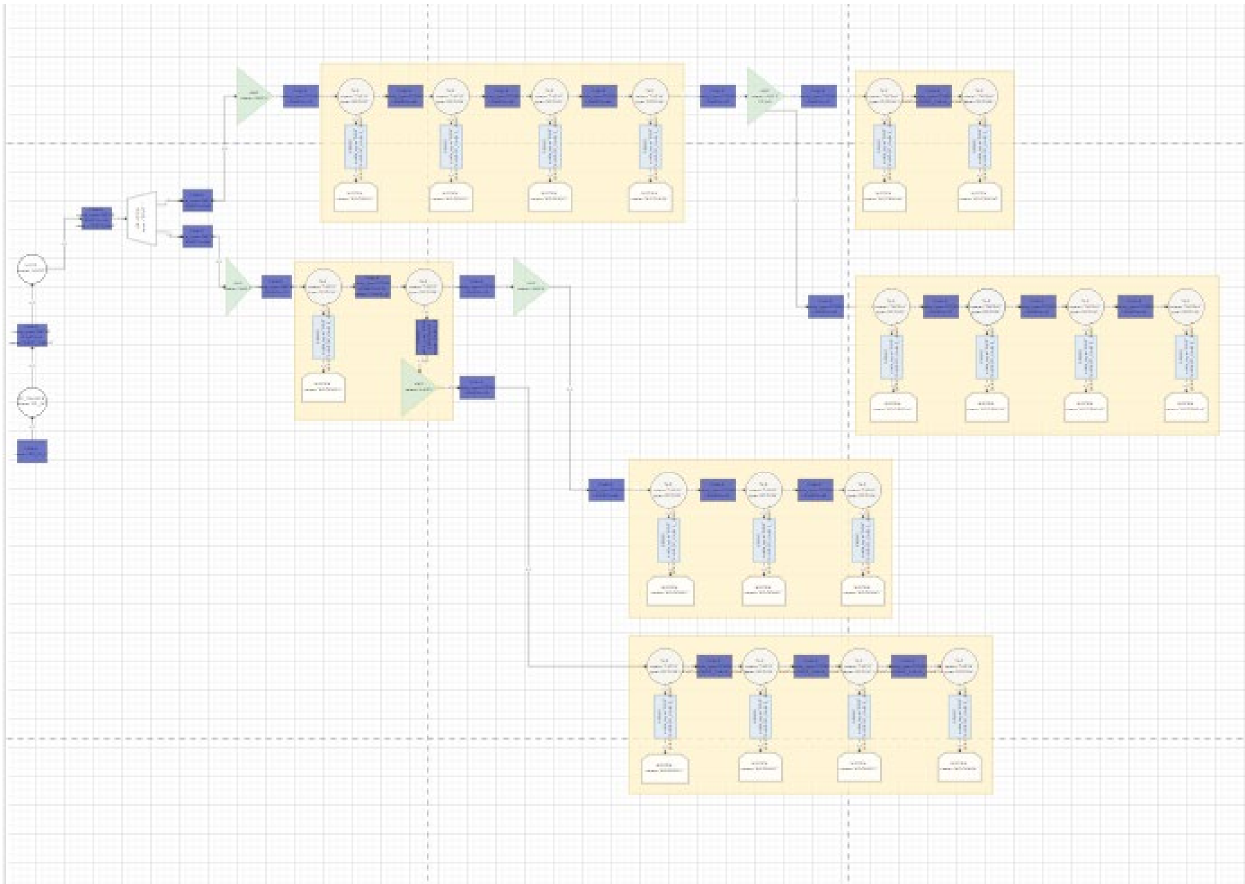

Figure 5 – Analyzed Plant Map

3.2.1. *Method*

Our network modeling involves the utilization of simulations that mirror real-world components like CMs, passives, amplifiers, and cables. These simulated elements emulate the behaviors and attributes of actual equipment. The internal configurations and settings of amplifiers in these simulations are reflective of their real-world counterparts, and passive losses are derived from empirical measurements. The network simulation process comprises two key components:

- Signal Propagation Simulation: This involves the propagation of signal levels through the network, emulating the real-world interactions between various components. This simulation provides insights into how the signal levels change as they traverse the network architecture. It sheds light on the dynamics of signal attenuation, amplification, and other factors that impact signal quality.
- Amplifier Settings Optimization: The second part of the simulation focuses on optimizing amplifier settings to achieve a specific objective. In this case, the optimization goal is to ensure that the majority of modems receive an optimal level of 0 dBmV. The amplifier settings are dynamically adjusted to achieve this objective, aiming for a flat distribution of signal levels across the network. This iterative process involves updating amplifier configurations based on real-time feedback to ensure that modems receive the desired signal level.

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Each simulation scenario is accompanied by a comprehensive report detailing crucial parameters. These parameters encompass the amplifier output total composite power (TCP) levels, which provide insights into signal strength, and the convergence metric indicating the deviation of modem receive levels from the optimal 0 dBmV target. The network model also introduces variability by randomizing the drop cable lengths to CMs, reflecting the diverse conditions encountered in real-world HFC setups.

3.2.2. Network Installation

A classical network installation scenario shown in Figure 6 represents a worst-case instance where all amplifiers share identical output levels. Within this setup, amplifiers 1, 2, and 3 are each equipped with a 45 dB gain capability, sufficient to overcome the loss incurred across 150 meters of COAX9 cable connecting amplifier 1 to amplifier 2. However, the heightened gain of amplifier 2 results in an excessively potent signal transmission to amplifier 3, initiating a situation wherein the latter excessively pads the signal. Consequently, this higher output power degrades signal quality. This intricate chain of events not only leads to energy waste, but also impacts the signal reception quality of CMs such as CM1A, 1B, and 1C, potentially yielding higher-than-optimal receive levels.

