COMPUTER BASED METHODS FOR PRODUCTION TUNING OF MICROWAVE COMPONENTS

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Abstract

Three multivariate discrimination methods are applied as computer based tuning algorithms during the manufacture of over 9000 C-band power amplifiers. The three methods are parametric, nearest neighbor, and Monte Carlo discrimination. The nearest neighbor and Monte Carlo algorithms are found to be the most useful for tuning microwave components. Monte Carlo discrimination is judged to be the best method.
Application of the nearest neighbor and Monte Carlo methods improved the rate of successfully reclaiming initially failing parts from 51% to 82% when compared with manual tuning techniques.

I. Introduction

Production tuning of microwave components is often necessary to meet performance specifications and increase yields. Traditionally, tuning is done manually by experienced technicians using a single pass or iterative process of measurement and adjustment. Such approaches have several drawbacks — time consuming, labor intensive, operator dependent results, experience difficult to transfer. Computer based analyses are preferable because they overcome these problems. In single pass tuning situations, computer based methods provide a higher rate of correct selections and require less evaluation time. In both iterative and single pass situations, computer based methods simultaneously assimilate many measured component responses better than human operators.

Three single pass algorithms used during the manufacture of a high power C band amplifier are presented. The algorithms arise from a field of multivariate statistics known as discriminant analysis. Discriminant methods assign an individual, part, or some other entity to one of several known groups using measurements of the entity. The techniques are particularly useful for tuning electronic parts because only measurements from the parts are needed. No detailed simulation model is required. Since measurements are often taken to verify specification compliance, applying discriminant analysis to a broad range of microwave tuning problems is both feasible and quite straightforward.

II. Multivariate Discrimination

Three multivariate discriminant analyses were employed parametric discrimination [1,3], nearest neighbor discrimination [2,3], and Monte Carlo discrimination. The parametric and nearest neighbor techniques assign parts to one of several known groups based on measurements taken on both the part to be classified and previously classified parts. The Monte Carlo method estimates the probability of a given action having the desired outcome. Monte Carlo discrimination requires an action to take place. The other two methods do not. This distinction does not impact which data are need, but Monte Carlo does alleviate the problem of initially establishing the known groups.

Parametric discrimination assumes an underlying joint Gaussian distribution for each of the groups to which parts are classified. Using measured data from previously classified parts, the method then estimates the mean and covariance matrices for the Gaussian distributions associated with each group. The mean and covariance matrices are then used to determine the relative proximity of parts under consideration to the group means (or locations). The part is assigned to the closest group after taking into consideration the variance exhibited by the measured data. The method's strength is that only the estimated mean and covariance matrices need be retained; the raw data can be discarded. The assumption that the underlying distributions are Gaussian is the method's greatest weakness.

Nearest neighbor discrimination makes no assumptions about underlying distributions in the data. The method uses a fast multidimensional sort and search method [4] to locate the nearest neighbors for each part under consideration. The group memberships of the nearest neighbors then indicate the classification of the part in question. The diagram in Fig. 1 illustrates how nearest neighbor classification works for a 2-D problem. The strength of the method is that it is nonparametric (i.e., no assumptions about underlying distributions). Its weakness is that the raw data must be retained.

Monte Carlo discrimination, like the nearest neighbor method, makes no assumptions about underlying distributions in the data and also overcomes an inherit problem with both parametric and nearest neighbor discrimination. Both methods implicitly hold the location of the specification window (or acceptability region) in the grouping of previous parts. If the specifications change, then a bias towards the previous settings exists. Monte Carlo discrimination uses the performance shifts

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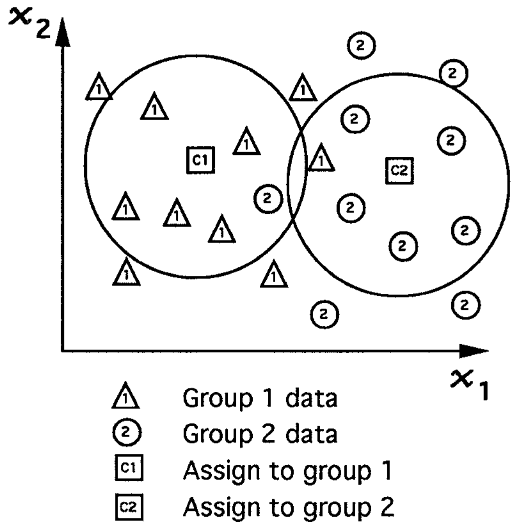

Fig. 1: Classification using the nearest neighbor method

arising from the various tuning treatments to estimate which, if any, of the treatments would be successful. The weakness of the method is that the raw data must be retained.

