Chapter 6

Fine Tuning and Performance Evaluation of Frequency-Response Based Approach

6.1 Introduction

The frequency-response based iterative modeling of subscriber loop structures is an effective approach to the problem. This chapter addresses three enhancements to the procedure:

- Refinement of line types (Section 6.2),
- Selection of segments to refine (Section 6.3), and
- Reduction of candidate models (Sections 6.4 – 6.5).

The line type refinement is the re-examination of line types associated with already-detected loop nodes. The difference in node line types often produces only minor differences in the SSE when the node is recently detected and the remainder of the loop is still unclear. Therefore, there is a greater chance of misidentification of these line types in their first evaluation. To mitigate the risk of misidentification, ambiguous line types are tested in subsequent iterations.

On the other hand, the identification process is already designed to refine all the finite length segments due to their dependent nature. Also, such multi segment length refinement is made possible by the quasi-Newton algorithm, which is defined for multidimensional case. However, the dependence between segments lengths is high only if their corresponding nodes are close. Consequently, near-end segments may reach their "practical convergence" before all the far-end segments are identified. Hence, some segment lengths can be excluded from the refinement process. Such exclusion improves the convergence speed of the quasi-Newton algorithm.

Another way to achieve more efficiency is to reduce the number of candidate models used in each iteration. A reduction in the number of candidates to be considered is achieved by

- Separation of node and TP line type estimations (Section 6.4), and
- Rejection of node types based on *a priori* knowledge (Section 6.5).

Lastly, the performance of the frequency-response approach is evaluated against the DSL industry's test loops that are listed in Appendix A (Section 6.6).

6.2 Line Type Refinement

Often the candidates with the same node type and different line types possess similar SSEs. Although, in most cases, the candidate with the correct line type configuration claims the minimum SSE, the difference between the selected (minimum SSE) and not selected candidates, in terms of SSE, is sometimes minimal. The latter leads to reduced confidence, and a greater probability of misidentification, especially if at least one of the estimated segments is short (< 300 m). A single wrong line type estimate may cause havoc in subsequent iterations.

To improve the confidence level of ambiguous line type estimates, and to reduce the risk of misidentification, these estimated line types that are considered *not-confident* can be re-examined in the subsequent iteration when an additional node is estimated and added to the model. Moreover, the reevaluation of the line type estimate may be repeated until the estimates are deemed *confident*. The confidence level is based on the relative SSE (RSSE) defined for the *j*-th candidate as

$$RSSE_j = \frac{SSE_j}{SSE_{\min}} \tag{6-1}$$

The estimates are said to be *confident* if RSSEs of the best candidate with respect to the rest of the candidates are above threshold η_{GI} (currently, $\eta_{GI} = 2$). If the line type estimates are found to be *not-confident*, they would be reevaluated in the next iteration. In addition, if the reevaluation results in modifying the line types, all the subsequent segments' line types must be reevaluated as well.

6.3 Refining Segment Length Selection

Another issue is to determine which segments to optimize for their length. Minimization of the SSE with respect to all the finite model segment lengths yields the most desirable and most accurate estimates. This approach is implied in Section 5.6. Practically speaking, such a global optimization — on a consistent basis — is both computationally expensive and redundant, especially with the existence of a long segment. The reflections from nodes that are far away (> 1.5 km) from the segment to be optimized produce very small contributions. Consequently, if all near-end nodes are identified, very accurate length estimates (< 10^{-4} m error) are already obtained without locating any of the far-end nodes. In other words, if convergence of near-end segment lengths to their optimal length has already occurred when a far-end segment is identified, only the new segment length requires optimization.

This observation can be implemented with a segment selection criterion based on the path length of nodes. The new node — and its associated leading segment — and its proximate nodes, those within a radius of 1,500 m; hereby defined as a cluster, are refined together. The cluster is defined in the sense of distance from the measurement node, which does not necessarily equate to actual physical proximity of the nodes in the cluster. For example, consider the network illustrated in Figure 6-1; the cluster contains nodes that are physically close (Nodes 2 and 3) as well as the bridged tap node (Node 1) which is physically far away from Nodes 2 and 3. However, their path distance from the measurement node is similar to that of the others, and as a result Node 2 is clustered with Nodes 3 and 4.