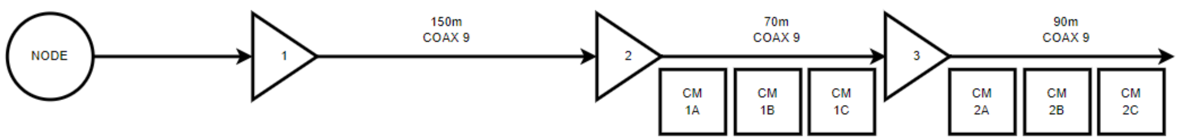

Figure 6 – Simulation Span

Unlike the uniform output level approach of the classical method, network alignment recommends a dynamic divergence in amplifier output levels. This strategic divergence holds the potential to drastically reduce energy consumption across the network while concurrently ensuring desirable signal levels for CMs. By distributing energy resources, network alignment establishes a harmonious balance wherein CMs receive optimal signal strength without the attendant wastefulness associated with uniform amplification. This adaptive strategy optimizes energy usage, eliminates energy waste, and enhances the quality of signal transmission to CMs, underscoring the promise of network automation in redefining efficient HFC network design and performance.

3.2.3 Amplifier Communication

In contrast to local amplifier control, network alignment involves the analysis of network data in a centralized location. This data encompasses measurements obtained from both digital amplifiers and CMs. The process of network alignment, as elaborated in the context of network optimization, requires the independent optimization of a specific service group or node, distinct from other service groups.

These dynamics extend across multiple service groups, particularly with regards to interdependencies shaped by external factors such as various plant conditions and operator-specific intricacies. The integration of such metadata holds the potential to enhance network optimization by considering these holistic influences. While details pertaining to service groups are likely to be shared efficiently within a cloud environment, this process remains detached from the communication that occurs between active elements in those individual service groups.

For the successful adoption of communication technology between amplifiers, certain prerequisites must be met. This includes the criteria of being cost-effective, energy-efficient, dependable, and easily

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implementable. The incorporation of communication technology into the network architecture relies on its alignment with these essential attributes. These requirements are summarized in Table 1.

Table 1 – Amplifier Telemetry Requirements

communication technology objectives				
Cost	Power	Ease of implementation	Reliability and robustness	Performance
not a sizable part of amplifier itself **<$5**	Not noticeable in the amplifier bill of material <1 W	Integratable in new amplifiers, pluggable in existing amplifiers. No extra elements in headend	Independent of DOCSIS, communication under misaligned network conditions	Enough data throughput for access network details to be communicated to headend. Calculated to be ~3 kbs

The communication method of network optimization has been thoroughly researched to come up with a method that fits the objectives mentioned in Table 1. G3PLC powerline communications turned up as a cheap, easily implementable solution, that does not rely on in-band method of communication. G3PLC is a highly reliable mesh protocol for communication under extremely noisy conditions. It is an open international ITU standard and described in ITU-T G.9903, ITU-T G.9901 and IEEE 1901.2. based on narrowband power line communication (NB-PLC) orthogonal frequency division multiplexing (OFDM) technology based on state-of-the-art narrowband PLC standards.

The G3PLC standard specifies a link budget of at least 60 dB, the G3PLC community states that this in practice is >80 dB. Meaning between transmission and reception there can be 80 dB of loss before 50% of the messages are lost.

Figure 7 demonstrates a possible implementation method for PLC in HFC amplifiers.

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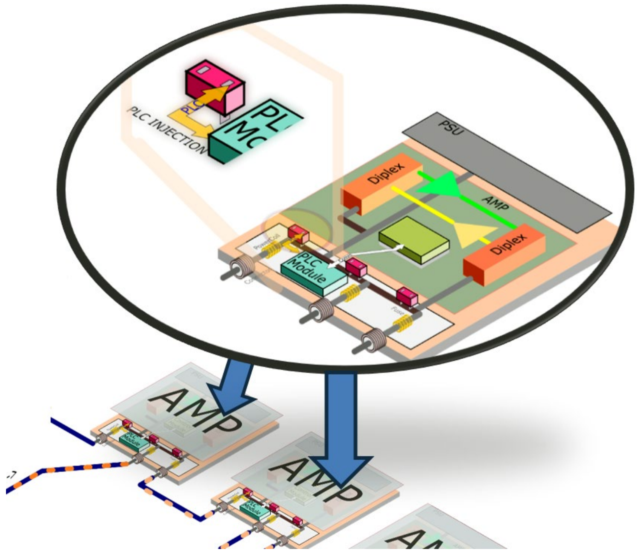

Figure 7 – PLC Implementation in HFC Amplifiers

Injection is done directly in the power passing section of the amplifier, thus bypassing all the RF circuitry, creating a communication path that is independent of existing spectrum plans. This is demonstrated in Figure 8.

