CASE 72

Exhaust Sensor Output Characterization Using the MTS

Abstract: The Mahalanobis–Taguchi system (MTS) evaluation described here considers the change in exhaust sensor signal performance resulting from an accelerated engine test environment. This study confirmed the feasibility and improved discrimination of the multivariable MTS approach to detect and quantify even small changes in signal output response. Future evaluations will increase the sample size and number of variables considered to verify the results. Implementation of this approach allows early detection of product performance shifts (enabling shortened testing), detailed evaluation of product design changes, and the potential to comprehend bias introduced by test conditions.

1. Introduction

Delphi Automotive Systems manufactures exhaust oxygen sensors for engine management feedback control. The stoichiometric switching sensor is located in the exhaust stream and reacts to rich and lean exhaust conditions. The sensor output signal (0 to 1 V) must maintain a consistent response throughout its life to ensure robust operation and allow tight engine calibrations that minimize tailpipe emissions.

Test Engineering at Delphi performs a variety of accelerated test schedules to expose the sensor realistically to representative vehicle conditions. Sensor performance measurements are conducted to monitor the sensor output characteristics throughout its life. Characterizing the sensor performance is often accomplished by recording and analyzing the sensor output voltage under a range of controlled exhaust conditions.

As emission control standards become more stringent and sensor technology improves to meet these demands, the testing community needs to improve its techniques to describe product performance accurately. The multivariable MTS evaluation presented here considers change in the stoichiometric exhaust oxygen sensor signal performance resulting from an accelerated test environment.

2. Sensor Aging Responses

The exhaust oxygen sensor is expected to perform in a high-temperature environment with exposures to water, road salt and dirt, engine vibration, and exhaust-borne contaminants with minimal change in performance from the manufacturing line to the end of vehicle life, which can exceed 150,000 miles. However, decreasing development cycles do not permit the accumulation of extensive vehicle mileage, so accelerated durability cycles have been developed in the test laboratory. These test schedules simulate the thermal, chemical, environmental, and mechanical demands that would be experienced on a vehicle.

A new sensor and an aged sensor will respond differently to these exposures based on product design combinations that include the electrodes,

 Taguchi's Quality Engineering Handbook. Genichi Taguchi, Subir Chowdhury and Yuin Wu

coatings, and package design selections. Test Engineering evaluates these design combinations by exposing the product to various accelerated durability tests and reports the sensor response. Figure 1 shows different sensor output responses after exposure to a few of these durability tests.

3. Sensor Performance Testing

Various methods exist to evaluate sensor performance, including electrical checks, flow bench tests using single or blended gases, and engine dynamometers. Engine dynamometers create a realistic exhaust gas stream as typical of a vehicle and with proper engine control can create a wide variety of stable engine running conditions.

One of the engine dynamometer performance tests is an open-loop perturbation test where the test sensor reacts to alternating rich and lean air/fuel mixtures about stoichiometry. These air/fuel ratio perturbations can be conducted at different frequencies and amplitudes and under different exhaust gas temperatures. From the simple output waveform, the measured signal is analyzed to derive more than 100 characteristics. The most descriptive characteristics were chosen for this preliminary evaluation. Figure 2 is a schematic of the system considered. The data used to support this analysis were available from previous traditional studies.

4. Experiment

Traditional methods of sensor performance analyses consider key characteristics of interest to customers and ensure that product specifications are met. Product development teams, however, want to understand not just time to failure but also the initiation and rate of signal degradation. Sensor output characteristics must indicate this response change over time.

The goals of this evaluation were to determine whether discrimination among aged test samples could be achieved, whether the analysis could comprehend both product and test setup variations, and whether it would provide a tool capable of detecting early sensor signal change. The MTS method used here generates a numerical comparison of a reference group to an alternative group to detect levels of abnormality. The method also identifies the key factors associated with these differences.

Definition of Groups

This evaluation was based on sensors with differing levels of aging. Twenty-six oxygen sensors were chosen as the reference (normal) group. These sensors had no aging and were of the same product design with similar fresh performance. These sensors were characterized in two groups with similar test conditions.