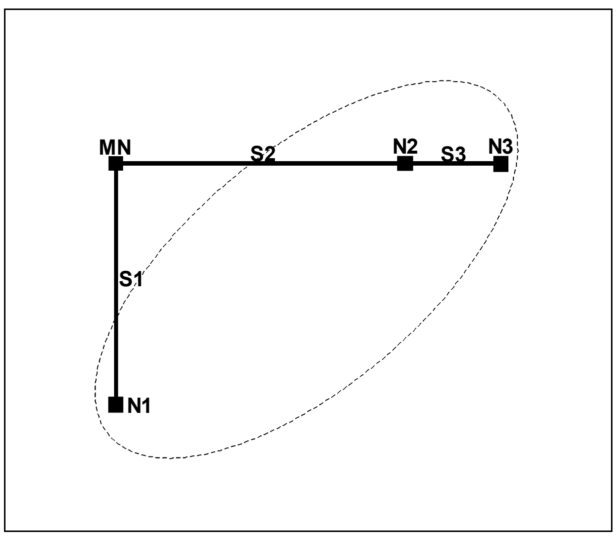

Figure 6-1: Example for node clustering. Dashed ellipse shows the cluster.

6.4 Separate Estimation of Node and TP Line Types

In the frequency-response based loop identification approach, most of the computational burden is associated with the candidate generation-refinement-selection process. Even with our assumption of three line types (22, 24, and 26 AWGs), placing a new node requires consideration of nine (on an infinitely long segment) or eleven (on a finite length segment) candidate models. With each candidate evaluation involving quasi-Newton optimization — the most time-consuming process — a reduction in the number of candidate models to be considered can result in a significant improvement in overall computational efficiency.

The first and more straightforward approach to reduce the number of candidates is to perform the selection process in two separate stages. The first stage is the node type estimation, followed by the line type estimation. The second stage candidates are based on the first stage estimate. Figure 6-2 illustrates the candidates to consider. The node type estimation requires three candidates, while the number of line type estimation candidates varies between 0 and 9. With this method, the total number of candidates varies from 3 to 10.