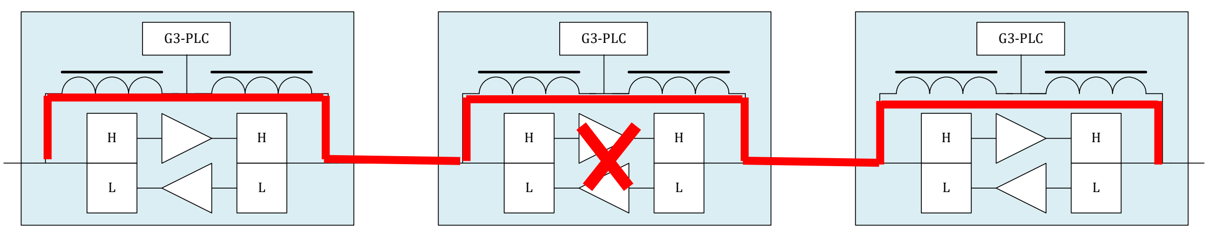

Figure 8 – Channel Loading Examples for Various Traffic Patterns

As shown in the middle amplifier in Figure 8, even if the amplifier themselves fail due to any reason, the communication path can still continue since only the power coils are used in the PLC communication path.

G3PLC uses OFDM modulation between 10 kHz and 490 kHz. Amplifiers can accommodate G3PLC modules so they can communicate to a centralized data polling and processing engine. Between each amplifier there can be many passives, which attenuate the signal. Often, specifications for loss below 500 kHz do not exist for passives. Thus, insertion loss has been measured on a many different passives (taps, splitters, cables). Additionally, PLC signal receive level and link quality were measured between PLC modules throughout a cascade of passives to determine signal degradation. The results are shown in Figure 9.

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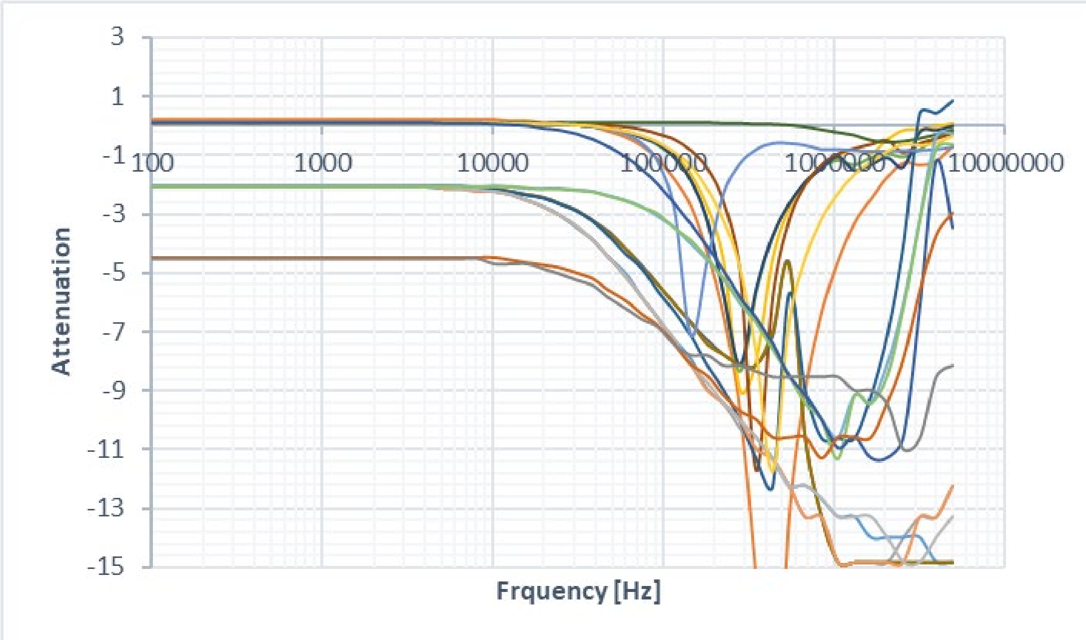

Figure 9 – Insertion Loss of 20 Different Passive Devices from 100 Hz to 5 MHz

3.3 Use Cases

The sections below discuss various applications and use cases of an AI-driven and optimized HFC system.

3.3.1 Carrier Expansion and Reduction

Operators may have the need to add or remove channels in response to fluctuations in bandwidth utilization, a prime example being the variation between low-demand periods like 2 AM and high-traffic times like 5 PM. However, this strategic maneuver, while effective, introduces a subtle realignment challenge to previously well-tuned networks. The arises from the modification of the spectrum plan, for which tilt and gain parameters of amplifiers had been calibrated. Consequently, with the expansion of the spectrum due to channel adjustments, the Rx (receive) levels shift to higher values. This transformation proves problematic when the receiving modems require a close-to-uniform input signal, as the spectrum's altered boundaries can potentially lead to an elevated Rx level, thus impacting network performance.

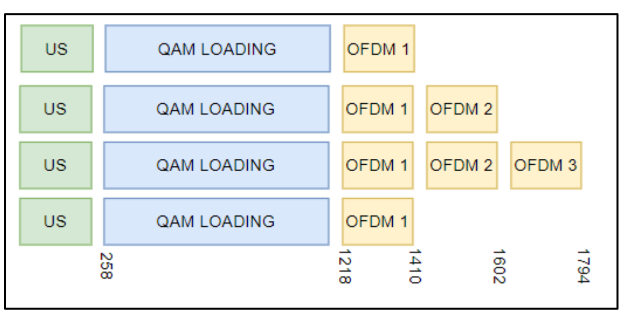

Figure 10 – Channel Loading Examples for Various Traffic Patterns

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Figure 10 demonstrates various channel plans as traffic patterns change in the field. From top to bottom, it can be observed that more OFDM carriers can be deployed as traffic demand grows before reducing the channel loading to 1400 MHz when there is lower demand. This of course is an example of what could happen in the field and is very operator dependent. Table 2 outlines the total composite power (TCP) of each amplifier based on the channel loading. The TCP reduction is primarily caused by the reduction in channel loading, but the output level and tilt can be further enhanced by the optimization algorithm, rather than the blanket output levels.