Monte Carlo discrimination is an application of classical multidimensional Monte Carlo integration [5,6]. The method integrates the probability density functions (PDFs) corresponding to a part's measured data summed with ensembles of tuning treatment performance shifts. These sums are samples from the PDFs of interest and, as such, can be used to do Monte Carlo integration over the specification window. An estimate for the probability of a treatment tuning the part into the specification window is simply a count of the points within the window divided by the total number of ensemble shifts applied. A graphical illustration of the concept is presented in Fig. 2

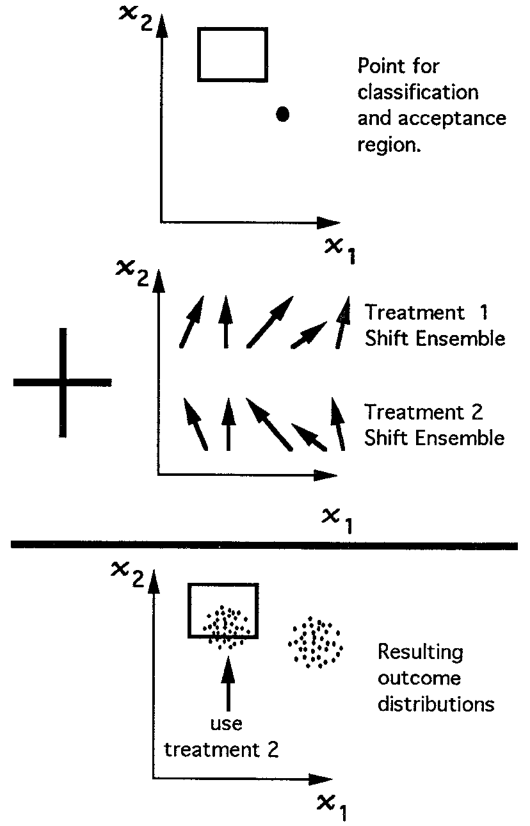

Fig. 2: Visualization of Monte Carlo discrimination

III. Application

The need for a computer based tuning algorithm arose from the assembly of over 9000 high power GaAs amplifiers. At the outset of the program, the final RF test yields were unacceptably low. Scraping the failing parts was undesirable because most of the manufacturing cost was already accrued. The problem was initially addressed by manually assessing which tuning stubs to autobond on the amplifier output tuning board. A drawing of the amplifier is given in Fig. 3.

Initially, experiments were conducted to correlate failing data patterns with successful tuning treatments. This activity required perusal of 70 element data matrices taken from failing parts. The matrices consist of 10 performance parameters measured at 7 C-band frequencies (see Table 1).

After the period of identifying effective tuning treatments, production technicians interpreted the data matrices on production parts and took the appropriate actions. Using this manual tuning method approximately 51% of the parts selected for tuning subsequently passed (i.e., 51% of the initially failing parts were correctly reclassified as good).

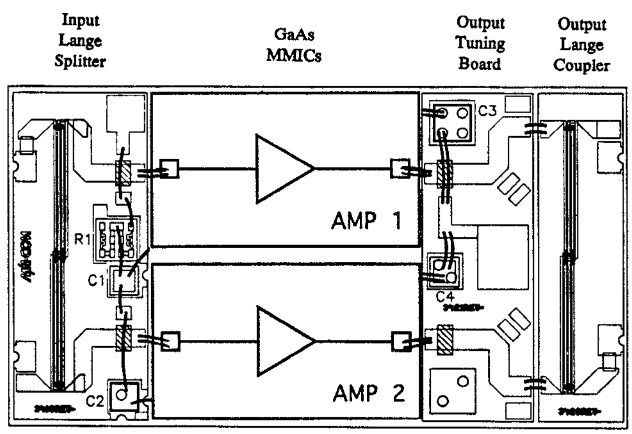

Fig 3: Schematic drawing of C-band high power amplifier showing input and output networks in detail

At this point, the parametric discrimination algorithm was introduced. The initial results were less than expected. The primary reason for these problems was that the underlying data distributions are not Gaussian. Inspection of data histograms indicated that many variables have skewed or multimodal distributions. Another problem is that very large numbers of data points are required to properly estimate the covariance matrices for high dimensional spaces.