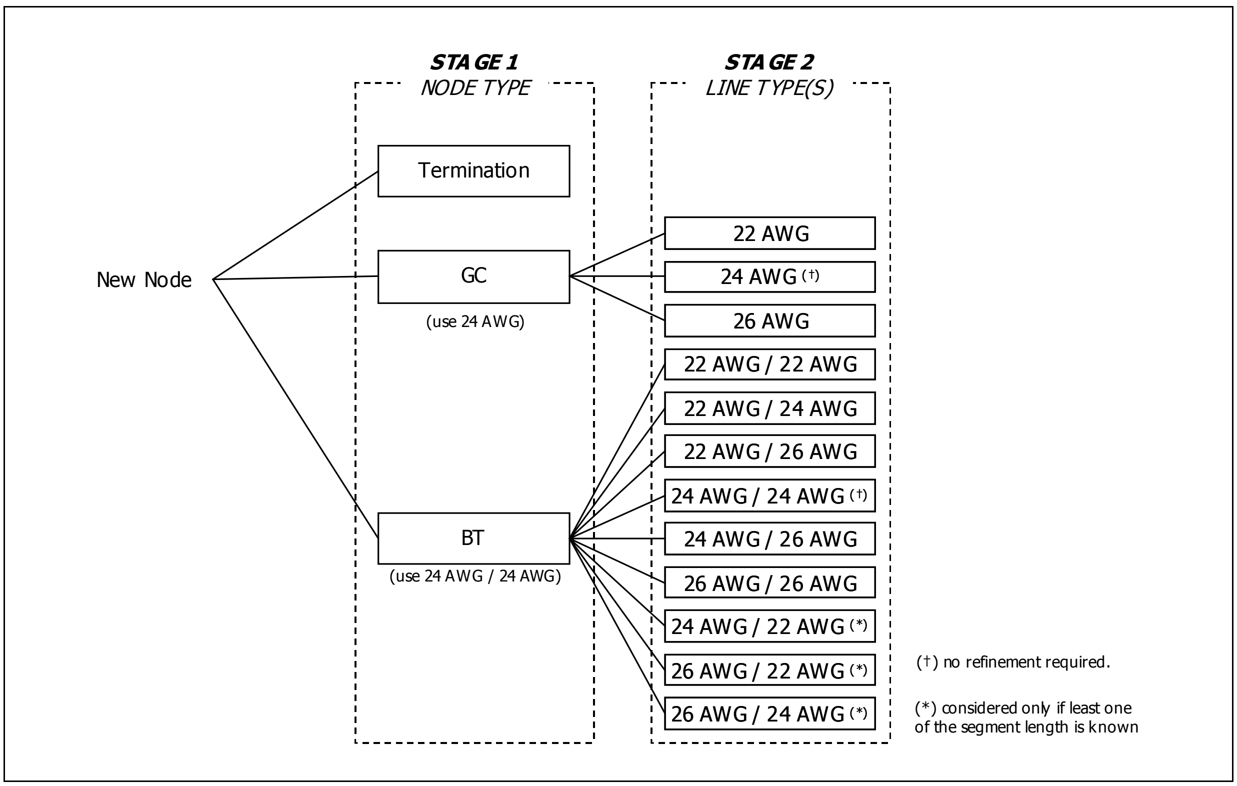

Figure 6-2: Two-step candidate selection process.

This method is facilitated by the greater variation in the reflection function $\Gamma(f)$ among node types than among line types, as readily shown in Figure 6-3. Note that this observed property may not hold true once other line types are introduced into the procedure, and careful examination is necessary when additional line types are considered.

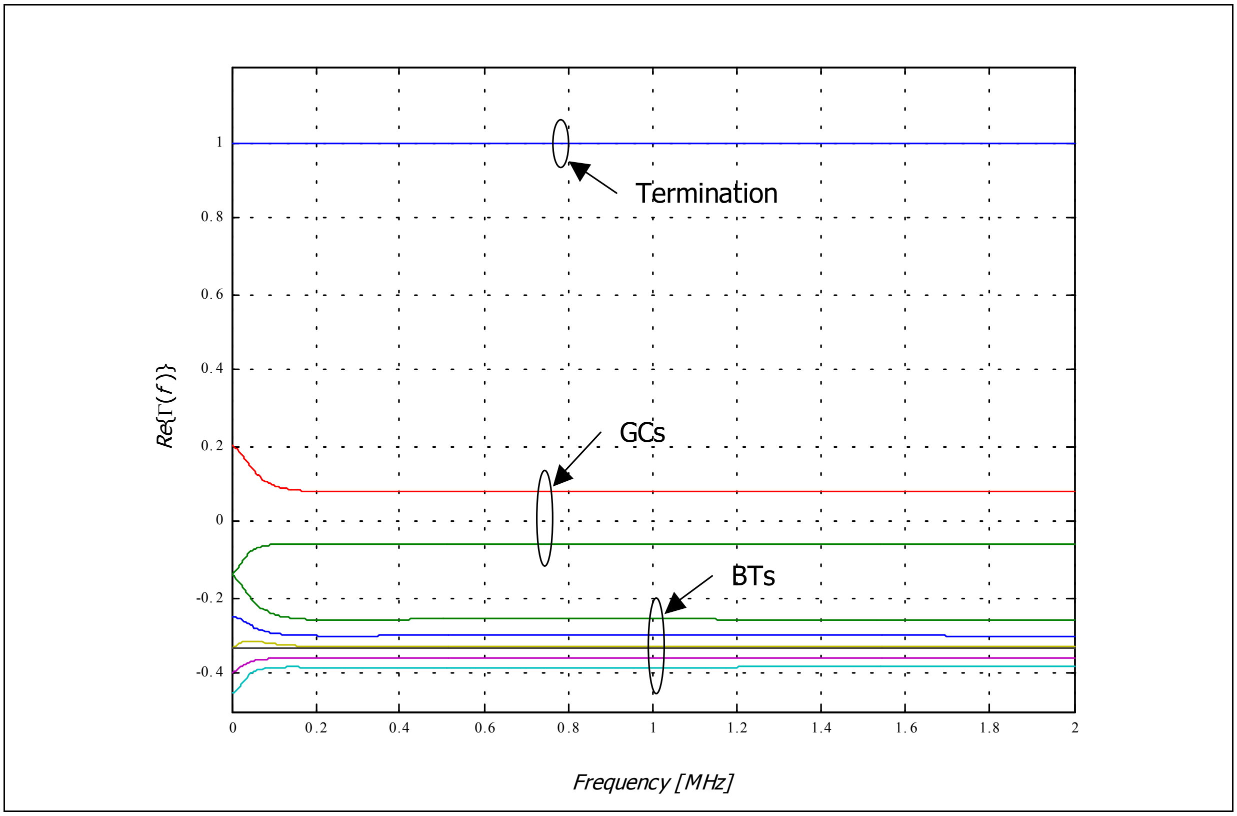

Figure 6-3: Typical $\Gamma(f)$ *of loop nodes.*

6.5 Node Type Rejection with *A Priori* Knowledge

Additional reduction of candidate models can be obtained when detecting a closer and weaker reflection after identification of a farther and stronger reflection. The strongest-reflection-first approach allows stronger reflections traveling farther along the loop path to be processed first, before weaker reflections from closer distances. Also, the reflection attenuates exponentially with respect to distance traveled.