It should be noted that in this example we are assuming that the amplifiers are optimized based on the span characteristics that they are exposed to. In reality, based on today's practices, these results will be much more exaggerated since every amplifier has the same rated output power regardless of the unique characteristics of each segment.

Table 2 – Amplifier Alignment – Channel Loading Changes

	AMP 1		AMP 2		AMP 3		AMP 4		AMP 5	
Amplifier TCP [dBmV]	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
1 OFDM block	*61.8*		*46.3*		*58.9*		*57.8*		*53.3*	
1 to 2 OFDM blocks	*65.0*	*64.1*	*48.8*	*47.9*	*62.1*	*61.1*	*60.3*	*59.8*	*55.7*	*55.1*
2 to 3 OFDM blocks	*67.1*	*66.4*	*49.9*	*49.2*	*64.2*	*63.1*	*62.2*	*61.4*	*57.6*	*56.7*
3 to 1 OFDM blocks	*61.0*	*61.8*	*45.6*	*46.3*	*57.6*	*58.9*	*57.0*	*57.8*	*54.4*	*53.3*

The results of the system optimization have been demonstrated in Figure 11, Figure 12, and Figure 13.

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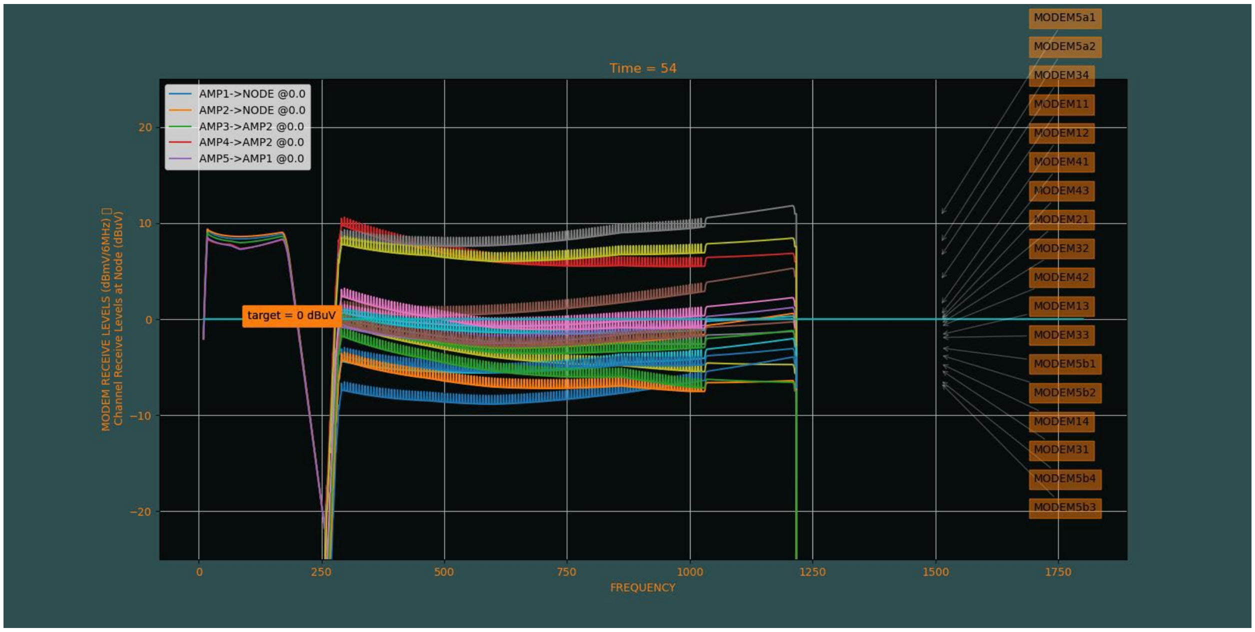