$\lvert S_{11} \rvert$	$\partial \lvert P_{OUT} \rvert / \partial V_{DS}$ (P_{OUT} Pushing)
$\lvert P_{OUT} \rvert$	$\partial \phi_{OUT} / \partial V_{DS}$ (Output Phase Pushing)
Power Added Efficiency	$\partial \lvert P_{OUT} \rvert / \partial t$ (P_{OUT} Droop)
I_{DS}	$\partial \phi_{OUT} / \partial t$ (Output Phase Droop)
I_{GS}	Total $\Delta \lvert P_{OUT} \rvert$ over Pulse (Correction Factor)

Table 1: Performance parameters used by discriminators

The parametric discrimination algorithm was replaced with the nearest neighbor method, which ultimately rendered the bulwark of production tuning decisions. The algorithm provided productivity gains in several areas. First, technicians no longer had to interpret test reports, as a classification report was instead forwarded to autobonder operators. Also, the rate of correctly reclassifying parts as good (recoverable) increased from 51% to 82%. The rate of correctly classifying parts as bad (unrecoverable) however declined to an estimated 92% from some unknown but higher value.

The Monte Carlo method was applied to remedy the specification bias inherent in the nearest neighbor method and to finish out production. The method was initially used to revaluate a large number of previously failed parts relative to new specifications. Since the number of parts evaluated during production with the Monte Carlo method was small, no reliable production build data is available for success rates. However, during the reevaluation work, 79% of the retested parts passed the new specifications. The success rate for the algorithm may well be higher because of the nonzero probability that some failures resulted from additional handling. (The data used for the reevaluation was taken before the parts were stored.)

All of the algorithms used four classification groups — 3 bond treatments and unrecoverable. The bond pattern associated with each treatment are summarized in Table 2. Note that treatment #1 is the configuration under which the part is initially measured. Treatments 2 through 4 correspond to the recovery treatments.

Treatment	Description
1	No stubs activated with bonds
2	On both amps both bend stubs bonded
3	Output stubs on both amps
4	Both bend & output stubs on both amps

Table 2: Summary of bond treatment bonding patterns

The bond configuration most often chosen was treatment 3. Bond treatment 3 was most effective against output power and phase pushing failures at the high end of the band, f_6 (f_1 and f_7 are out of band and are not specified). Treatment 3 is also useful on phase droop and correction factor failures. In Fig. 4 marginal density scatterplots, albeit only 2-D, of the before and after performances resulting from application of bond treatment 3 is presented. Note that the density scatter plot does not show other bond treatment marginal data densities. To date, rendering density plots with clear separation in only two dimensions has proved elusive. Nonetheless, studying probabilities of success as computed by the Monte Carlo algorithm indicate separation. Other tests based on Gaussian statistics could be applied, but they are of dubious value given the data is known to be non-Gaussian.

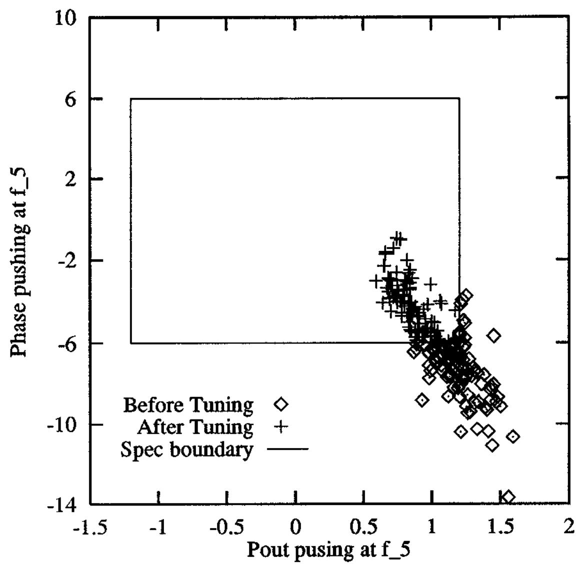

Fig. 4: Marginal density scatterplots showing transition across the specification boundary

An experimental study was undertaken to determine how each of the tuning treatments alters the electrical characteristics of the output tuning board. At this point, analysis of the data is qualitative. Further study requires deembedding of probe pad structures that were added on the amplifier side of the output board. Also, the leg attached to the output of Amp 2 is terminated in 50Ω to permit a two port measurement. Measurements were also done the Amp 1 leg terminated. The results are similar for both termination schemes.