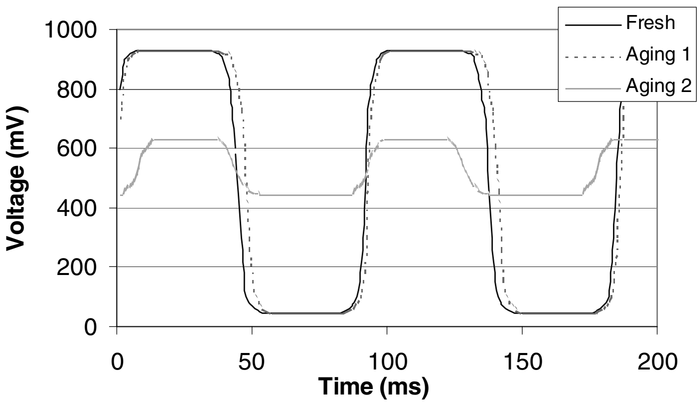

Figure 1
Sensor output for different sensors after various aging tests

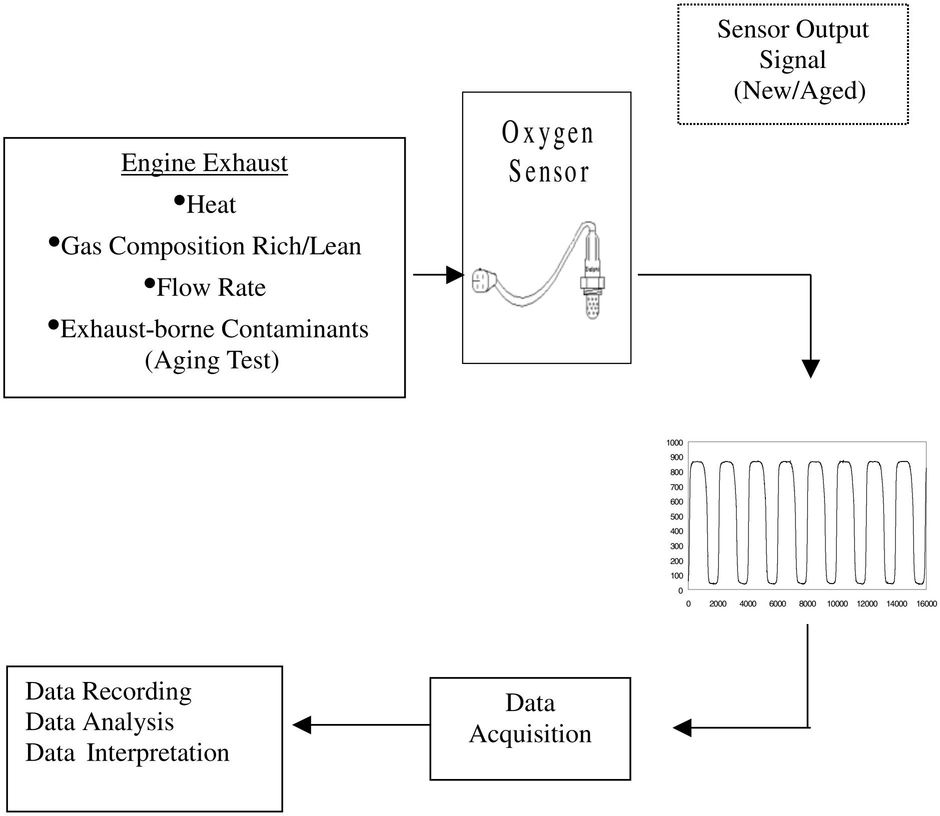

Figure 2
System, subsystems, and components

Next, the abnormal population was selected. A total of nine sensors were selected based on end-of-test postaging performance. The sensors had completed the full exposure of a highly accelerated engine-aging environment. Six of the sensors showed excellent posttest performance with little to no signal degradation ("aged"). Three of the abnormal sensors selected showed noticeable degradation, although they were still switching and functional ("degraded"). Representative voltage signals are shown in Figure 3. The "fresh" belonged to the reference group, and the "aged" and "degraded" were in the abnormal group.

