Exploring Programmatically Generated HFC Plant Topology

Using Data and AI/ML to Automate Your Network Documentation Process

A Technical Paper prepared for SCTE by

Lin Cheng
Principal Architect
CableLabs
858 Coal Creek Cir, Louisville, CO 80027
l.cheng@cablelabs.com

L. Alberto Campos
Fellow
CableLabs
858 Coal Creek Cir, Louisville, CO 80027
a.campos@cablelabs.com

Justin Riggert
Engineer 5, Product Development Engineer
Comcast Corporation
183 inverness Dr W, Englewood CO 80112
justin_riggert@cable.comcast.com

Larry Wolcott
Comcast Fellow Engineer
Comcast Corporation
183 inverness Dr W, Englewood CO 80112
larry_colcott@cable.comcast.com

Table of Contents

List of Figures

List of Tables

Title **Page Number**

1. Introduction

Hybrid fiber/coax (HFC) network element and connectivity information in operator databases is sometimes inaccurate, out-of-date, or even missing. Many operational, administrative, and business functions rely on accurate plant data. A solution for programmatically generating coaxial plant topology using Data-Over-Cable Service Interface Specifications (DOCSIS®) network telemetry, spatial and address information, and deployment practices is presented. The approach proposed enables cable operators to keep their system designs up-to-date in real time without relying on manual processes, thereby reducing delays and associated manual burden. By automating the process of map recording, the proposed solution offers significant time savings while ensuring that accurate plant design information is available for efficient field operations, tool development, network planning, and effective service activation and delivery. This approach leverages machine learning (ML) and spatial analysis techniques to extract network topology from DOCSIS network telemetry, deployment practices, and geodata. The effectiveness of the approach is demonstrated through simulations and experiments on real-world data. This solution has the potential to revolutionize how cable operators manage their coaxial plant infrastructure, evolve their networks, and improve overall network efficiency.

2. Background and Scope

In HFC network designs, technological advancements have been met with numerous challenges, resulting in a constant evolution of system designs. Traditionally, these designs are prepared by trained engineers using computer aided design (CAD) systems and specialized tools. This paper proposes a revolutionary automated system for generating HFC network topology and geographic information system (GIS) data, focused on enhancing the efficiency and accuracy of these designs while grappling with their inherently dynamic nature.

The engineering and design of HFC networks can be a complex process, with inherent difficulties caused by several issues. During the initial network design, various factors can lead to the network designs not being implemented as intended. For example, construction teams may lack specific equipment, necessitating substitutions not accounted for in the initial design. There are also environmental factors and unforeseen infrastructure elements, such as pre-existing conduits, that may also compel modifications to the initial design. There are also legal and regulatory elements such as easement access, local permit processes, and homeowner association (HOA) regulations that could potentially force alterations to the design.

Data integrity is a crucial aspect of the design process. Inaccuracies can result in flawed network parameters, jeopardizing the construction process and compromising the effectiveness of the network. Post-activation, the network continues to evolve, with countless factors contributing to divergence from the original design. Field conditions, such as unanticipated drop cable lengths and the addition of home splitters, can cause technicians to alter tap values and conditioning. Technicians may modify designs by adding taps where needed, a necessity not foreseen during the initial design. Amplifier setup, a frequent point of deviation from the initial design, can be altered due to a multitude of reasons, including natural temperature changes or cable impairments.

Major changes to the system to accommodate damaged cables, additional capacity, or improved redundancy can further exacerbate the disparity between design and implementation. This divergence necessitates constant updates to the design, known as the red line process, which can be a laborious and time-consuming task. System upgrades, such as node splitting, often come with their own set of challenges. Additional nodes can intensify existing issues and introduce new complexities, leading to delays in construction and activation of new services, thus impacting the efficiency of ongoing network maintenance.

Given this extensive array of factors that contribute to the dynamic nature of HFC network designs, the traditional methods of design and maintenance can be fraught with inefficiencies. This paper proposes an automated approach, addressing these challenges and paving the way for a more streamlined and effective way of maintaining HFC network designs.

3. Use Cases, Benefits, and Examples

3.1. Generating a Topology With No As-Built Maps

In older cable networks, particularly those built before the advent of modern CAD software and GIS, there can be a significant lack of documentation about the network's topology. This can cause a wide range of issues, from difficulty identifying and fixing network issues to problems planning upgrades or expansions.

The problem compounds when we consider that these networks may have been operating for several decades. Over time, modifications, repairs, and upgrades are likely to have been made to these networks that deviate from any original designs. Furthermore, the physical geography in which these networks are deployed may have also changed over time due to new construction or other factors.

This presents a challenge: How can we obtain accurate, up-to-date network topology information from these older systems that may not have any digital documentation? The answer lies in a process often referred to as reverse-engineering the network topology. However, without any data to start with, this can prove to be a challenging task.

With traditional methods, creating an accurate topology from these systems would require a combination of physical inspection (which could be both time-consuming and costly, especially for larger networks), interviews with long-term staff (who may or may not remember the specifics), and potentially sorting through old, possibly outdated paper documentation.

Therefore, the challenge is to generate a current as-built topology for older, undocumented systems with the potential for significant deviations from any existing documentation. This involves the identification of all nodes and connections within the network, their characteristics, and their geographical locations, which is a substantial task without initial data or documentation.

3.2. Audit and Update Existing As-Built Maps

In this scenario, a system design is already in place, but due to a multitude of reasons previously outlined, the actual network might have deviated from the original design. These reasons can include but are not limited to:

- Infrastructure modifications and repairs over time that weren't correctly documented.
- Construction that differed from the original design due to inaccuracies or misinterpretation of design parameters.
- Physical and geographical changes in the environment around the infrastructure.
- Technological upgrades and network expansions that may have been inadequately recorded.

Despite having an initial system design, these discrepancies can result in the as-built network topology diverging significantly from the as-designed or "as is" map. The challenge here is to validate the existing system design and generate an accurate, up to date as-built topology that reflects the network's current state. One option would be for the operator to conduct a full physical audit of the network performed either by in-house staff or contracted field engineers to generate up to date as-built maps. This is a labor-intensive approach that would have to be conducted continuously to maintain validity.

The solution to this problem could be an automated auditing tool. The auditing tool would cross-verify the actual network performance and topology against the existing design, effectively producing an audit score that quantifies the level of accuracy or confidence in the original designs compared to the current network status.

By implementing such an audit tool, operators would gain a more reliable and accurate understanding of their network topology and be better equipped to make informed decisions on future work, prioritization of physical audits, and improvements in documentation accuracy.

3.3. Tap-to-Home Association

A typical issue in cable networks is the uncertainty in associating customer locations to specific network taps. A tap is a connection point in a network that provides a junction between the primary network cable and individual drop connections to households or businesses. They are often organized in a sequential manner along a feeder line. However, taps can often be fed in ways that are counter-intuitive to a casual observer.

Given their configuration, it is not uncommon for multiple taps on a feeder to be approximately equidistant to a service location. This presents a challenge in accurately associating a given service location with its respective tap based on distance and sequence.

Furthermore, the choice of a tap for a specific location isn't always driven by proximity. There can be various practical or environmental factors that influence the selection. For instance:

- Physical barriers: Trees, buildings, and other structures can impact the choice of tap. For example, it might be more feasible to connect a household to a tap that is farther away but has a clear line-of-sight, rather than a closer tap that requires navigating around a building.
- Access issues: Fences, easements, and other access restrictions can also influence the choice of tap. Taps that are easier to access, even if they're slightly farther away, might be preferred over closer but less accessible taps.

Given these considerations, the choice of tap for a service location may not be immediately evident from the network design or based solely on geographical proximity. This can result in a level of uncertainty in the network topology, making network management and troubleshooting more challenging.

Therefore, there's a need to accurately determine the correct association between service locations and physical taps based on actual network configuration and installation considerations, rather than just relying on geographical proximity or sequence. This would lead to a more accurate network topology, which in turn would improve network management, performance, and planning for future upgrades.

3.4. Drop Length

Cable network designs typically include the main network infrastructure, outlining the main lines of communication and significant hardware components such as amplifiers and nodes. However, one area often not included or lacking detail in these designs is the drop connection – the final link that connects the network to individual users or households.

This lack of drop connection information in network designs primarily arises because these connections are typically the responsibility of other teams or are installed and activated well after the initial construction of the plant. This practice often results in a network design that doesn't include the accurate drop lengths and types. This poses a significant problem as drop connections are a crucial part of the network. Their length, type, and quality can significantly impact network performance parameters, such as signal strength, error rates, and overall link quality.

Moreover, standard design parameters and design guidance that inform the selection of tap parameters may not always align with the realities of drop installations. There may be deviations in drop lengths or types due to on-site realities, end-user requirements, or other factors not considered in the initial design stages.

This presents an incomplete and possibly inaccurate picture of the actual network. Without an accurate understanding of drop connections, the effectiveness of network management, troubleshooting, optimization, and planning for future upgrades can be impacted. Therefore, there's a need to find ways to infer these missing details and complete the network design based on the actual parameters of the network.

3.5. Verification of Link Budget, Loss, and Performance Targets

In cable network operations, a key aspect is being able to assess whether the network is performing as it was designed. This involves validating various network parameters, such as frequency response, signal strength, and error rates, against the theoretical values outlined in the system design.

One specific area of interest is the radio frequency (RF) link budget, a calculation that considers all the gains and losses from the transmitter, through the coaxial and passive network elements, to the receiver in a system. This includes factors like transmission power, cable losses, tap losses, connector and splitter losses, and noise figures.

The RF link budget forms an integral part of the network design, outlining the expected performance of each link in the network. However, due to a multitude of factors, the actual network performance can deviate from these theoretical expectations.

This could be due to changes in network components over time, including impairments, connector degradation, and even environmental factors like water, temperature, and humidity fluctuations affecting signal propagation. Alternatively, the actual drop lengths and types might deviate from the standard design parameters, impacting the RF link budget.

Being able to validate the actual network performance against the designed RF link budget is important for cable operators. This is because it enables them to:

- Confirm Service Delivery: By verifying that the network's actual performance aligns with the design, operators can confidently confirm the level of service they can deliver to their customers.
- Identify Network Issues: Deviations between actual performance and the design can highlight potential network issues, like faulty equipment or connections, which can be proactively addressed.
- Plan for Network Upgrades: Understanding the real-world performance of the network can guide future planning for network upgrades and improvements, ensuring that the network continues to meet customer service requirements.

Therefore, an important use case for DOCSIS network telemetry is to verify network performance against the system design, including validating the actual RF link budgets against their designed values. This allows for effective network management and optimizes service delivery based on the network's actual, rather than theoretical, performance.

3.6. Real-Time Repair and Construction Verification

Cable operations involve regular repair and construction activities, ranging from routine maintenance to infrastructure upgrades. However, validating the completion and efficacy of these operations often requires manual inspection or relying on field reports, which can be time-consuming, labor-intensive, and possibly prone to error.

This use case involves leveraging DOCSIS network telemetry in real-time to automate the validation of repair and construction activities. The process would be akin to a digital "red line" procedure that provides instant feedback and validation of completed tasks.