Figure 11 – System Operating at 204 MHz Split

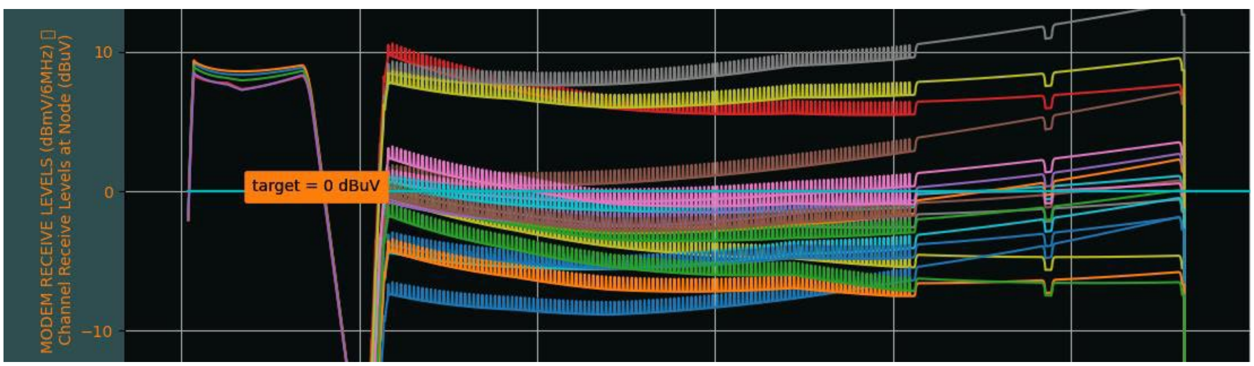

Figure 12 – Carriers Added with No Optimization

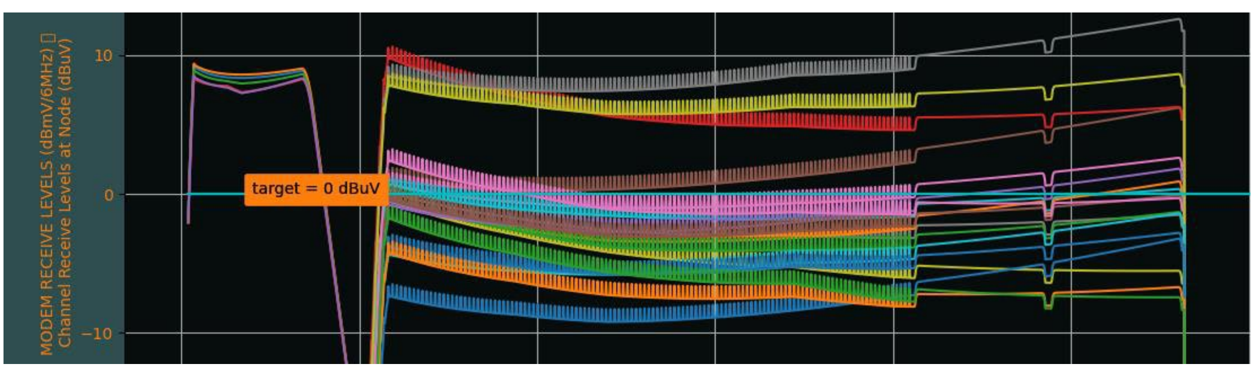

Figure 13 – Optimized System Post Carrier Expansion

It can be observed from Figure 11, Figure 12, and Figure 13 that the system can be further optimized based on the channel loading that each amplifier sees. As previously mentioned, this phenomenon is more exaggerated based on today's practices where every amplifier has the same output. In our example, even

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with added or removed carries, we can observe how the system can be fine-tuned based on the unique characteristics of each span, rather than a blanket approach.

3.3.2 Split Change

This section explores network realignment following a split change. In the conventional static installation approach, the task of recalibrating each amplifier to accommodate the updated split configuration is requisite. Conversely, the subsequent scenario demonstrates the seamless automation of network alignment, rendering the process effortlessly orchestrated.

Figure 14 demonstrates the different splits that be deployed through time in a selected serving group. Table 3 demonstrates the difference in TCP before and after optimization for each split. This demonstrates why automation can further enhance deployment decisions since each segment and amplifier span needs to be optimized based on the end-to-end performance that is expected, rather than blanket output levels.

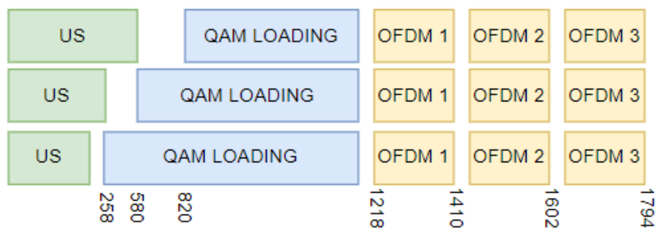

Figure 14 – Channel Loading Examples for Various Splits

Table 3 – Amplifier Alignment – Split Change

TCP [dBmV]	AMP 1		AMP 2		AMP 3		AMP 4		AMP 5	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
204-258	*65.9*		*48.6*		*62.4*		*61.0*		*56.6*	
204-258 to 492-580	*63.7*	*66.4*	*46.6*	*48.8*	*59.3*	*63.0*	*57.6*	*61.4*	*53.1*	*56.6*
492-580 to 684-820	*64.4*	*66.4*	*47.2*	*48.7*	*60.3*	*63.1*	*58.23*	*61.3*	*53.2*	*56.4*

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Table 4 – Average CM Rx Level Before and After

Average modem Rx level [dBmV]	**Average modem Rx level Before Alignment**	**Average modem Rx level After Alignment**
204-258	0.4	
204-258 to 492-580	-10	+0.2
492-580 to 684-820	-5.1	+0.2

It is important to highlight that Table 3 shows a fundamental rationale underscoring the value automation offers to operators. With each split change, the task of realigning and optimizing the entire system becomes evident. Even in scenarios where the amplifiers feature switchable diplex filters, the process is not as straightforward as merely adjusting the split. Rather, a comprehensive optimization is necessitated, from the headend through the amplifiers and finally at the cable modem, to ensure optimal network performance. In contrast, system level optimization and automation can seamlessly overcome this challenge, while monitoring areas where performance is sub-optimal that may need manual intervention. This is done by optimizing output power and TCP based on the unique characteristics of each segment depending on the split that is deployed at the time.

Table 4 further drives the point by showing the convergence of Rx levels by the modems. In the blanket approach the ranges and receive levels can be sub-optimal in comparison to a fine-tuned and optimized system, as shown in the second column of the table.

Figure 15 and Figure 16 summarize the analyses in this section. Figure 15 shows a system operating at 204 MHz split while Figure 16 demonstrates the same system operating at 684 MHz split. It can be observed that with changes of splits, the results converge to the extrapolation of where each Rx level was prior to the split change, which demonstrates the high level of confidence in the optimization algorithm.