Definition of Characteristics

As discussed, the open-loop engine-based performance test generates an exhaust stream to which the test sensors respond. Traditional sensor output characteristics that are often specified include maximum voltage, minimum voltage, voltage amplitude, response time in the lean-to-rich direction, and response time in the rich-to-lean direction. These parameters are denoted in Figure 4 and were included in the evaluation. One test-related parameter indicating the location of the test sensor (nest position) was also included, as multiple sensors were tested simultaneously. Considering the reference

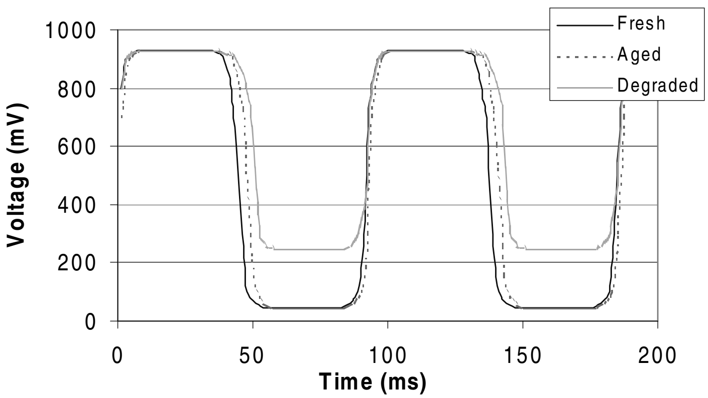

Figure 3
Sensor output voltage traces before and after aging

group sample size of 26, only nine additional characteristics were selected, for a total of 15 (referred to as factors *A* to *O*). The other characteristics, although not defined here, comprise a best attempt at variables that describe the waveform.

5. Mahalanobis Distance

The purpose of an MTS evaluation is to detect signal behavior outside the reference group. Existing data for the 15 characteristics of interest were organized for the 26 reference (nonaged) sensors. The data were normalized for this group (Table 1) by considering the mean and standard deviation of this population for each variable of interest:

$$Z_i = \frac{x_i - \overline{x}_i}{\sigma_i} \tag{1}$$

The correlation matrix was then calculated to comprehend all 15 variables and their respective correlations:

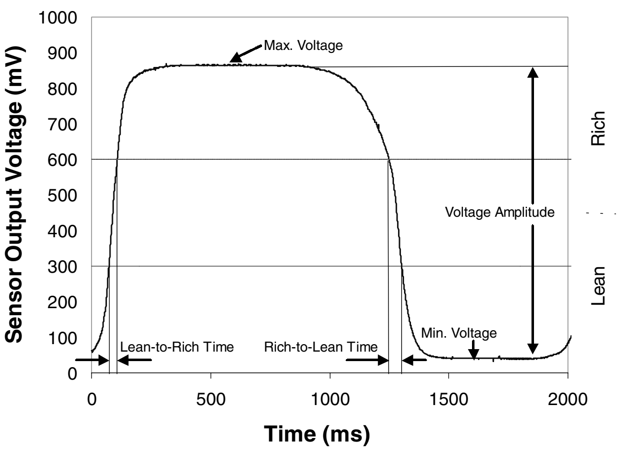

Figure 4
Sensor output parameters during the engine perturbation test

Table 1
Reference group output data normalization

	Reference Data					Normalized Data				
No.	Variable 1 X_1	Variable 2 X_2	Variable 3 X_3	⋯ ⋯	Variable 15 X_{15}	Variable 1 Z_1	Variable 2 Z_2	Variable 3 Z_3	⋯ ⋯	Variable 15 Z_{15}
1										
2										
3										
4										
5										
6										
7										
8										
⋮										
26										
Mean	X_1	X_2	X_3	⋯	X_{15}	0.0	0.0	0.0	⋯	0.0
Std. Dev.	σ_1	σ_2	σ_3	⋯	σ_{15}	1.0	1.0	1.0	⋯	1.0