For instance, if a work ticket outlines a construction job that requires adding a specific length and type of cable to a segment, network telemetry can be used to validate the job completion. After the cable installation, the network's RF levels and tilt can be checked through telemetry data. If these values align with the expected results for the added cable's type and length, it validates that the job has been completed as intended.

This real-time verification not only helps ensure accuracy in construction and repair tasks but also may reduce the need for subsequent manual checks.

Additionally, the same real-time telemetry data can be used to close the loop on repair recommendations made by other artificial intelligence (AI)/ML systems used by cable operators. For example, if an AI system suggests a specific repair to address a detected network issue, the telemetry data can be used post-repair to verify if the recommended action has effectively resolved the problem.

Therefore, another potential use case of network telemetry is real-time repair and construction verification. This application can greatly enhance the accuracy, efficiency, and effectiveness of network maintenance, construction, and repair activities, contributing to optimal network performance and reliability.

4. MIND™ Overview

The origin of the MIND or Methodology for Intelligent Network Discovery concept was driven to answer the previously discussed challenges existing from the partial or total unavailability of HFC network data. From the realization that just a single source of data generation may not be sufficient to discover HFC network elements, MIND leverages and integrates multiple data sources and a diverse set of tools in a coordinated fashion to enhance:

- capabilities in type and number of HFC elements discovered,
- granularity in determining HFC element values or characteristics,
- sensitivity in detecting common traits for grouping or clustering.

MIND targets to discover all possible HFC network elements, from their types, values, and connectivity relations to other elements as well as their location in a programmatic fashion. (A list of network elements targeted for discovery is provided in Appendix A.) MIND assumes that no prior knowledge of HFC network topology and elements is necessary as these will be determined through the MIND process. If they are available, MIND can be used to verify the characteristics and location within the fiber node topology of the HFC network elements. While the discovery in MIND is processed one RF domain at a time, which is typically a fiber node serving area at a time using DOCSIS service groups that link cable modems (CMs) to fiber nodes. As machine learning is leveraged, the learnings and tools derived from the larger population of RF service groups are applied to the fiber node serving area being processed.

4.1. Multiple Sources of Information

A single source or single tool may not uncover with certainty topology or HFC network element values. But when multiple sources of information are intelligently combined, the accuracy and confidence level in defining the HFC network topology and its network elements are increased.

The sources of information considered in MIND include:

- **DOCSIS and proactive network maintenance (PNM) metrics** – Available through DOCSIS management information base (MIB) and/or command line interface, PNM collection tools, etc. [1-5] Initial DOCSIS metrics considered in MIND are included in Appendix B.
- **Geodata** – Streets, lot boundary, home construction perimeter, pedestals, attachment poles, aerial, or underground network identification, etc.
    - **CM association to street address** - CM latitude and longitude estimate
- **HFC network deployment rules and guidelines** – Includes guidelines on the placement of pedestals, aerial versus underground practices, practices when distribution coaxial cable is deployed in front of homes or when it runs in rear easements, multiple dwelling unit (MDU)/building deployment practices, taps deployed in decreasing value and operator specific practices such as range of tap values, etc.
- **Non-DOCSIS instrumentation results** – Includes those obtained through RF tools, optical time domain reflectometer (OTDR)/ metallic time domain reflectometer (TDR), alternating current (AC) voltage readings at different actives, etc.
    - **Network element type characteristics** – Network element models or specification datasheets.
    - **Existing as-built plant data**- If available for verification of accuracy.

An example of how multiple sources of information can be used to assess a specific parameter is given when we measure distance or length. We can represent distance measurements from fiber node to CM, by comparing metrics at these two network devices or by adding the individual segment lengths of the cascaded elements between the fiber node and CM. These metrics can be based on DOCSIS, PNM, geodata or others (Table 1)

Table 1 – Sources describing distance/length.

Metrics	Coverage	Source
Timing Offset	End-to-end	DOCSIS
Group Delay	End-to-end	PNM - Ch. Estimate / S_{21}
Reflection Cavity Ripple	Segment	PNM
Dist. between Pedestals/Poles	Segment	Geodata / Deployment practices
Power Level Difference	Segment	DOCSIS Rx Power/Attenuation
AC Voltage Drop	Segment	Non-DOCSIS - Attenuation / Pwr. Consumption

4.2. Analysis Mechanisms

The mechanisms for uncovering HFC network data fall into two main categories:

The first category is rules-based mechanisms such as direct analysis, which can be used to estimate the values that characterize the network. For example, a micro-reflection ripple is indicative of a reflection or echo cavity between two interfaces, likely between two HFC network elements. From the ripple and coaxial cable characteristics, one estimates the length between these two interfaces.

The second category is machine learning-based mechanisms where, through training, CMs with common characteristics can be clustered together to uncover bifurcations, topology, or CM-tap association.

Both rules-based and machine learning-based mechanisms can be used to discover the same network feature or characteristic, combining the different analysis mechanisms increases the confidence level in approaching “truth” (approaching “as is”). Section 6 discusses in detail the types of analysis.

4.3. Normalization, Calibration, and Correlation

MIND extensively leverages correlation tools. In order to compare and differentiate component types, component values, component connectivity, and location, these comparisons and/or differentiation exercises must be done using components described following the same rules, formats, and definitions, to compare apples with apples. Once the data is deemed to be consistently defined then discrimination and correlation processes can take place. Curating the data can range from a simple formatting process to a comprehensive and elaborate calibration process. Parameters such as timing offset, group delay and power level that could benefit from calibration and normalization are discussed next.

4.3.1. Timing Offset

In one case in particular, curation of timing offset data takes the form of a calibration process. In DOCSIS, timing offset is defined as the compensation delay the CM must apply so that from a timing perspective it appears to be located right next to the cable modem termination system (CMTS). Successful timing offset compensation results in CM transmissions to be time aligned as they are received by the CMTS. The original purpose for such an alignment was to minimize guard time between transmissions. In DOCSIS 3.1, the granularity of timing offset was refined to meet the tighter orthogonal frequency division multiplexing (OFDM)/ orthogonal frequency division multiple access (OFDMA) synchronization requirements. The mandatory timing offset resolution in time division multiple access (TDMA) has a granularity of 6.25 μs/64 or 97.65625 ns. A TDMA optional/ synchronous code division multiple access (SCDMA) mandatory higher resolution of 1/(256*10.24 MHz) or 381 ps is available, while an optional granularity of high-resolution timing offset (OFDMA) of 1/(256*204 MHz) or about 19 ps is also available. This high-resolution granularity is defined by the timing adjust fractional part in Section 6.4.6 of DOCSIS MULPI specification [6]. Assuming coaxial transmission with a velocity of propagation of 87% of the speed of light, regular TDMA resolution timing offset provides a distance granularity of 25.47 meters, SCDMA results in a distance granularity of about 10 cm, while OFDMA high resolution timing offset provides a distance granularity of 4.974 mm or about half a cm. This higher resolution option in principle makes timing offset a powerful tool for clustering and discrimination of HFC network components.

The challenges are that timing offset was designed to align transmissions of a specific CM and the CMTS. Internal delays at the CM such as processing delays that might be included in the timing offset need to be calibrated out so that the timing offset metric can be used for comparison across different CMs.

MIND conducts a timing offset calibration exercise to remove this CM model and chip dependent variability to leverage this powerful tool.

4.3.2. Group Delay

Another parameter that can benefit from calibration is group delay. In single carrier quadrature amplitude modulation (SC-QAM) signals, equalization parameters are provided in the time domain and main tap information is typically fixed at tap number 8, providing a good common time reference to calculate and compare equalization information as well as parameters that are derived from equalization information such as group delay. In DOCSIS 3.1 equalization coefficients are in the frequency domain. Tom Williams described a calibration process to compare OFDMA equalization across CMs [7]. This mechanism can also be used to compare group delay across CMs which helps in discrimination based on distance in addition to distortion. Metrics that at first glance may not appear useful become powerful tools with the proper normalization and calibration.

4.3.3. Power Level

Power level has always been an important metric in the verification of the proper operation of the CM. Nevertheless, it has not yet been used in the discovery of HFC plant characteristics and its elements. One important change with the introduction of DOCSIS 3.1 is that both the downstream as well as the upstream spectrum have been increased. In the upstream DOCSIS is covering up to 204 MHz while in the downstream 1.2 GHz and 1.8 GHz upper frequency limit options are feasible. This means that with much wider bandwidth, power variation effects are easier to detect, characterize, and compare with other CMs. PNM is also playing a role since full band capture (FBC) is becoming more widely used and operators are recording spectrum readings at amplifiers and taps, either from embedded CMs or test ports at amplifiers or at tap drop ports. This provides useful reference information that can be compared with the CM FBC and to extract the delta performance to gain detailed information on the drop-home portion of the network. Along with FBC channel estimate or equalization information at the tap are powerful network discovery metrics.

The coaxial segment in Figure 1 has been analyzed to highlight the use of power level signatures from CMs.

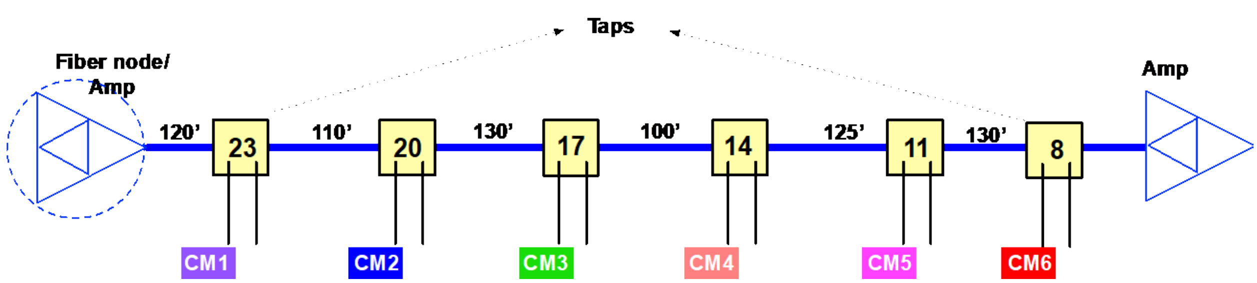


Figure 1 – Analyzed coaxial segment with hardline cable (blue) and drop cable (black).

In this coaxial segment scenario, CMs connected at different taps with different drop lengths are evaluated. Figure 2 shows CMs connected at the first tap (a), fourth tap (b) and sixth tap (c).

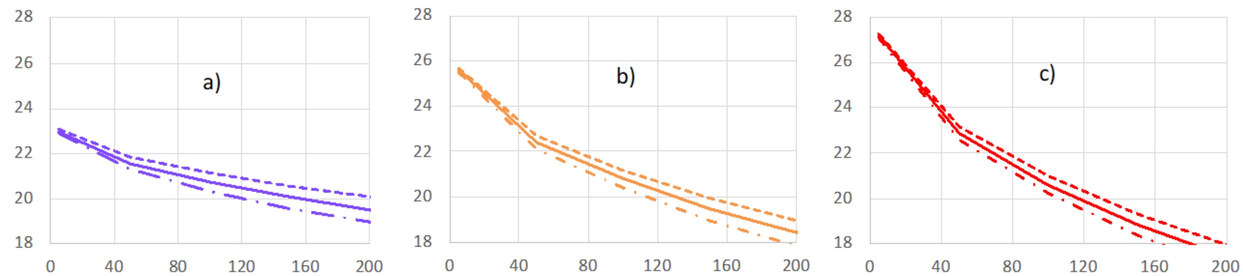


Figure 2 – Relative CM US power versus frequency for 80' drop (dashed), 100' drop (solid), 120' drop (dashed-dot) a) at 23 dB tap drop b) at 14 dB tap drop c) at 8 dB tap drop all with no upstream tilt.