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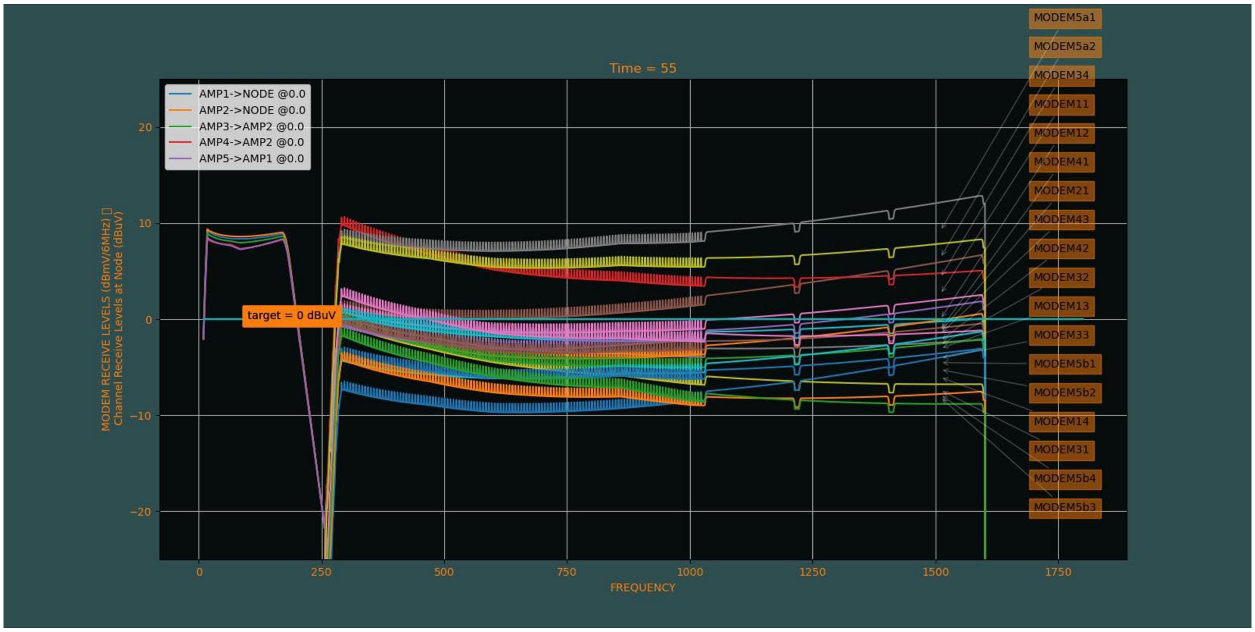

Figure 15 – 1.8 GHz System Operating at 204 MHz Split

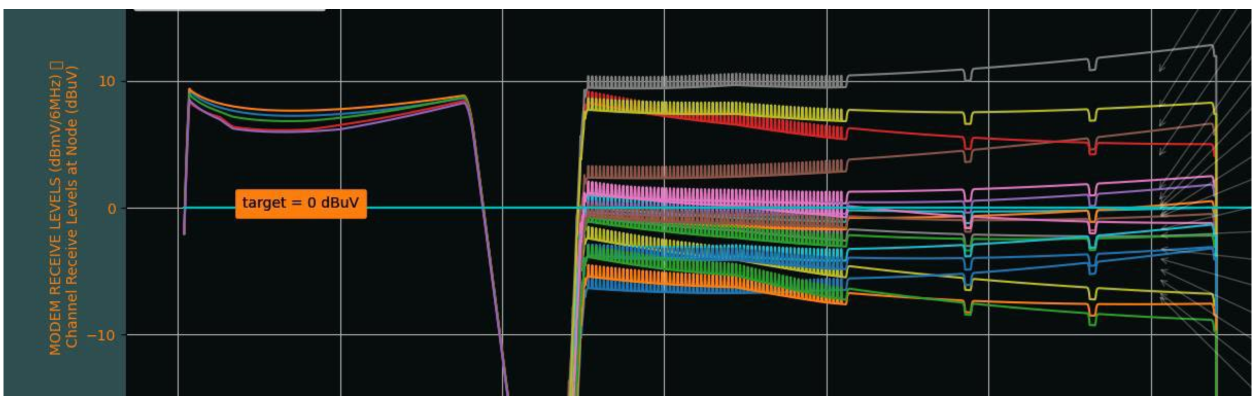

Figure 16 – The Same System Operating at 492 MHz Split – Post Optimization

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3.3. Power Optimization

Amplifiers in a network have always operated utilizing a single output setting, in both forward and return. They are also constantly operating at full power to provide the maximum gain they can to feed signals to the subsequent receiving devices, whether amplifiers or modems. The amplifiers today are balanced at a certain voltage and current, which is referred to the bias point. This bias point ultimately defines the power consumption of the amplifier.

The performance of the amplifier is characterized by the carrier-to-interference-noise ratio (CINR) curve. In Figure 17, the y axis is CINR, a measure of signal quality. The x axis often represents the output power of the amplifier or the TCP. The more power the amplifier consumes, the wider this curve becomes. In other words, with more power the quality can become better.