Table 2
Correlation matrix results for the reference group

		A 1	*B* 2	*C* 3	V_{min} 4	V_{max} 5	V_{ampl} 6	LR_{Time} 7	RL_{Time} 8	*I* 9	*J* 10	*K* 11	*L* 12	*M* 13	Position 14	*O* 15
A	1	1.000	0.956	0.679	0.696	0.710	−0.096	0.116	0.732	0.933	−0.772	−0.478	−0.043	0.597	0.388	0.005
B	2	0.956	1.000	0.636	0.542	0.631	0.042	0.135	0.611	0.897	0.597	−0.304	−0.056	0.618	0.389	−0.046
C	3	0.679	0.636	1.000	0.553	0.305	−0.480	−0.123	0.456	0.659	0.599	−0.572	−0.326	0.074	0.218	0.144
V_{min}	4	0.696	0.542	0.553	1.000	0.815	−0.446	0.208	0.439	0.812	0.968	−0.538	−0.364	0.048	0.236	0.231
V_{max}	5	0.710	0.631	0.305	0.815	1.000	0.156	−0.156	0.393	0.850	0.796	−0.112	−0.295	0.241	0.414	0.244
V_{ampl}	6	−0.096	0.042	−0.480	−0.446	0.155	1.000	0.119	−0.150	0.075	0.422	0.743	0.167	0.286	0.230	−0.025
LR_{Time}	7	0.116	0.135	−0.123	−0.208	−0.156	0.119	1.000	0.174	−0.090	−0.052	−0.366	0.899	0.719	0.281	−0.948
RL_{Time}	8	0.732	0.611	0.456	0.439	0.393	−0.150	0.174	1.000	0.544	0.597	−0.581	0.213	0.587	0.281	−0.005
I	9	0.933	0.897	0.659	0.812	0.850	−0.075	−0.090	0.544	1.000	0.826	−0.337	−0.304	0.358	0.353	0.167
J	10	0.772	0.597	0.599	0.968	0.796	−0.422	−0.052	0.597	0.826	1.000	−0.660	−0.206	0.200	0.291	0.119
K	11	−0.478	−0.304	−0.572	−0.538	−0.112	0.743	−0.366	−0.581	−0.337	−0.660	1.000	−0.251	−0.282	−0.093	0.326
L	12	−0.043	−0.056	−0.326	−0.364	−0.295	0.167	0.899	0.213	−0.304	−0.206	−0.251	1.000	0.717	−0.241	−0.822
M	13	0.597	0.618	0.074	0.048	0.241	0.296	0.719	0.587	0.358	0.200	−0.282	0.717	1.000	0.453	0.561
Position	14	0.388	0.389	0.218	0.236	0.414	0.230	0.281	0.281	0.353	0.291	−0.093	0.241	0.453	1.000	−0.225
O	15	0.005	−0.046	0.144	0.231	0.244	−0.026	−0.948	−0.005	0.167	0.119	0.326	−0.822	−0.561	−0.225	1.000

Table 3
Mahalanobis distances for the reference and abnormal groups

No.	SN	0 hours Normal Group MD	Aged Abnormal Group MD
1	24,720	0.9	14.1
2	24,716	1.2	15.7
3	24,730	0.8	9.6
4	24,719	0.6	14.3
5	24,728	1.4	15.1
6	24,723	1.6	5.3
7	22,963	0.8	79,651.8
8	23,013	1.5	86,771.7
9	23,073	1.1	84,128.8
10	24,673	1.4	
11	24,700	0.8	
12	24,694	0.9	
13	24,696	1.1	
14	24,701	1.2	
15	24,697	1.1	
16	24,633	0.6	
17	24,634	1.0	
18	24,635	1.1	
19	24,636	1.0	
20	24,637	0.6	
21	24,593	1.1	
22	24,595	0.5	
23	24,598	0.7	
24	24,599	1.2	
25	24,602	1.0	
26	24,603	0.7	