Even though CMs have some variability in reporting absolute power for the behavior versus frequency, the delta power level between highest and lowest frequency and the shape of the curve is very telling of the tap it is connected to and of the tap-to-CM cable length. If tap measurements are available, then greater insight of the drop-home becomes available. A calibration process would have to take place as you would need to subtract the RF contributions up to the tap. Similar analysis can take place in the downstream (Figure 3).

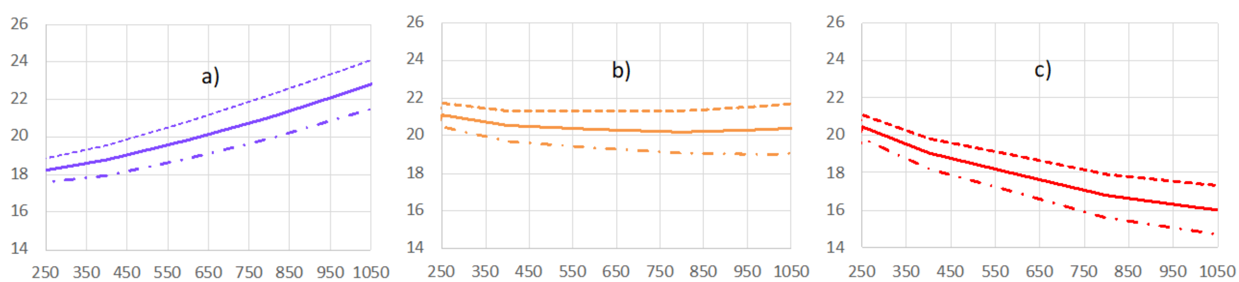


Figure 3 – CM Rx power vs. frequency for 80' drop (dashed), 100' drop (solid), 120' drop (dashed-dot) a) at 23 dB tap drop b) at 14 dB tap drop c) at 8 dB tap drop in a 1dB/100 MHz uptilt.

Comparing the responses of CMs at the different taps, one can easily observe how the tilt changes as you move along the coaxial segment. One implementation complexity is that to maximize the US and DS spectrum coverage, CMs may have to move to MAC domains that include the edges of the US and DS bands.

4.4. Relative versus Absolute Metrics

In some cases, absolute metrics may be available, while in most other cases metrics relative to a reference point may be everything that is needed to perform valuable analysis. For example, if a fiber node is used as a known reference point, finding relative distances from each of the components to that reference point/fiber node is all that is needed for an accurate representation of the coaxial network covered by that fiber node. MIND uses the fiber node as a reference point or anchor point to provide latitude-longitude reference to the rest of the network elements.

4.5. Sequential and Iterative Discovery Processes

In MIND, different analytical and ML-based processes take place in a sequential manner. This means that after each process new network elements and their values are discovered or updated improving our level of confidence in the network. This improved knowledge is refined after running the algorithms that follow. As the network is not static and new information becomes available or as one accumulates greater knowledge of the network, the overall process is run again and in a continuous fashion to attain further refinement of network knowledge and to detect changes that may have happened in the network so that knowledge of the network is always current, thereby moving from an as-built to an "as is" knowledge paradigm of the network.

4.6. Network Modelling

Network models are useful tools in estimating the performance of a network. MIND uncovers the network components within a fiber node serving area to a large degree by understanding the performance and behavior measured at the CMTS and CM located at the edges of that HFC network portion or serving area. Knowledge of the behavior of HFC network elements within that fiber node serving area, even in a partial or approximate fashion, is useful in determining what components are there, how they are connected, and their characteristics. Network models can help us make sense of the readings measured at the edge by the CMs and CMTS.

Since the HFC network targeted for discovery operates in a stable RF environment, a useful linear RF frequency characterization mechanism is provided by S-parameters or scattering parameters [8, Appendix C], which are designed to capture the transmission and reflection characteristics of RF devices.

Even if actual S-parameter measurements of specific devices are not available, specification datasheets with return loss and transmission loss versus frequency datapoints or formulas describing behavior versus frequency can be converted into S-parameter matrices needed for modelling. S-parameters describe system reflection and transmission characteristics using complex numbers (using amplitude and phase information). Phase information versus frequency allows network operators to derive group delay versus frequency, enabling delay versus frequency estimation across elements and end-to-end system.

Historically, the cable industry has described and specified network components using magnitude information. Components used at higher frequencies such as microwave frequencies are specified using S-parameters with phase information. As our industry operates at higher frequencies, it is only natural to evolve into using phase. The modelling of cable networks proposed by Narayanaswamy, Prodan and team [9] will achieve accurate results if we characterize and specify our components in magnitude and phase. In fact, our industry, through the CMTS and CM in-phase (I) and quadrature (Q) information already gathered, leverages amplitude and phase. This additional information of network elements will not just enable accurate modelling and simulation but will also improve detection, localization, and resolution of plant problems.

The two most prevalent element types in HFC networks are the amplifier and the tap. S-parameter characterization measured on a vector network analyzer (VNA) of a sample amplifier is shown in Figure 4, Figure 5, and Figure 6, and S-parameter characterization of a sample tap is shown in Figure 7 and Figure 8.

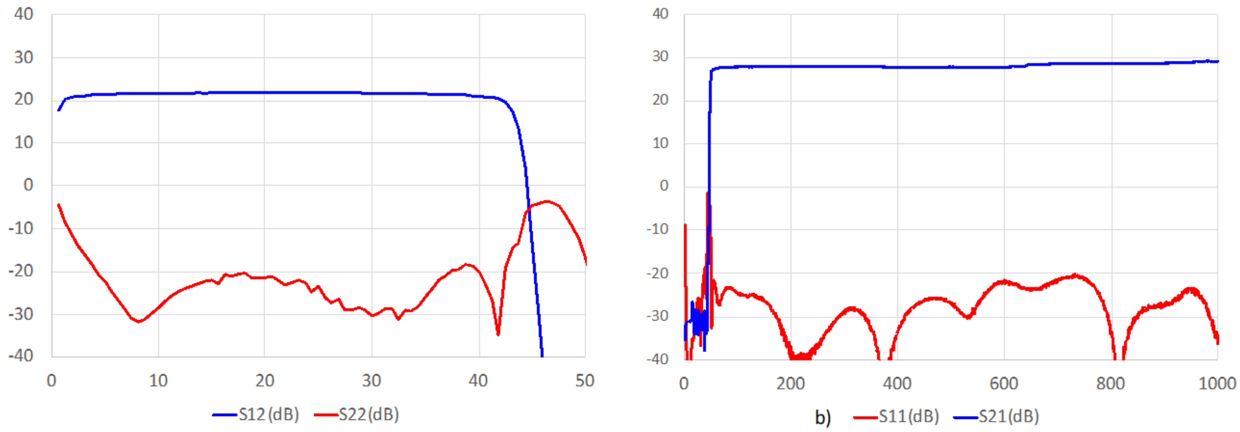


Figure 4 – Amplifier S-parameters a) reverse transmission and reflection b) forward transmission and reflection.

Figure 5 shows S-parameter characteristics of an amplifier upstream band. From the phase information in Figure 5a we can derive group delay shown in Figure 5b. This group delay is the delay in traversing the amplifier on the reverse path. While instrumentation will provide a good assessment of group delay, DOCSIS devices provides relative group delay information that may include additional elements such as the front end of a CM or CMTS.

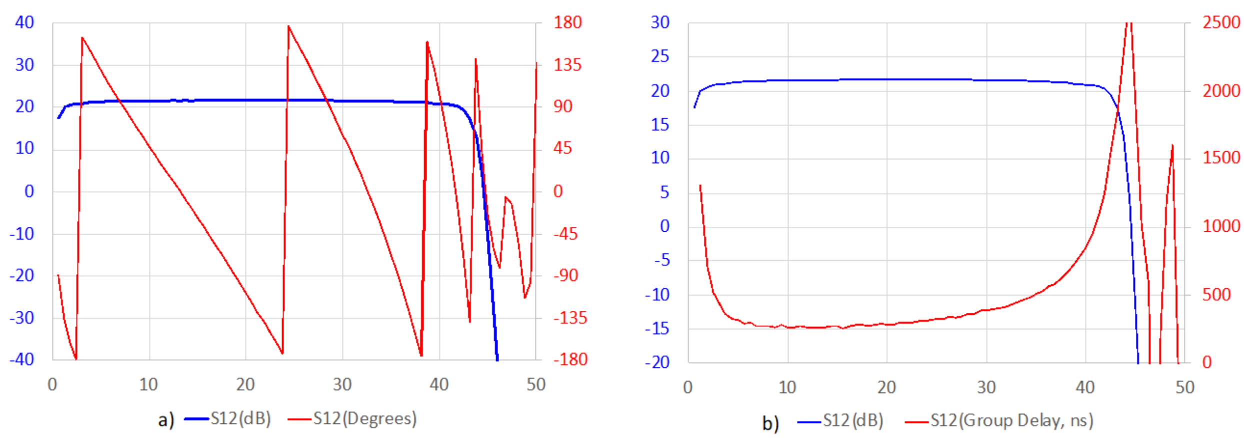


Figure 5 – Amplifier reverse transmission S-parameters a) magnitude and phase b) magnitude and group delay.

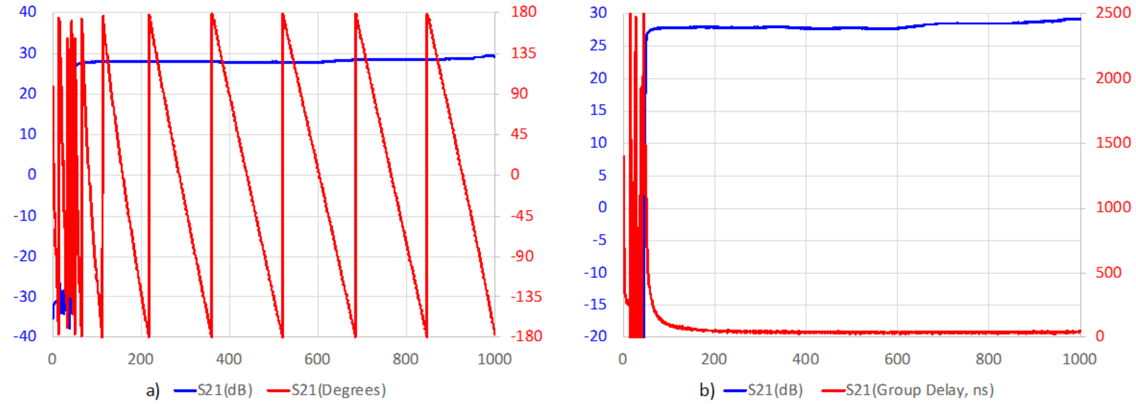


Figure 6 – Amplifier forward transmission S-parameters a) magnitude and phase b) magnitude and group delay.