The above observations lead to a hypothesis that in order to have a stronger reflection at farther distance than a node closer to the measurement node is that the reflection coefficient of the farther node is greater than of the closer node (i.e. enough larger to compensate for the attenuation loss). In other words, the only circumstance in which a later reflection can be stronger is by having two different node types approximately the same distance away from the measurement node with the closer one having weaker reflecting characteristics.

Based on the reflection coefficient comparison in Figure 6-3, the order of node types which results in greater energy is Termination, BT, and GC, in descending order of strength. Furthermore, Figure

6-4 illustrates the reflection frequency response from a node at the end of a 24-AWG 300-m segment followed by the node with one of three node types. About 10 dB differences in reflection strength between neighboring node types are observed.

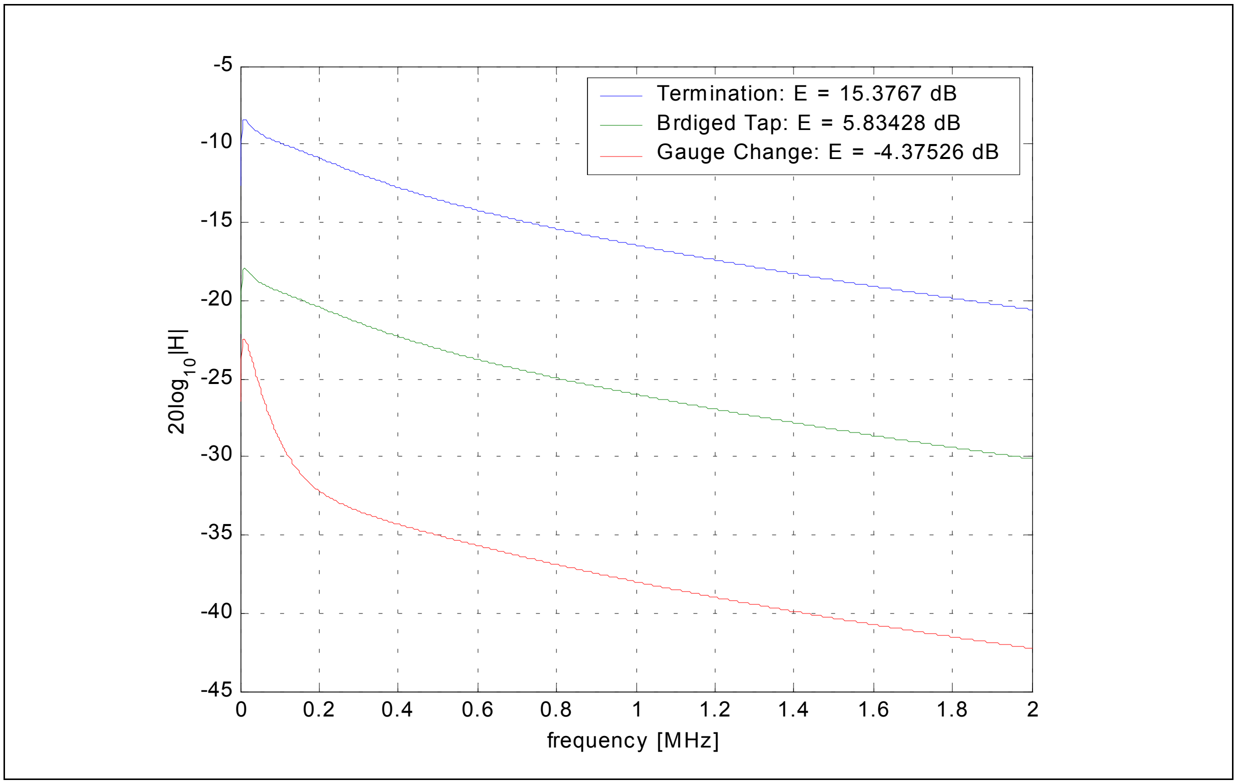

Figure 6-4: Reflection energy strength for all node types. Total energy levels are shown in the legend.