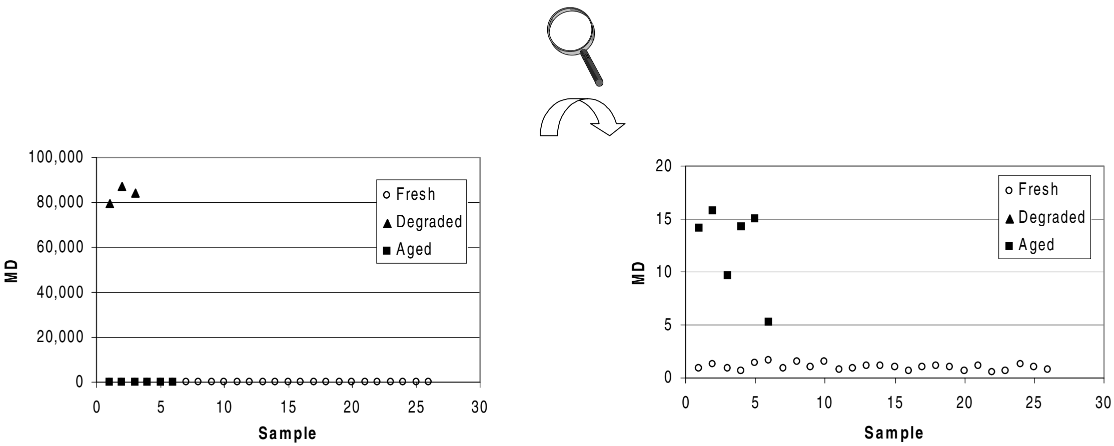

Figure 5
Power of discrimination for the reference to abnormal groups

$$R = \begin{bmatrix} 1 & r_{12} & \cdots & r_{1k} \\ r_{21} & 1 & \cdots & r_{2k} \\ \vdots & \vdots & & \vdots \\ r_{k1} & r_{k2} & \cdots & 1 \end{bmatrix} \qquad (2)$$

$$r_{ij} = \frac{\Sigma x_{il} x_{jl}}{n} \ (l = 1, 2, \ldots , n)$$

Upon review of the correlation matrix (Table 2), it is clear that a correlation exists between parameters. For this reason, application of the multivariable MTS approach makes sense because no single characteristic can describe the output fully.

The inverse of the matrix was then calculated [equation (3)] and finally, the Mahalanobis distance [equation (4)], denoted by MD. This completes the calculations for the normal group. All reference samples had MD distances of less than 2 (Table 3):

$$R^{-1} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & & \cdots \\ a_{k1} & a_{k2} & \cdots & a_{kk} \end{bmatrix} \qquad (3)$$

$$\mathrm{MD} = \frac{1}{k} Z R^{-1} Z^{\mathrm{T}} \qquad (4)$$

where k is the number of characteristics, Z is the 1×15 normalized data vector, R^{-1} is the 15×15 inverse correlation matrix, and Z^{T} is the transposed vector (15×1).

The MD values for the abnormal samples were then calculated. Again the data are normalized, but now the mean and standard deviations of the reference group were considered. The inverse correlation matrix of the reference group solved previously was also used. The resulting MD values of the abnormal samples were calculated and are summarized in Table 3. As evident in the MD values of the abnormal samples, clear discrimination between fresh and degraded performance was made possible (Figure 5). Additionally, complete discrimination of the aged samples from the fresh samples was seen. Although the MD value calculated is nondirectional and does not indicate "goodness" or "badness," it does indicate differences from normal. A consistent signal (low MD over time) is one goal for sensor output.

Importantly, this performance separation is not apparent in the traditional one-variable-at-a-time approach. For this type of aging test, typical performance metrics that are recognized to change are $V_{\min}$ and $\mathrm{RL}_{\mathrm{Time}}$. As shown in Figure 6, this independent variable consideration would merely allow detection of the degraded sensors with no clear discrimination of the aged sensors.