A 17 dB four port tap main path insertion loss can be compared with coupled port loss (Figure 7).

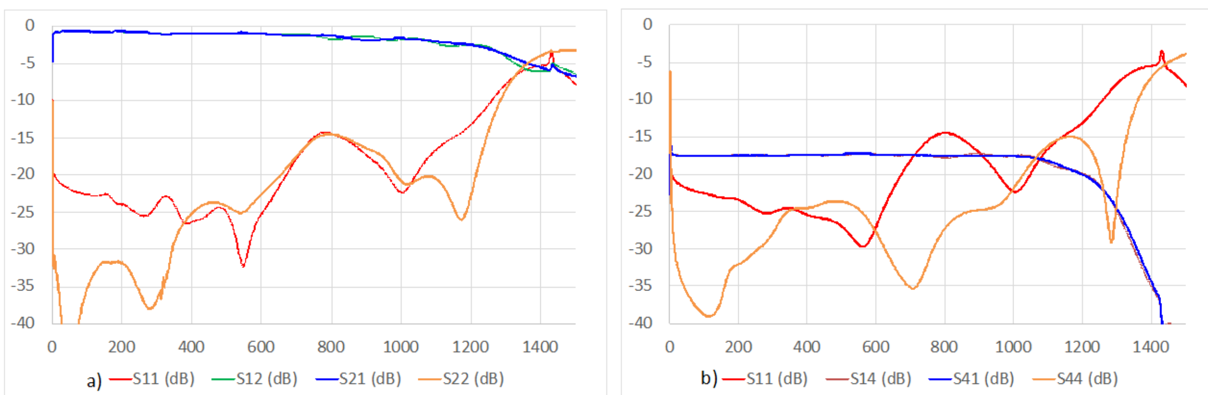


Figure 7 – 17 dB Tap S-parameters a) main path b) coupled port path.

In this example, the passive tap rated for 1 GHz can operate way beyond 1 GHz (Figure 8), introducing a transmission delay of about 9 ns.

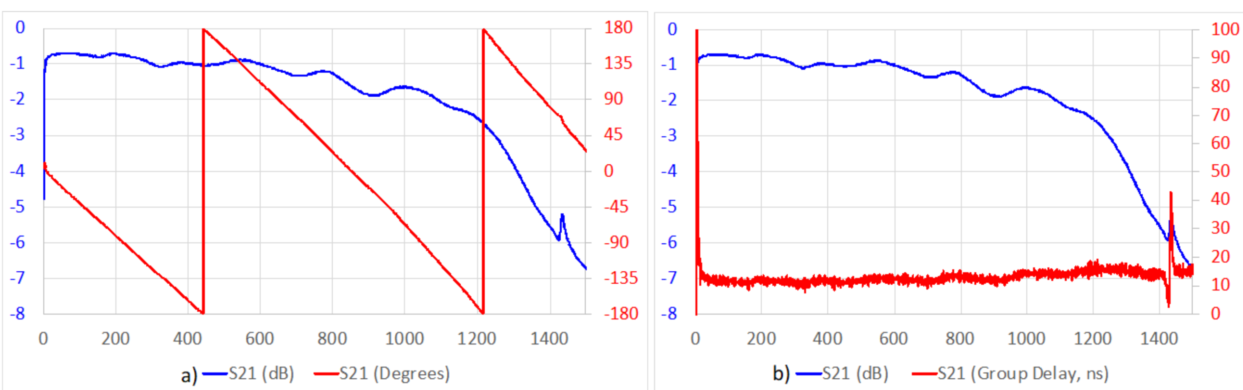


Figure 8 – 17 dB tap main path S-parameters a) magnitude and phase b) magnitude and group delay.

DOCSIS channel estimation by CM or by CMTS through complex equalization coefficients provide transmission S-parameters assessment for the DOCSIS channel frequency range. Tom Williams [7] also shows a way to also obtain reflection S-parameter by inserting a CM probe into the network. One must keep in mind that CM and CMTS-based estimates will include internal distortions such as front-end CM/CMTS receiver distortion which would have to be calibrated out for an accurate delay assessment. Nevertheless, even without calibration, comparison of signal distortion from the same CM models can provide good insights of network characteristics.

While an S-parameter model is good for assessing an individual component, when assessing components that are connected in cascade, related and more practical parameters are defined, they are called the T-parameters. The relationship between S-parameters and T-parameters is shown in Appendix C.

If you have HFC elements A and B in cascade, each expressed in their T-parameter representation, the T-parameter equivalent of the cascaded system is given by the matrix product of the individual T-parameters matrices A and B.

$$[T_{Equiv}] = [T_A][T_B]$$

So, if you have a coaxial segment represented by cascading HFC network elements, they can be modelled using T-parameters.

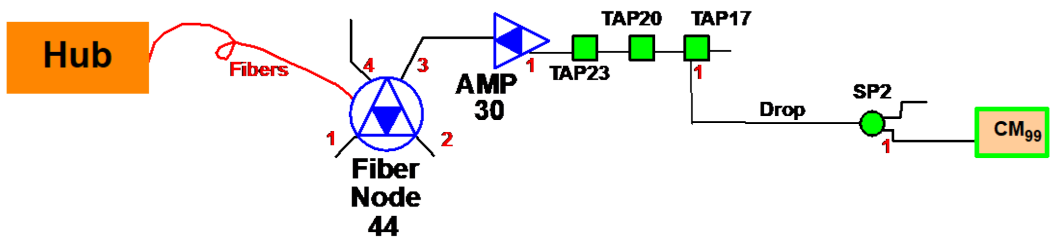


Figure 9 – Coaxial path within a fiber node serving area 44 to CM 99.

The coaxial segment using the long name convention described in [10] is represented as:

$FN44_3$-C.5(200)-AMP30 -TAP23-C.5(125)-TAP20 C.5(102)-$TAP17_1$-RG6(90)-$SP2_1$-RG6(30)-CM99

The port numbers in red in Figure 9 are used as subscripts in the long name representation, where the half inch hardline cable is depicted as C.5() with the number in parenthesis being the cable length in feet. The coaxial segment in Figure 9 is modeled using T parameters by cascading its individual T-parameters resulting from the following matrix product.

$$[T_{Equivalent}]=[T_{C.5(200)}][T_{AMP30}][T_{TAP23}][T_{C.5(125)}][T_{TAP20}][T_{C.5(102)}][T_{TAP171}][T_{RG6(90)}][T_{SP21}][T_{RG6(30)}]$$

So given a known input/output of FN44, the input/output at CM99 can be derived using the $T_{Equivalent}$ matrix representing the HFC elements in cascade. This analysis can be used when comparing measurement at the CM to measurements at the tap for estimating drop/home cable distance, or when comparing elements that share a common portion of a coaxial segment or to estimate the number of actives in cascade, etc.

5. Analysis

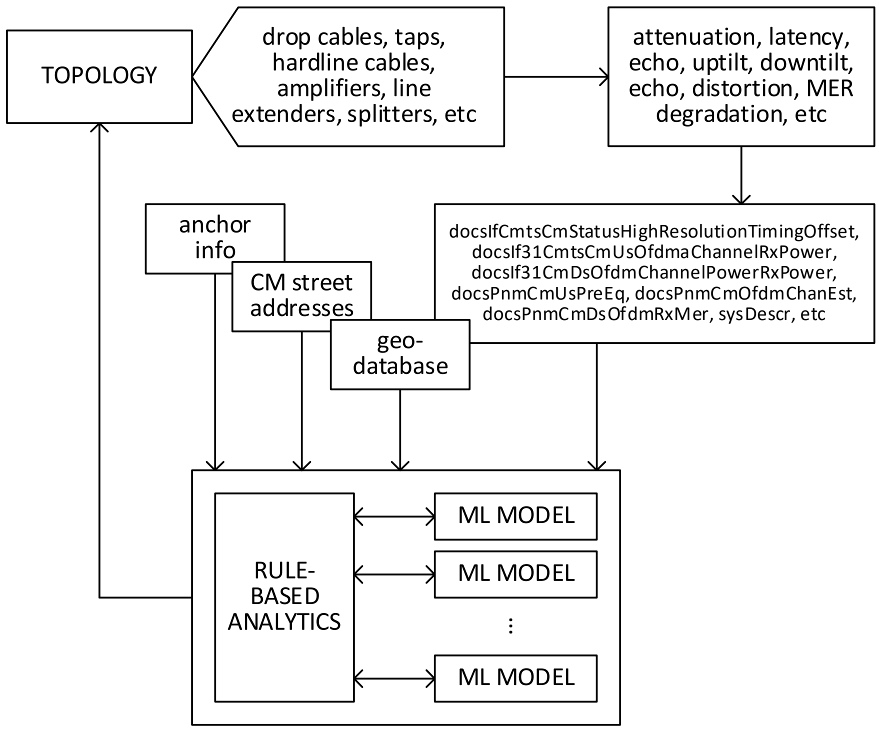


Figure 10 – Analysis flow of MIND.

Figure 10 presents the analysis flow of MIND in our preliminary study. The process begins by utilizing latitude-longitude information from an HFC network element, typically a fiber node, as an anchor point. Additionally, the analysis relies on street addresses of CMs and leverages lot parcel data and street layout information. To further enhance the understanding of the network and differentiate between different topologies, geodata information and common network deployment practices are incorporated. This includes factors like the typical locations of pedestals, the choice between underground and aerial deployment, and other relevant details. This information is represented in a logical format that can be embedded in the analytics.

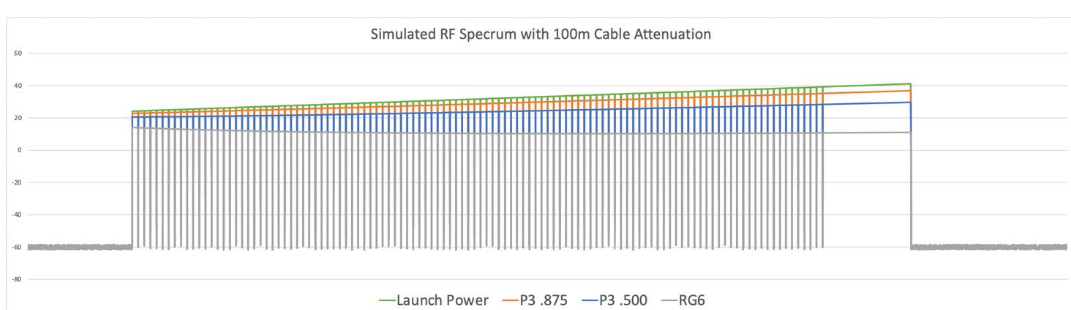


Figure 11 – Example of loss prediction of 100 meter coaxial cables.

As DOCSIS signals traverse the network, they are influenced by various plant characteristics, leaving distinctive signatures on the signals (Figure 11). By analyzing and correlating these signal signatures, we can discover network elements, their connectivity, and characteristics. In the HFC network, every cable modem communicates with the CMTS through multiple network components, forming a unique topology. Each component contributes to the signal's channel response. For example, a drop cable causes greater power loss compared to a same-length hardline cable, and a tap introduces loss and potential spectrum uptilt in scenarios of taps with conditioning plug-in modules. Hardline cables introduce signal latency, where, for instance, a 1,000-ft cable with 87% velocity of propagation results in a 1170 ns latency. Active components introduce dispersion and roll-off, distorting the signal's magnitude and phase. Different CMs accumulate distinct channel responses induced by the network components and the topology.