Furthermore, the total energy levels as a function of length are shown in Figure 6-5 for the three node types. As indicated with the dashed lines in the figure, the ~3,300 ft. (~1,005 m) termination and ~1,500 ft. (~457 m) GC configurations produce equivalent energy level reflections as the 2,500 ft. (762 m) BT configuration. The relationships remain the same for all energy levels. Also, a clear and consistent energy level hierarchy is evident (termination > BT > GC) for the same segment length. This observation leads to the following hypothesis: for a reflection energy level of a node with weaker node type to exceed that of another node with one-level stronger node type (*i.e.* BT to GC, or termination to BT), a path length of the former must be shorter than that of the latter by more than ~1,000 ft. (305 m).

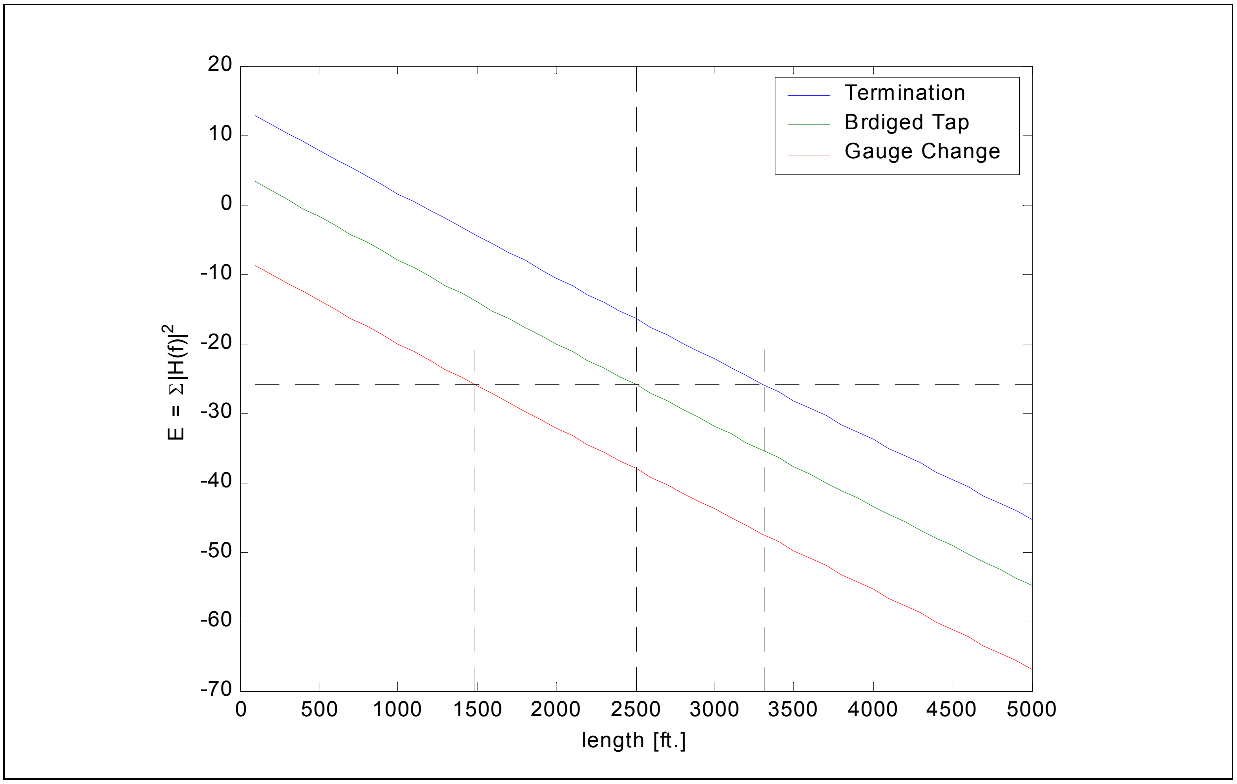

Figure 6-5: Energy level of reflections as a function of segment length for various node types. Dashed lines indicate segment lengths for different node types that produce same reflection strength level.

Based on the latter hypothesis, a simple rule is devised to reject unlikely node types from the candidates in case a new node's distance out from the measurement node is shorter than any of the existing model nodes' distances. Under such circumstances, Table 6-1 indicates which new node type may qualify as candidate node types.