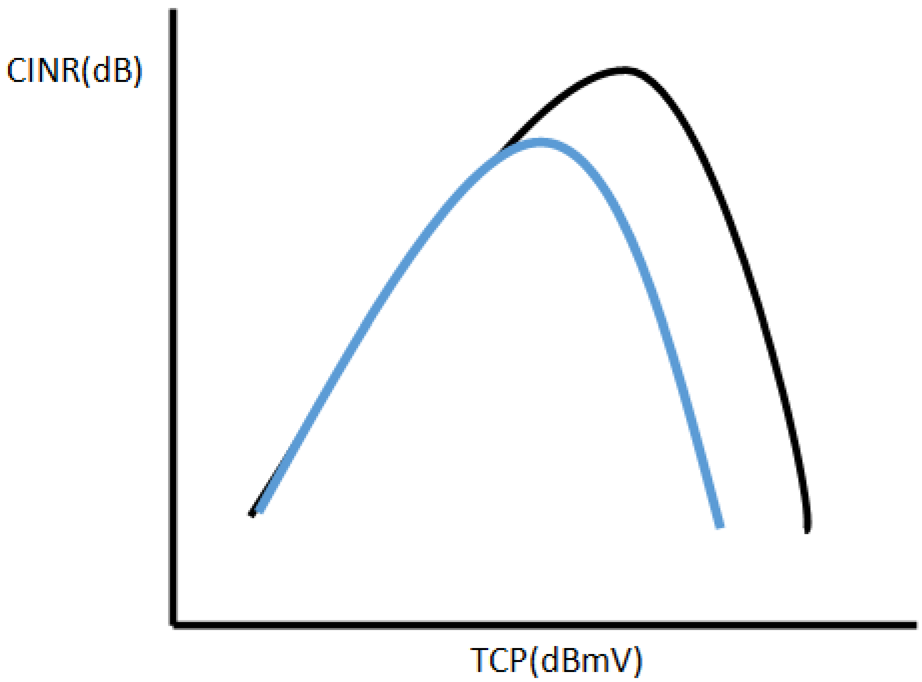

Figure 17 – Example Amplifier CINR Curve

In Figure 17, the blue line represents an amplifier operating with low power and the black line represents an amplifier operating with high power.

State of the art amplifiers have the possibility of changing the power consumption depending on the performance that is required by the amplifier chain. As an example, let us assume that a cable operator is willing to turn off the last OFDM block from 1 GHz to 1.2 GHz during off-peak hours. Figure 18 and Figure 19 demonstrate the required TCP for amplifiers in cascade, depending on the channel loading. The green line represents the TCP the amplifier needs to provide and the orange dashed line represents the required CINR performance. In our example, Figure 19 demonstrates a scenario where the last OFDM block is turned off and therefore the green line is shifted to the left. The amplifier can now operate in low power mode since it can be seen that the intersection of the green TCP threshold and the blue CINR curve are above the performance threshold shown by the orange dashed line.

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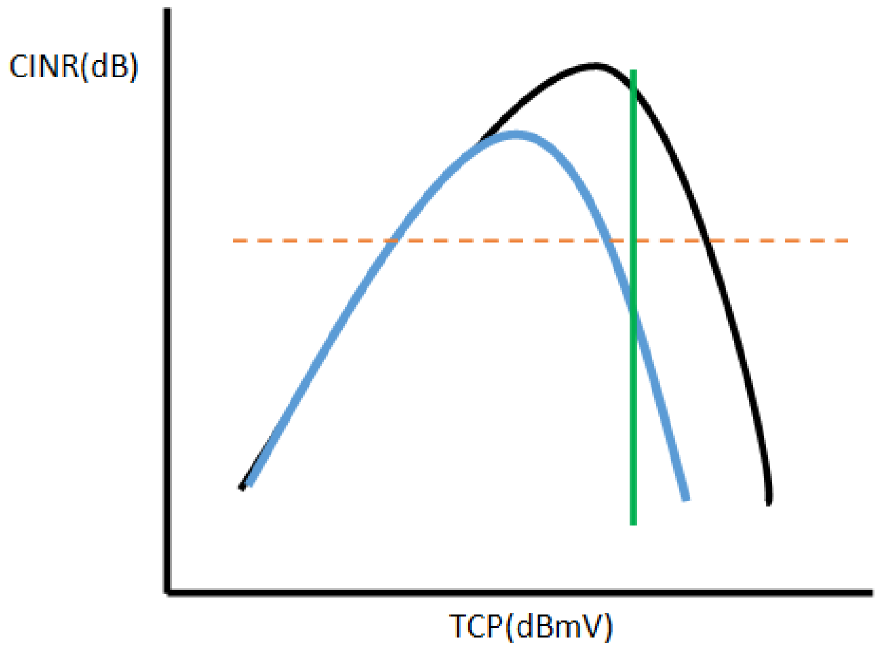