DOCSIS facilitates the recording of this information. MIND leverages the granular monitoring tools available in DOCSIS, such as the DOCSIS MIB information from the CMTS and CMs within the analyzed fiber node serving area. DOCSIS 3.1 has introduced new tools like PNM with improved resolution, offering additional information that can expedite convergence to a decision and increase confidence in the results.

Using these sources of input information, the core analysis consists of two approaches: rule-based analytics and ML models. Rule-based analytics draw upon engineering knowledge to make decisive judgments rather than soft decisions. ML models enhance MIND's performance by detecting features that may not be immediately apparent through direct analysis or observation of management metrics. Supervised ML requires extensive training data for a complex HFC network. Therefore, comprehensive datasets encompassing the aforementioned information, as well as a logical representation of the topology, are necessary to support the ML training process.

5.1. Rule-based Analytics

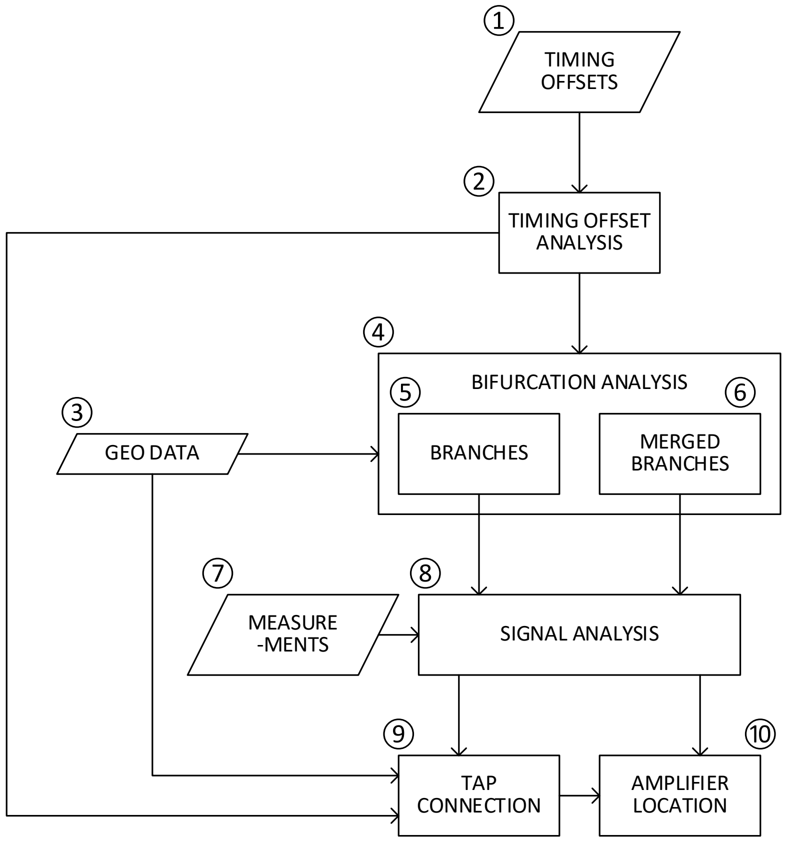


Figure 12 – Example flow of rule-based analytics in MIND.

As previously mentioned, the objective of the algorithm is to provide a comprehensive visualization of the cable network's layout on a map, including the precise locations of all network components. Straightforwardly, the algorithm follows rule-based analytics that align with the layout of the network. For instance, in a tree-like network, branches can be segmented by amplifiers; if two CMs have similar signatures except for a higher latency in one, the algorithm can infer that they likely belong to the same cable segment, with one being farther downstream than the other; additionally, the presence of different distortions suggests the presence of an amplifier between the two CMs.

In rule-based analytics, measurements that explicitly reflect topology relations are utilized. Timing offsets reflect relative CMTS-CM distances, street addresses reflect both location and candidate anchoring point, and signal-related measurements and their variations reflect channel conditions, among others. By adhering to these rules, the algorithm can hierarchically depict the network's structure and identify the relative positions of components. Figure 12 illustrates the following steps, which demonstrate an example of rule-based analytics.

Step 1: Timing Offset Information Collection

This initial step gathers the timing offset, which serves as latency information, from each CM. Tools like MIB, network management interface (NMI), and Simple Network Management Protocol (SNMP) are employed for this purpose.

Step 2: Timing Offset Analysis

Building upon the information obtained in Step 1, this step analyzes the relative latency between each cable modem and the CMTS by comparing and calibrating a large data set of CMs with redundant attribute combinations. By interpreting the latency as a measure of distance, the algorithm derives an estimate of the spatial arrangement.

Step 3: Geodata Collection

In this step, the algorithm collects geographical data for each cable modem, including details such as street address, latitude/longitude, and building parcels.

Step 4: Bifurcation Analysis

While all CMs analyzed are associated with the same fiber node, they may belong to various branches of coaxial cables connected to the node. Using the distance offset information obtained in Step 2 and the geodata from Step 3, this step determines which cable modems belong to the same cable branch.

Step 5: Branch Grouping

The outcome of Step 4 is a set of cable modems grouped based on their respective branches.

Step 6: Merged Branches

Considering the nature of cable connections, certain branches identified in Step 5, despite being separate, might belong to the same branch. This step identifies pairs of branches that are potentially cascaded head-to-tail and merges them into a single branch.

Step 7: Measurement Collection

Utilizing tools like MIB, NMI, and SNMP, this step gathers various measurements from each cable modem, including pre-equalization data, channel estimates, transmitted and received power, modulation error ratio (MER), spectrum density, and non-linearity measurements.

Step 8: Signal Analysis

This step examines the branches one-by-one. For each branch, it clusters the CMs belonging to that branch into small groups based on their measurements collected from Step 7. After adjusting the clustering conditions, these small groups are then clustered into larger groups.

Step 9: Tap Connection

Using the group clustering results from Step 8, this step determines which cable modems are connected to the same tap. The distance offset results from Step 2 guide the placement of these taps, which are anchored to pedestal or utility pole candidates identified in Step 3.

Step 10: Amplifier Location

Building on the large-group clustering results from Step 8 and the tap identification from Step 9, this final step estimates the existence and locations of amplifiers. Each amplifier's location is potentially associated with multiple adjacent pedestal or pole candidates that share a similar likelihood.

5.2. ML-Based Analytics

In contrast to the conventional analysis flow of rule-based analytics, ML methods are employed to leverage the implicit information hidden within the measurements, rather than relying on explicit utilization. By applying ML techniques, these methods can extract valuable insights and patterns from the data that may not be easily discernible through explicit rule-based approaches. This allows for a more comprehensive and nuanced utilization of the underlying information contained within the measurements.

ML methods can primarily be categorized based on their degree of supervision or reinforcement. In our preliminary study, considering the limited availability of training data, we have investigated unsupervised clustering methods, including K-means, density-based spatial clustering of applications with noise (DBSCAN), and even as simple as manually drawing a threshold line in between data points. Among these methods, we have found that agglomerative clustering proves to be the most effective. It is used in Step 8 in Section 5.1 to cluster US power values (~10-dimension space), DS power values (~10-dimension space), and spectrum measurements (~1000-dimension space).

Agglomerative clustering initially treats each cable modem as an individual cluster and then progressively merges the closest pairs of clusters based on proximity. Various metrics, such as signal strength, latency, or spatial distance (or to be precise, the difference on a GIS grid), can be employed to determine the proximity of clusters. In our agglomerative clustering implementation, we adopted Ward linkage defined as

$$\frac{|A|\cdot|B|}{|A\cup B|}\|\mu_A-\mu_B\|^2=\sum_{x\in A\cup B}\|x-\mu_{A\cup B}\|^2-\sum_{x\in A}\|x-\mu_A\|^2-\sum_{x\in B}\|x-\mu_B\|^2$$

where A and B are the two clusters to be merged, μ is the centroid of a cluster, and $\|\cdot\|$ expresses the difference between two values if scalar measurements or the 2-norm distance if vector measurements. Utilizing Ward linkage for cluster merging offers the advantage of minimizing variance growth. However, this approach has a time complexity of $O(n^3)$, which is relatively slow when compared to alternative methods. Nonetheless, this should not pose significant issues since the algorithm is designed to run infrequently and with a limited number of CMs in each clustering operation.

When performing clustering, we have the option to utilize either multiple types of measurements or a single type as input. Using multiple types of measurements is often ideal in ML, as it allows us to consider potential dependencies or correlations among observations. However, encoding multi-type input data can be challenging when we have limited data available. In our preliminary work, we opted for using a single type of measurement, which resulted in multiple clustering results. To make joint decisions in this scenario, we employed Silhouette scores, which are calculated based on the clustering results. Specifically, for each value x within the set C of a measurement, assuming x is clustered into C_x by the clustering of $\{C_i\}$, we define the Silhouette score at x as

$$s_x=\frac{\min\limits_{k\neq x}\frac{1}{|C_k|}\sum_{y\in C_k}\|x-y\|-\frac{1}{|C_x|-1}\sum_{y\in C_x,y\neq x}\|x-y\|}{\max\left(\min\limits_{k\neq x}\frac{1}{|C_k|}\sum_{y\in C_k}\|x-y\|,\frac{1}{|C_x|-1}\sum_{y\in C_x,y\neq x}\|x-y\|\right)}.$$

The average score of the clustering for that measurement is determined by calculating the mean of all such scores, $\sum_{x\in C}s_x/|C|$. Finally, topology-related decisions are made based on the scores obtained from multiple measurements.

On top of clustering models, it becomes possible to uncover even more complex and implicit patterns and relationships between cable modems and their associated network components by applying supervised learning techniques, such as classification or regression algorithms, to the available data. For instance, a decision tree can be employed to determine if a CM is adjacent to an active component; long short-term memory (LSTM) or a transformer can be used to ascertain the length of the next cable segment; support vector machine (SVM), or a kernel method can segmentate cable branches; and multilayer perceptron (MLP) can classify CMs with specific types of impairments and determine their proximity. These algorithms necessitate labeled datasets where cable modem measurements and locations are paired with known information about the network topology and component locations, or other suitable representations. The ML problem posed by a cable network is highly complex due to the vast number of potential latent spaces, correlations, and intricate features. Therefore, it is essential to explore a wide range of methods, models, and transformations. Equally important is the acquisition of a substantial amount of labeled data for training.

5.3. Data Processing

Both rule- and ML-based analytics require the calibration and normalization of input data before utilization. However, this calibration process can sometimes be tedious and ambiguous, primarily because some of the measurements collected from the plant were not originally designed for network discovery. For instance, the timing offset measurement, which serves as an intermediate parameter for ranging, is highly influenced by multiple factors. To illustrate this, in our tests, we observed that when two CMs of different models are in media access control (MAC) domain 1, CM A reports a timing offset 2.1531 microseconds (549 meters) greater than CM B for the same plant location. Similarly, when both CMs are in MAC domain 2, CM A reports a timing offset 2.1299 microseconds (543 meters) greater than CM B at the same plant location. Furthermore, MAC domain 2 exhibits a timing offset 0.0068 microsecond (1.73 meters) higher than MAC domain 1 for the same CM B and plant location. Conversely, MAC domain 2 reports a timing offset 0.0164 microsecond (4.18 meters) lower than MAC domain 1 for the same CM A and plant location. To make this data usable, calibration of these biases is necessary, requiring the collection of an extensive amount of data that covers all possibilities and is labeled with the ground truth values. This calibration process constitutes a major task within our project.