Table 6-1: Possible (✓) and improbable (×) node type candidates based on a model node existing farther out than new node.

Farthest Node Type	Termination	Bridged Tap	Gauge Change
Figure 3.15 (a)	×	×	×
Figure 3.15 (b)	✓	×	×
Figure 3.15 (c)	✓	✓	×
Figure 5.5 (a)	✓	×	×
Figure 5.5 (b)	✓	✓	×

6.6 Performance Evaluation

To evaluate the effectiveness of the frequency-response based identification procedure (with fine-tuning), all the CSA and ANSI loops (Appendix A) are simulated and identified. The test setting consists of the source impedance of 120 Ω, and frequency responses are sampled between 1 MHz and 2 MHz with uniform 10 kHz spacing (total of 101 samples). All the loops are measured from Node 1 (CO side).

With simple two-step evaluation of either success or failure, Table 6-2 shows the result of the test. Currently 18 out of 25 loops (~70 %) are successfully identified. Success is defined here as correct identification of the loop topology, correct line type selection, and segment length estimation correct to within one foot. Correspondingly, the failure does not indicate that none of the loop segments is identified properly; the procedure has always found first several segments properly but failed toward the end of the loop. Studying the identification process for those failed loops suggests that there are three types of loop features, which cause the failures:

- Long segments (> 5 km)
- Short segments (< 30 m)
- Complex loop structure

Table 6-2: Identification of CSA & ANSI test loops based on the proposed frequency-response procedure. Measurement generated from Node 1 (CO node). Success (✓) and Failure (×).

Loop		Loop		Loop		Loop		Loop	
CSA #1	✓	CSA #6	✓	ANSI #1	✓	ANSI #6	×	ANSI #11	✓
CSA #2	✓	CSA #7	✓	ANSI #2	✓	ANSI #7	✓	ANSI #12	✓
CSA #3	×	CSA #8	✓	ANSI #3	×	ANSI #8	✓	ANSI #13	×
CSA #4	×	CSA #9	✓	ANSI #4	✓	ANSI #9	✓	ANSI #14	×
CSA #5	✓	CSA #10	✓	ANSI #5	✓	ANSI #10	×	ANSI #15	✓

If a loop contains long segment followed by a network of short segments, the reflection frequency responses of those far-end nodes becomes small; sometimes small enough to reach the computational limitation which caused the failures on such loops as ANSI #6 and #10 loops. While the problem may be corrected with the use of a computer with even higher word length under noiseless assumption, in practical cases, the true limitation would be caused by the noise in the measurement.

On the other hand, if a loop contains very short segment, the MODE-type algorithm often fails to separate the reflections returning from the segment's end nodes (CSA #3). If the two reflection frequency responses are closer to each other than the resolution of the MODE-type algorithm, the corresponding nodes are essentially indistinguishable by the identification procedure; consequently, the error caused by modeling two nodes with one causes the subsequent identification to derail.

Finally, the highly perplexing loops such as ANSI #3 and ANSI #14 (also CSA #4 to the lesser extent) also cause the similar problem as the above short segment problem with temporal closeness. Also, the complex loops introduce more possibility for the new node placement which often increases the chance of misplacement.

6.7 Summary

This chapter presented several fine-tuning features that can be applied to the frequency response approach originally presented in Chapter 5. These are primarily advanced to improve the computational efficiency of the algorithm. The exception is the idea of the line type refinement (Section 6.2). Varying the line types often results in only minor frequency-response differences and hence *not-confident* determination of the line type without knowing additional loop features. Confidence in line type identification is improved by defining a confidence level for an identified line type, and later reevaluation if estimated line types had been deemed *not-confident*.

The remaining enhancements addressed in this chapter reduce the frequency of use of the quasi-Newton algorithm for length optimization; three methods are suggested. The first is local length optimization; only optimize the segments that are local to the new node. The other two methods reduce the number of candidate models to optimize over. The second method is the separation of the node type and line type estimations. The node type causes much greater deviation in the frequency-response than the line type; hence the node type can be estimated before the line types. The last approach suggests a reduction in the number of candidates to be considered for a new node for which the distance out is shorter than the farthest node. The reflection behavior reveals when such a case occurs, and the candidate models can be limited accordingly.

With the above enhancement, the frequency-response based algorithm is evaluated with the CSA and ANSI test loops for its effectiveness. It has successfully identified about 70 % of these loops. The further study of those failed has shown that three loop features often are the causes for the misidentification.