Figure 18 – Amplifier CINR and Required TCP – Full Channel Loading

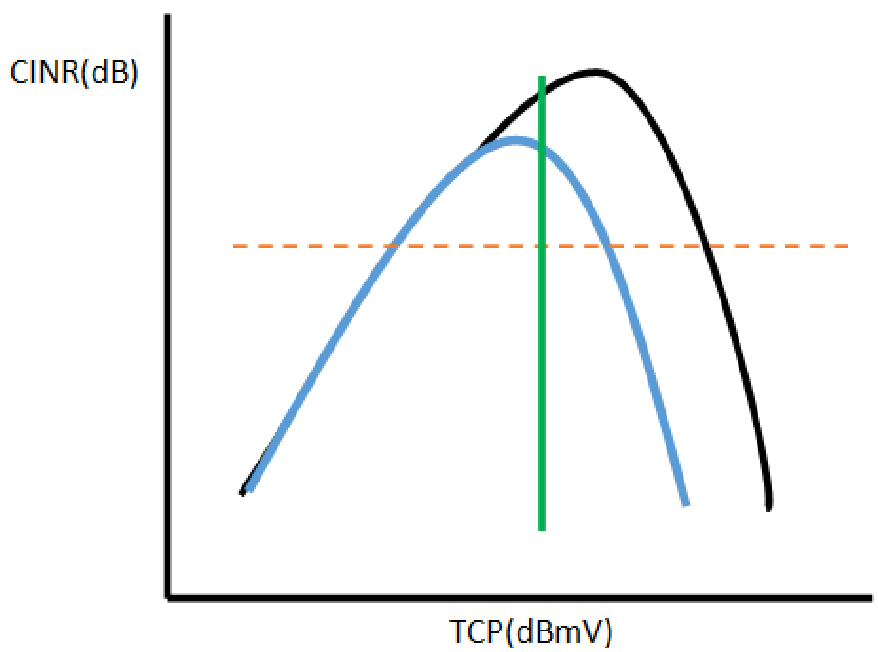

Figure 19 – Amplifier CINR and Required TCP – Reduced Channel Loading

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Let us analyze a real-life example. Figure 20 shows an example cascade of amplifiers.

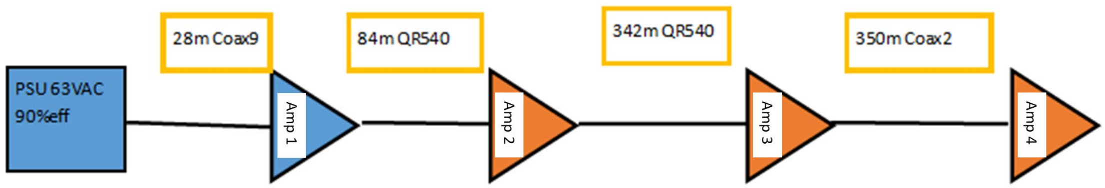

Figure 20 – Amplifer Cascade Analyzed for Power Saving Mode

Amplifier 1 is a three-output amplifier with the following power consumption:

- High power: 34 W
- Low power: 30 W

Amplifiers 2-4 are line extender amplifiers with the following power consumptions:

- High power: 19 W
- Low power: 17 W

The power consumption of this cascade at the mains in high power mode is 118.4 watts, as shown in Figure 21.

Figure 21 – Amplifer Cascade High Power Mode Consumption

In contrast Figure 22 demonstrates the same cascade's consumption at the mains in low power mode is 97.3 watts.

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Figure 22 – Amplifer Cascade Low Power Mode Consumption

A total saving of 20 W has been shown in this example cascade of amplifiers. Assuming that the node has four identical output legs, the saving could be 80 W when all amplifiers are operating in low power mode.

The theoretical power reduction should be 10 W (4 W in three output amplifiers and 2 W in each line extender). The remainder of the savings are from the power dissipated in the cable by I^2*R losses. Low power mode reduces the current in the network and therefore a reduction of the power wasted in the cables is realized.

4. Conclusion

The landscape of HFC networks is undergoing rapid transformation, particularly with the impending mass adoption of next-generation DOCSIS standards and spectrum expansion. These networks, which synergize optical fiber and coaxial cable technologies, require increasing intricacies in design and maintenance. Among the foremost challenges is the web of interdependencies that connect various departments engaged in the process of designing and maintaining HFC networks. The alignment of functions across network planning, engineering, and operations is now more crucial than ever to ensure seamless operation of the networks.

This paper navigated the potential of network automation and software-defined solutions to assuage a majority of these concerns, both in plant upgrades and ongoing maintenance. A central theme of this exploration is the transformative power of artificial intelligence in reshaping the entire landscape of end-to-end design and maintenance within the HFC network domain. The deployment of AI opens avenues for reimagining conventional methodologies governing the optimization of nodes and amplifiers, overall capacity management, and power optimization. Employing AI-driven algorithms and predictive analytics offers a revolutionary method for tackling the challenges to these areas, promising higher efficiency, reliability, and adaptability.

Linked with the potential benefits of AI in HFC network design are the various impacts that extend across various facets of network management. The advantages span from substantial cost savings stemming from optimized resource allocation, to enhanced decision-making through data-driven insights provided by AI models. Moreover, the integration of AI stands to enhance the plant reliability of HFC networks, as predictive maintenance and anomaly detection algorithms can proactively identify and mitigate potential issues.

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Abbreviations

AI	artificial intelligence
CCN	carrier-to-composite noise
CNR	Carrier-to-noise ratio
CIN	composite intermodulation noise
CINR	carrier-to-interference-noise ratio
CM	cable modem
CSO	composite second order
CTB	composite triple beat
dB	decibels
dBmV	decibels relative to one millivolt
DOCSIS	Data-Over-Cable Service Interface Specification
GHz	gigahertz
HFC	hybrid fiber-coax
MER	modulation error ratio
MHz	megahertz
NB-PLC	narrow band powerline communication
OFDM	orthogonal frequency division multiplexing
PDF	probability density function
PLC	powerline communication
QAM	quadrature amplitude modulation
RPD	remote PHY device
RF	radio frequency
Rx	receive
SCTE	Society of Cable Telecommunications Engineers
SNR	Signal-to-noise ratio
TCP	total composite power

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