Normalization is also an essential step, particularly for MLP models in ML. As an example, we utilize the group delay of a signal to estimate various topological information, such as the presence of an amplifier. Group delay is derived from the DS channel estimate and US pre-equalization data through unwrapping and removing the linear phase shift of the complex data. This process necessitates a proper normalization practice to strike a balance between revealing and erasing the data's features while maximizing the accuracy of the ML model.

6. Implementation

The MIND prototype was implemented over an HFC network in the laboratory that mimics a network in the field (Figure 13). The network is designed to have the dimensions of a portion of a network located close to CableLabs' facilities in Louisville, Colorado. The advantage of building the network is that, for verification purposes, we know the exact dimensions and characteristics of each component and we have control of the CMTS and CMs used for this proof of concept. So even though we start with very basic information, we have all the DOCSIS CMTS/CM and PNM data as well as geodata from the replicated coaxial network. This re-created network has approximately 5,000 feet of coaxial cable and 47 DOCSIS 3.1 CMs of different models.

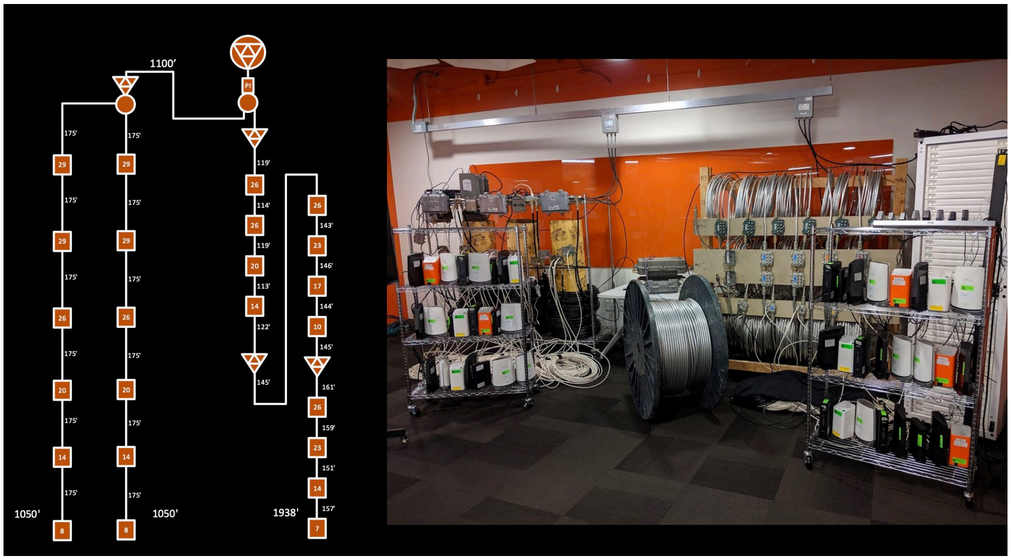


Figure 13 – Laboratory example of HFC network topology.

As the DOCSIS signals traverse the different HFC network components, they are modified or marked according to the characteristics of each traversed component, which by the time the accumulated signature is collected at the edge, it has the history of components traversed.

The diversity of metrics MIND collects provides a rich set of composite signatures that are analyzed to deduce network characteristics. As indicated at the beginning of the process, we assume very limited plant map knowledge. We use an anchor point with latitude and longitude information. A convenient anchor point is the fiber node. Using DOCSIS service group information we determine which CMs are associated with the fiber node. We also assume that we have access to street addresses that correspond to the subscriber's CMs. MIND translates street addresses to latitude and longitude. Even though this lat-lon information is approximate, it allows discovery of topology features. In the next step MIND gathers geodata information corresponding to parcel boundaries, construction footprint and street data. Even though there are exceptions, pedestal locations or pole locations are typically at the corner of the property lot to have easier access to homes served. This is one of the deployment rules that we leverage and provides a clue where pedestals or poles might be located. So, at this point we just have candidate pedestal or pole locations. Later processes will associate which amplifiers and taps are housed in which pedestal or mounted on which pole. These processes will also allow us to discard certain candidate pedestal/pole locations until we are left just with the actual locations. The deployment rules that we follow will vary if the plant is aerial or if the plant is underground. At this point we assume that we have this information, as we refine MIND algorithms this is something that could also be discovered.

One parameter that we take advantage of is timing offset. In DOCSIS 3.0, a higher resolution option was made available for TDMA and in DOCSIS 3.1 the timing offset granularity was increased even further to support subcarrier orthogonality. One challenge with timing offset is that it has been designed to adjust ranging between CMTS and a specific CM. There is an internal processing delay at the CM that changes depending on model and chipset. We need a process that normalizes timing offset across all CMs in a fiber node serving area so that delay comparison and therefore cable lengths can be estimated. Since we built this network, we know our coaxial cable lengths and we use this information to build a calibration table that removes this model/chipset variability. This way the enhanced resolution that can be obtained through timing offset can be realized.

The next process is to figure out where the bifurcations or branches are in the coaxial network. Different coaxial branches have different signatures. Analysis of these signatures allows MIND to cluster or group CMs that are connected through one branch or another. Distortion metrics such as equalization information are key in this clustering exercise.

The next task is to determine pedestal/pole locations. Remember that, at this point, we only have candidate pedestal/pole locations. Through analysis, MIND discards certain candidate pedestals/poles because if they would be in a specific candidate location, the timing offset would not be consistent with that pedestal/pole location. Clustering along with street address information can help determine if the coaxial distribution cable runs behind properties or in front of the homes.

The next process allows you to identify amplifier location relative to CMs. In the upstream, group delay at the band edges is very indicative if signals have traversed one, two, or more amplifiers. Downstream tilt characteristics, transmit and received power-level analysis, and other metrics allows you to determine how close you are to the amplifier, which can help to figure out if amplifier and tap share the same physical location (e.g., pedestal/cabinet or pole). After amplifier-to-pedestal/pole association, a similar process takes place to associate splitters and couplers to tap.

The final network topology discovered that we observed to be a good match was between the programmatically derived and the built network.

In this prototype implementation, not all possible tools have been leveraged. In an actual field scenario, it is expected the need for additional discovery algorithms that are only possible after training with a much larger data set. A limited set of different CM models allows us to generate a timing-offset calibration database. In the field you have a combination of DOCSIS 3.0 and DOCSIS 3.1 CMs. In the lab we had the luxury of using the higher capability DOCSIS 3.1 CMs. We must weigh in the pros and cons of whether to develop tools for DOCSIS 3.0 or wait for DOCSIS 3.1 to reach a higher percentage of deployment. Limiting MIND to DOCSIS 3.1 devices makes timing offset calibration easier as the population of different CM models and chipsets is more manageable. As we investigate field deployment, we also must verify that different CMTSs and CMs provide all the MIBs populated and formatted according to the DOCSIS specifications. There are still a good number of remaining tasks to migrate MIND into the field and as our networks cover higher frequencies the benefits are greater.

7. Future Work

This paper describes a complex process which involves significant data collection, processing, and analysis. While a significant amount of work has been done to explore the efficacy of the approaches described, there is much more work that needs to be done to deliver solutions to the use cases that were discussed in Section 3.

8. Conclusion

Programmatic discovery of HFC network topology and elements is becoming feasible as we have more and more accurate tools to deduce the HFC network characteristics. We have described an approach and have demonstrated it through the MIND prototype tool. MIND programmatically discovers the HFC network leveraging DOCSIS, PNM, geodata and deployment rules, without a pre-existing as-built map. MIND relies on a very comprehensive set of data and the calibration of the DOCSIS timing offset among other metrics. This paper discusses the challenges in using these techniques in the field and the benefits of the different use cases it enables. Prevalence of DOCSIS 3.1 technology in the network along with its full set of MIBs and capabilities provides better insight and higher resolution in the discovery process. As we evolve to network discovery in the field, machine learning will play a greater role both in the generation of new discovery algorithms as well as in the increase in sensitivity to distinguish the more subtle features of the HFC network.

Abbreviations

AI	artificial intelligence
AC	alternating current
CAD	computer aided design
cm	centimeter
CM	cable modem
CMTS	cable modem termination system
dB	decibel
DBSCAN	density-based spatial clustering of applications with noise
DOCSIS	Data-Over-Cable Service Interface Specifications
DS	downstream
FBC	full band capture
GHz	gigahertz
GIS	geographic information system
HFC	hybrid fiber/coax
HOA	homeowner association
I	in-phase
LSTM	long short-term memory
MAC	media access control
MDU	multiple dwelling unit
MER	modulation error ratio
MHz	megahertz
MIB	management information base
MIND	Methodology for Intelligent Network Discovery
ML	machine learning
MLP	multilayer perceptron
mm	millimeter
NMI	normalized mutual information
ns	nanosecond
OFDM	orthogonal frequency division multiplexing
OFDMA	orthogonal frequency division multiple access
OTDR	optical time domain reflectometer
PNM	proactive network maintenance
pre-EQ	pre-equalization
ps	picosecond
Q	quadrature
RF	radio frequency
Rx	receive
SCDMA	synchronous code division multiple access
SC-QAM	single carrier quadrature amplitude modulation
SCTE	Society of Cable Telecommunications Engineers
SNMP	Simple Network Management Protocol

SVM	support vector machine
TDMA	time division multiple access
TDR	time domain reflectometer
US	upstream
VNA	vector network analyzer
µs	microsecond

Bibliography & References

[1] Data-Over-Cable Service Interface Specifications DOCSIS® 3.1 Physical Layer Specification (CM-SP-PHYv3.1-I20-230419); Cable Television Laboratories

[2] Data-Over-Cable Service Interface Specifications DOCSIS® 3.1 Cable Modem Operations Support System Interface Specification (CM-SP-OSSIv3.1-I24-230613); Cable Television Laboratories

[3] Data-Over-Cable Service Interface Specifications DOCSIS® 3.1 Converged Cable Access Platform Operations Support System Interface Specification (CM-SP-CCAP-OSSIv3.1-I26-230613); Cable Television Laboratories

[4] "Pre-equalization based Pro-active Network Maintenance Methodology", SCTE Cable Tec Expo 2008 by Alberto Campos, Eduardo Cardona, and Lakshmi Raman (June 2008, Philadelphia, Pennsylvania)

[5] PNM Current methods and Practices in HFC Networks (DOCSIS® 3.1) CM-GL-PNMP-V04-230213, February 13, 2023, Cable Television Laboratories, Inc.