S_{11} over the first through fourth harmonic bands is presented in Fig. 5. Examination of the data indicates that the tuning treatments have only a small effect over the fundamental frequency band. The major differences appear in the second through fourth harmonic bands. This situation indicates that considerable attention must be paid during the design phase to terminating the higher harmonic components.

IV. Conclusion

When program requirements and cost/benefit analyses mandate production tuning, computer based tuning algorithms can offer substantial productivity gains compared to manual tuning. The author applied three different tuning algorithms during the production of over 9000 GaAs high power amplifiers. Nearest neighbor and Monte Carlo discrimination proved adequate for production tuning. The Monte Carlo method is judged superior because it is nonparametric and handles specification changes gracefully.

Data is presented to show the bond treatments effect the electrical behavior of the output tuning network. The data indicates that differences in the network at higher harmonics account for improvements in the overall assembly's performance relative droop and pushing specifications.

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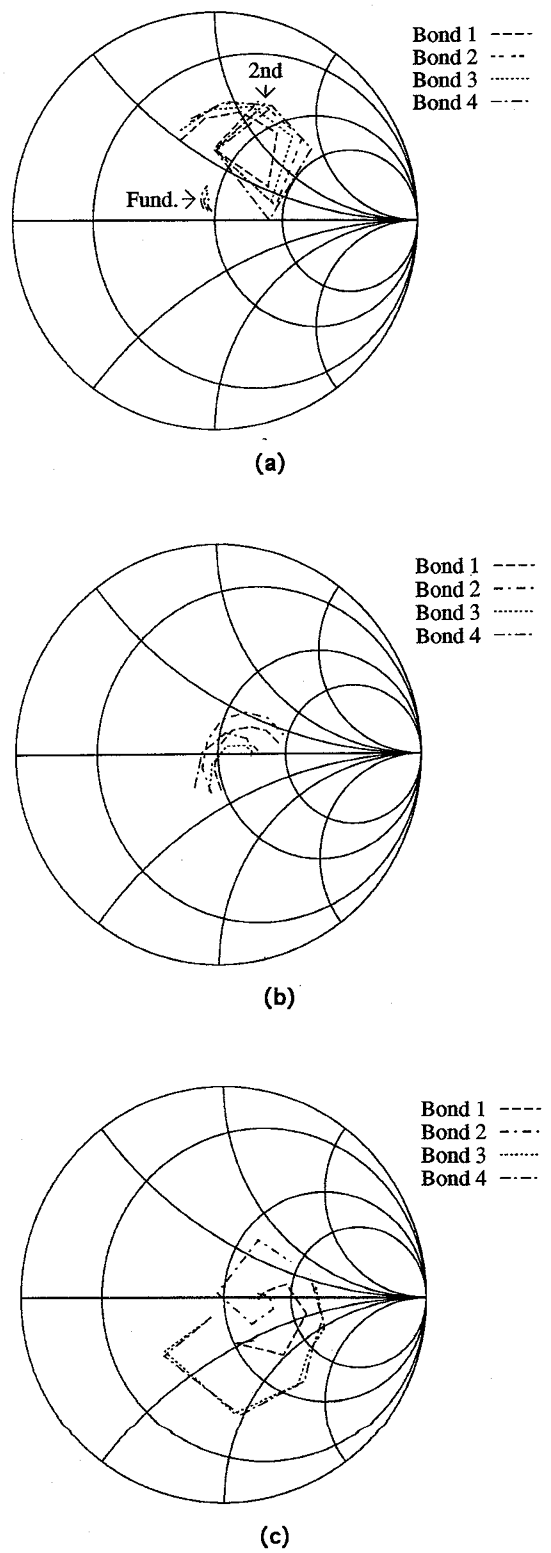

Fig. 5: S-parameter data for output network configured in each of the four tuning treatments. (a) gives first and second harmonic band data, (b) and (c) present the third and fourth harmonic data, respectively.