[6] Data-Over-Cable Service Interface Specifications DOCSIS® 3.1 MAC and Upper Layer Protocols Interface Specification (CM-SP-MULPIv3.1-I25-230419); Cable Television Laboratories

[7] "OFDMA Predistortion Coefficient and OFDM Channel Estimation Decoding and Analysis" SCTE Cable Tec Expo 2021 by Tom Williams, Alberto Campos, Lin Cheng, James Lin, Jason Rupe, and Jay Zhu (October 2021, Atlanta, Georgia)

[8] "Microwave Engineering" by David Pozar, (2011 Edition Chapter 4), Wiley and Sons, ISBN-13 978-0470631553

[9] "When Physical Layer Simulation Gets Real" SCTE Cable Tec Expo 2022 by Ramya Narayanaswamy, Karthik Subramanya, Dr. Richard Prodan & Larry Wolcott (October 2022, Philadelphia Pennsylvania)

[10] "Cable Network Management Infrastructure Evolution", L. Alberto Campos, Jennifer Andreoli-Fang, Vivek Ganti, NCTA 2014 (May 1 2014, Los Angeles California)

Appendix A

RF Network Elements

Abbreviated – full name (description/comments)

Attributes

SPLC – RF Distribution Splice (Connects coaxial segments together)

Diameter

Insertion Loss (dB) / Insertion Loss vs. Frequency

SP – RF Distribution Splitter (Splits/Combines RF energy from one port to two ports, sometimes 3 ports)

Number of Ports

Nominal Loss Value (dB)

Loss vs. Frequency

DC – RF Directional Coupler (Single port RF Coupler, Taps RF energy from main path to secondary path)

Value (dB)

Type

Coupling Loss vs. Frequency

TAP – RF Distribution Tap (Multiport RF Coupler, Taps RF energy from main path to drop ports)

Nominal Value (dB)

Number of Ports

Type ()

Insertion Loss vs. Frequency

Coupling Loss vs. Frequency

Term – Termination (End of line device to avoid reflections, terminates coaxial path)

Coax Cable (a.k.a Hardline) (Rigid coaxial transmission line carrying RF energy and AC power)

Length

Type – (e.g., 715QR, 540QR, 500P3)

Diameter

Velocity of Propagation

Atten vs. Frequency

AMP – Amplifier (Amplifies signal to compensate attenuation in cable and devices)

Housing

Number of Ports

Port(i)

Lo/Md/Hi Power

Gain vs. Freq

FN – Fiber Node (Converts optical signal to RF signal, typical multiple RF ports)

Number of RF Ports

Port(i)

Lo/Md/Hi Power

Power vs. Freq

EQ – External Equalizer (compensates for cable's higher losses at higher frequencies, typically after traversing some coaxial cable distance)

Value (dB)

Max Freq

Drop – Coaxial Drop Cable (flexible coaxial cable that extends from the tap drop port to the premise/home point of entry)

Length

Type –Series 6, Series 11

Diameter

Velocity of Propagation

Atten vs. Frequency

PI – Power Inserter (Inserts AC power into coaxial hardline cable to power fiber node amplifiers and other devices)

Home AMP – Drop Amplifier

Home Splitter –

DOCSIS Network Elements

CMTS

Type (Integrated, RMD, RPD)

Configuration

CM

Model, Silicon, Version

Facility Elements

Pedestal

Pole

Cabinet

Splice box

Power Supply

Hub

Appendix B

MIND PNM & DOCSIS MIBs

PNM

docsPnmCmUsPreEq
docsPnmCmUsPreEqPreEqCoAdjStatus
docsPnmCmOfdmChanEst
docsPnmCmDsOfdmRxMer`
docsPnmCmDsOfdmSym
docsPnmCmDsOfdmSymTrigGroupId
docsPnmCmDsOfdmSymPlcExtTimestamp
docsPnmCmDsOfdmSymFftLength
docsPnmCmDsOfdmFec
docsPnmCmDsOfdmFecSumType
docsPnmCmDsHist
docsPnmCmDsHistSymmetry
docsPnmCmDsHistDwellCnts
docsPnmCmDsHistHitCnts
docsPnmCmDsHistCntStartTime
docsPnmCmDsHistCntEndTime
docsPnmCmtsDsOfdmSym
docsPnmCmtsDsOfdmSymTrigGroupId
docsPnmCmtsDsOfdmSymFirstActSubCarIdx
docsPnmCmtsDsOfdmSymLastActSubCarIdx
docsPnmCmtsDsOfdmSymPlcExtTimestamp
docsPnmCmtsDsOfdmSymFftLength
docsPnmCmtsUsOfdmaAQProbe
docsPnmCmtsUsOfdmaAQProbeCmMacAddr
docsPnmCmtsUsOfdmaAQProbeUseIdleSid
docsPnmCmtsUsOfdmaAQProbePreEqOn
docsPnmCmtsUsOfdmaAQProbeTimeout
docsPnmCmtsUsOfdmaAQProbeNumSymToCapt
docsPnmCmtsUsOfdmaAQProbeMaxCaptSymbols
docsPnmCmtsUsOfdmaAQProbeNumSamples
docsPnmCmtsUsOfdmaAQProbeTimeStamp
docsPnmCmtsUsHist
docsPnmCmtsUsHistSymmetry
docsPnmCmtsUsHistDwellCnts
docsPnmCmtsUsHistHitCnts
docsPnmCmtsUsHistCntStartTime
docsPnmCmtsUsHistCntEndTime
docsPnmCmtsUsOfdmaRxMer
docsPnmCmtsUsOfdmaRxMerCmMac
docsPnmCmtsUsOfdmaRxMerPreEq
docsPnmCmtsUsOfdmaRxMerNumAvgs

CM

docsIf3CmSpectrumAnalysisMeasFrequency
docsIf3CmSpectrumAnalysisMeasAmplitudeData
docsIf31CmDsOfdmProfileStatsProfileId
docsIf31CmDsOfdmProfileStatsTotalCodewords
docsIf31CmDsOfdmProfileStatsCorrectedCodewords
docsIf31CmDsOfdmProfileStatsUncorrectableCodewords
docsIf31CmDsOfdmChannelBandIndex
docsIf31CmDsOfdmChannelPowerCenterFrequency
docsIf31CmDsOfdmChannelPowerRxPower
docsIf31CmUsOfdmaChanTxPower
docsIf31CmUsOfdmaChanSubcarrierZeroFreq
docsIf31CmUsOfdmaChanFirstActiveSubcarrierNum
docsIf31CmUsOfdmaChanLastActiveSubcarrierNum
docsIf31CmUsOfdmaChanNumActiveSubcarriers
docsIf31CmUsOfdmaChanSubcarrierSpacing
docsIf31CmUsOfdmaChanCyclicPrefix
docsIf31CmUsOfdmaChanRollOffPeriod
docsIf31CmUsOfdmaChanNumSymbolsPerFrame
docsIf31CmUsOfdmaMinislotCfgStateStartMinislotNum
docsIf31CmUsOfdmaMinislotCfgStateFirstSubcarrierId
docsIf31CmUsOfdmaMinislotCfgStateNumConsecutiveMinislots
docsIf31CmUsOfdmaMinislotCfgStateMinislotPilotPattern
docsIf31CmUsOfdmaMinislotCfgStateDataSymbolModulation
docsIf31RxChStatusPrimaryDsIndicator
docsIf31CmDsOfdmChanChannelId
docsIf31CmDsOfdmChanPlcFreq
docsIf31CmDsOfdmChanNumPilots
docsIf31CmDsOfdmChanTimeInterleaverDepth
docsIf31CmDsOfdmChanPlcTotalCodewords
docsIf31CmDsOfdmChanPlcUnreliableCodewords
docsIf31CmDsOfdmChanNcpTotalFields
docsIf31CmDsOfdmChanNcpFieldCrcFailures
docsIf31CmDsOfdmChanChanIndicator
docsIf31CmDsOfdmChanSubcarrierZeroFreq
docsIf31CmDsOfdmChanFirstActiveSubcarrierNum
docsIf31CmDsOfdmChanLastActiveSubcarrierNum
docsIf31CmDsOfdmChanNumActiveSubcarriers
docsIf31CmDsOfdmChanSubcarrierSpacing
docsIf31CmDsOfdmChanCyclicPrefix
docsIf31CmDsOfdmChanRollOffPeriod

CMTS

docsIfCmtsCmStatusMacAddress
docsIfCmtsCmStatusIpAddress
docsIfCmtsCmStatusInetAddress
docsIfCmtsCmStatusDownChannelIfIndex
docsIfCmtsCmStatusHighResolutionTimingOffset
docsIfCmtsCmStatusTimingOffset
docsIf3CmtsCmUsStatusChIfIndex
docsIf3CmtsCmUsStatusHighResolutionTimingOffset
docsIf3CmtsCmUsStatusIsMuted
docsIf3CmtsCmUsStatusRangingStatus
docsIf3CmtsCmUsStatusModulationType
docsIf3CmtsCmUsStatusRxPower
docsIf3CmtsCmUsStatusSignalNoise
docsIf3CmtsCmUsStatusMicroreflections
docsIf3CmtsCmUsStatusEqData
docsIf3CmtsCmUsStatusUnerroreds
docsIf3CmtsCmUsStatusCorrecteds
docsIf3CmtsCmUsStatusUncorrectables
docsIf31CmtsDsOfdmChanChannelId
docsIf31CmtsDsOfdmChanNumActiveSubcarriers
docsIf31CmtsDsOfdmChanSubcarrierSpacing
docsIf31CmtsDsOfdmChanLowerGuardbandWidth
docsIf31CmtsDsOfdmChanUpperGuardbandWidth
docsIf31CmtsDsOfdmChanCyclicPrefix
docsIf31CmtsDsOfdmChanRollOffPeriod
docsIf31CmtsDsOfdmChanTimeInterleaverDepth
docsIf31CmtsDsOfdmChanNumPilots
docsIf31CmtsDsOfdmChanPilotScaleFactor
docsIf31CmtsDsOfdmChanNcpModulation
docsIf31CmtsDsOfdmChanLowerBdryFreq
docsIf31CmtsDsOfdmChanUtilization
docsIf31CmtsDsOfdmChanUpperBdryFreq
docsIf31CmtsDsOfdmChanLowerBdryEncompSpectrum
docsIf31CmtsDsOfdmChanUpperBdryEncompSpectrum
docsIf31CmtsDsOfdmChanPlcFreq
docsIf31CmtsDsOfdmChanSubcarrierZeroFreq
docsIf31CmtsDsOfdmChanFirstActiveSubcarrierNum
docsIf31CmtsDsOfdmChanLastActiveSubcarrierNum
docsIf31CmtsDsOfdmSubcarrierStatusStartId
docsIf31CmtsDsOfdmSubcarrierStatusEndId
docsIf31CmtsDsOfdmSubcarrierStatusModulation
docsIf31CmtsDsOfdmChanPowerBandIndex
docsIf31CmtsDsOfdmChanPowerCenterFrequency
docsIf31CmtsDsOfdmChanPowerTxPower
docsIf31CmtsUsOfdmaChanTemplateIndex
docsIf31CmtsUsOfdmaChanPreEqEnable
docsIf31CmtsUsOfdmaChanFineRngGuardband
docsIf31CmtsUsOfdmaChanFineRngNumSubcarriers
docsIf31CmtsUsOfdmaChanFineRngPreambleLen
docsIf31CmtsUsOfdmaChanInitRngGuardband
docsIf31CmtsUsOfdmaChanInitRngNumSubcarriers
docsIf31CmtsUsOfdmaChanInitRngPreambleLen
docsIf31CmtsUsOfdmaChanProvAttribMask
docsIf31CmtsUsOfdmaChanTxBackoffStart
docsIf31CmtsUsOfdmaChanTxBackoffEnd
docsIf31CmtsUsOfdmaChanConfigChangeCt
docsIf31CmtsUsOfdmaChanRangingBackoffStart
docsIf31CmtsUsOfdmaChanRangingBackoffEnd
docsIf31CmtsUsOfdmaChanUtilization
docsIf31CmtsUsOfdmaChanId
docsIf31CmtsUsOfdmaChanTargetRxPower
docsIf31CmtsUsOfdmaChanLowerBdryFreq
docsIf31CmtsUsOfdmaChanUpperBdryFreq
docsIf31CmtsUsOfdmaChanSubcarrierSpacing
docsIf31CmtsUsOfdmaChanCyclicPrefix
docsIf31CmtsUsOfdmaChanNumSymbolsPerFrame
docsIf31CmtsUsOfdmaChanRollOffPeriod
docsIf31CmtsUsOfdmaDataIucStatsDataIuc
docsIf31CmtsUsOfdmaDataIucStatsMinislotPilotPattern
docsIf31CmtsUsOfdmaDataIucStatsMinislotModulation
docsIf31CmtsUsOfdmaDataIucStatsTotalCodewords
docsIf31CmtsUsOfdmaDataIucStatsCorrectedCodewords
docsIf31CmtsUsOfdmaDataIucStatsUnreliableCodewords
docsIf31CmtsUsOfdmaDataIucStatsInOctets
docsIf31CmtsUsOfdmaDataIucStatsCtrDiscontinuityTime
docsIf31CmtsUsOfdmaDataIucDetailStatusLowerFreq
docsIf31CmtsUsOfdmaDataIucDetailStatusUpperFreq
docsIf31CmtsUsOfdmaDataIucDetailStatusMinislotPilotPattern
docsIf31CmtsUsOfdmaDataIucDetailStatusMinislotModulation
docsIf31CmtsUsOfdmaRangingIucStatusIuc
docsIf31CmtsUsOfdmaRangingIucStatusGuardband
docsIf31CmtsUsOfdmaRangingIucStatusNumSubcarriers
docsIf31CmtsDsOfdmSubcarrierTypeStartSubcarrierId
docsIf31CmtsDsOfdmSubcarrierTypeEndSubcarrierId
docsIf31CmtsDsOfdmSubcarrierTypeSubcarrierType

CMTS cont'd

docsIf31CmtsUsOfdmaSubcarrierTypeStartSubcarrierId
docsIf31CmtsUsOfdmaSubcarrierTypeEndSubcarrierId
docsIf31CmtsUsOfdmaSubcarrierTypeSubcarrierType
docsIf31CmtsCmRegStatusAssignedEmIds
docsIf31CmtsCmRegStatusPartialChanState
docsIf31CmtsCmRegStatusDsProfileIdList
docsIf31CmtsCmRegStatusUsProfileIucList
docsIf31CmtsCmRegStatusTcsPhigh
docsIf31CmtsCmRegStatusTcsDrwTop
docsIf31CmtsCmRegStatusMinUsableDsFreq
docsIf31CmtsCmRegStatusMaxUsableDsFreq
docsIf31CmtsCmRegStatusMaxUsableUsFreq
docsIf31CmtsCmRegStatusPartialSvcState
docsIf31CmtsCmUsOfdmaChannelRxPower
docsIf31CmtsCmUsOfdmaChannelRangingStatus
docsIf31CmtsCmUsOfdmaChannelCurPartialSvcReasonCode
docsIf31CmtsCmUsOfdmaChannelLastPartialSvcTime
docsIf31CmtsCmUsOfdmaChannelLastPartialSvcReasonCode
docsIf31CmtsCmUsOfdmaChannelNumPartialSvcIncidents
docsIf31CmtsCmUsOfdmaChannelNumPartialChanIncidents
docsIf31CmtsCmUsOfdmaChannelMeanRxMer
docsIf31CmtsCmUsOfdmaChannelStdDevRxMer
docsIf31CmtsCmUsOfdmaChannelRxMerThreshold
docsIf31CmtsCmUsOfdmaChannelThresholdRxMerValue
docsIf31CmtsCmUsOfdmaChannelThresholdRxMerHighestFreq
docsIf31CmtsCmUsOfdmaChannelMicroreflections
docsIf31CmtsCmUsOfdmaChannelHighResolutionTimingOffset
docsIf31CmtsCmUsOfdmaChannelIsMuted
docsIf31CmtsCmUsOfdmaProfileTotalCodewords
docsIf31CmtsCmUsOfdmaProfileCorrectedCodewords
docsIf31CmtsCmUsOfdmaProfileUnreliableCodewords
docsIf31CmtsCmUsOfdmaProfileLastPartialChanTime
docsIf31CmtsCmUsOfdmaProfileLastPartialChanReasonCode
docsIf31CmtsCmUsOfdmaProfilePartialChanReasonCode
docsIf31CmtsCmDsOfdmChannelCurPartialSvcReasonCode
docsIf31CmtsCmDsOfdmChannelLastPartialSvcTime
docsIf31CmtsCmDsOfdmChannelLastPartialSvcReasonCode
docsIf31CmtsCmDsOfdmChannelNumPartialSvcIncidents
docsIf31CmtsCmDsOfdmChannelNumPartialChanIncidents
docsIf31CmtsCmDsOfdmProfilePartialChanReasonCode
docsIf31CmtsCmDsOfdmProfileLastPartialChanTime
docsIf31CmtsCmDsOfdmProfileLastPartialChanReasonCode

Appendix C

S-parameters and T-parameters

Using S-parameter definitions, a multiport network can be expressed in terms of the incident voltage waves and the outgoing or reflected voltage waves. A two port S-parameter network has an incident wave a_1 and an outgoing or reflected wave b_1 on port 1 and an incident wave a_2 and an outgoing or reflected wave b_2 on port 2 (Figure Y)

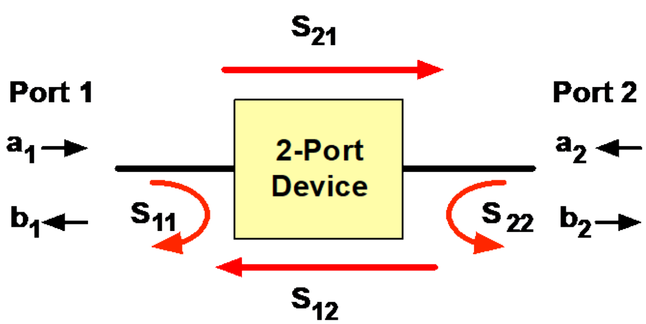


Figure Y - Two-port scattering or S-parameters defined by incident and reflected or outgoing waves.

The ratio of the reflected wave on port 1 and the incident wave on port 2 when there is no incident wave on port 2 is S_{11} parameter

$$S_{11} = \left.\frac{b_1}{a_1}\right|_{a_2=0}$$

The ratio of the outgoing wave on port 2 and the incident wave on port 1 when there is no incident wave on port 2 is S_{21} parameter

$$S_{21} = \left.\frac{b_2}{a_1}\right|_{a_2=0}$$

The ratio of the outgoing wave on port 1 and the incident wave on port 2 when there is no incident wave on port 1 is S_{12} parameter

$$S_{12} = \left.\frac{b_1}{a_2}\right|_{a_1=0}$$

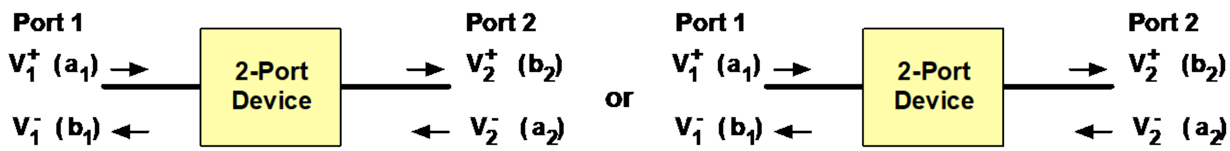
The ratio of the reflected wave on port 2 and the incident wave on port 2 when there is no incident wave on port 1 is S_{22} parameter

$$S_{22} = \left.\frac{b_2}{a_2}\right|_{a_1=0}$$

These S-parameters in matrix representation are described as:

$$\begin{vmatrix} b_1 \\ b_2 \end{vmatrix} = \begin{vmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{vmatrix} \cdot \begin{vmatrix} a_1 \\ a_2 \end{vmatrix} \qquad S_{11} = \frac{b_1}{a_1}\Big|_{a_2=0} \quad S_{21} = \frac{b_2}{a_1}\Big|_{a_2=0} \quad S_{12} = \frac{b_1}{a_2}\Big|_{a_1=0} \quad S_{22} = \frac{b_2}{a_2}\Big|_{a_1=0} \Rightarrow \begin{matrix}\text{2-Port}\\ \text{S-Parameter}\\ \text{Matrix}\end{matrix} = \begin{vmatrix} S_{11} & S_{21} \\ S_{12} & S_{22} \end{vmatrix}$$

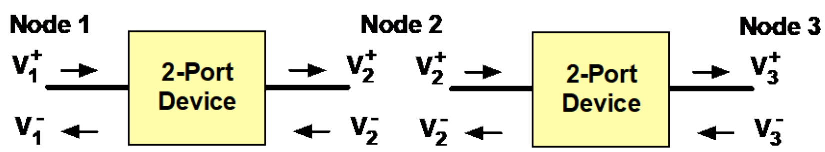
Also using incident and reflected or outgoing voltage waves, T-parameters are defined but is a slightly different fashion.



Where the + and – notation indicates the direction of the wave and leads to the following matrix representation

$$\begin{vmatrix} a_1 \\ b_1 \end{vmatrix} = \begin{vmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{vmatrix} \cdot \begin{vmatrix} b_2 \\ a_2 \end{vmatrix} \qquad \begin{vmatrix} V_1^+ \\ V_1^- \end{vmatrix} = \begin{vmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{vmatrix} \cdot \begin{vmatrix} V_2^+ \\ V_2^- \end{vmatrix}$$

The second matrix shows the usefulness in cascading elements to obtain the equivalent system representation



This way of defining T-parameters allows for representing systems comprised of cascading elements.

$$\begin{vmatrix} V_1^+ \\ V_1^- \end{vmatrix} = \begin{vmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{vmatrix} \cdot \begin{vmatrix} T_{22} & T_{23} \\ T_{32} & T_{33} \end{vmatrix} \cdot \begin{vmatrix} V_3^+ \\ V_3^- \end{vmatrix}$$

From the T-parameter definition we can obtain its relationship with S-parameters that are typically obtained from the individual characterization of network element.

$$T_{11} = \frac{-\det(S)}{S_{21}} \qquad T_{12} = \frac{S_{11}}{S_{21}}$$

$$T_{21} = \frac{-S_{22}}{S_{21}} \qquad T_{22} = \frac{1}{S_{21}} \qquad \det(S) = S_{11}\, S_{22} - S_{12}\, S_{12}$$

Providing us the flexibility to go back and forth between T- and S-parameters.