6. Selection of Characteristics

Optimization with L_{16} Orthogonal Array

To reduce data processing complexity, it is desirable to consider fewer characteristics and eliminate those

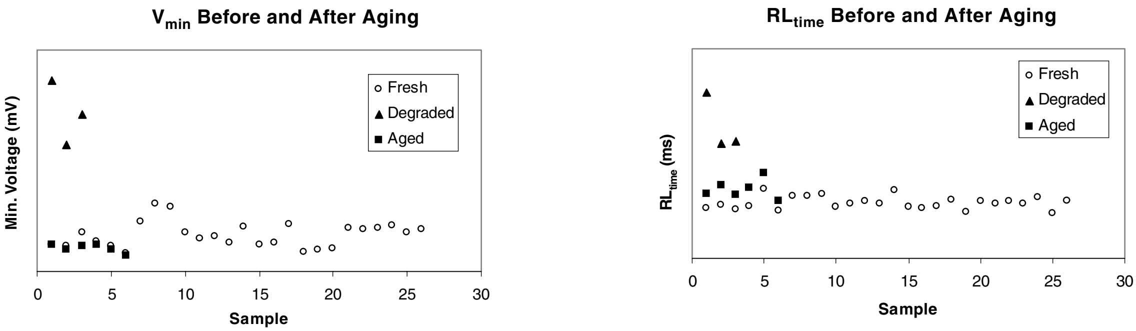

Figure 6
Discrimination not evident with traditional single variable approach

not contributing to product discrimination. An L_{16} orthogonal array was used for this purpose (Table 4).

All 15 characteristics were considered at two levels. Level 1 used the variable to calculate the Mahalanobis distance, and level 2 did not use the variable to calculate the MD. Reconsideration of both the reference group and abnormal group MD was made for each run. The experiment design and results are shown in Table 4.

From these runs, SN ratios and mean responses were calculated for the main effects of each variable. As the goal was to improve discrimination, larger MDs were preferred and the larger-the-better SN ratio was used:

$$\eta = -10 \log \left(\frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right) \tag{5}$$

Response charts and tables are shown in Figure 7 and Table 5.

Variables C, F, I, and J are shown to have little contribution to the SN ratio and could be considered for elimination. This would reduce the MD calculation to 11 characteristics. All variables, however, contributed positively to the mean.

Confirmation

A confirmation run with 11 variables (eliminating the low-SN contributors) showed reduced discrimination. However, these variables all contribute significantly to the mean (Figure 7) and therefore cannot be eliminated. This conclusion is somewhat indicated within the results of the L_{16} array (Table 4). Run 1, which considered all the variables, had by far the largest calculated MD compared to any other run, which considered only seven variables each. Therefore, all of the 15 variables initially selected should be used to maximize discrimination.

Discussion

Although the optimization evaluation may seem disappointing, as no variables can be eliminated, it is not an unlikely conclusion, as there are over 100 variables output in an effort to characterize the waveform. This initial evaluation only considers 15 "best guess" candidates, and more than likely, other important variables are still to be identified. The MTS method does, however, confirm the value of combining the influence of many variables to interpret a change in response, as compared to considering one variable or even a few variables at a time.

The ranking of the "traditional" metrics, factors D and H, used to detect signal degradation, are ranked high, but not the highest in terms of contribution (Table 5). The influence of factor N, the nest position during test, is seen to have a low influence on variability and a low contribution to the mean, as is desired.

7. Conclusions

The feasibility of use of the MTS multivariable approach has been demonstrated. The combination of 15 variables from the sensor output waveform allowed much improved discrimination compared to

Table 4
MDs calculated for abnormal group within the L_{16} orthogonal array

	Factor															MD for Nine Abnormal Samples								
No.	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*N*	*O*	1	2	3	4	5	6	7	8	9
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14.1	15.7	9.6	14.3	15.1	5.3	79,651.8	86,771.7	84,128.8
2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1.6	2.2	1.5	2.2	6.5	1.0	9,722.0	11,988.6	11,349.3
3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	2.9	5.2	1.8	3.3	8.0	1.1	25,731.9	32,363.5	30,961.9
4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	2.4	2.8	1.6	3.0	9.5	1.5	6,300.9	7,283.8	7,102.0
5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	2.5	2.8	1.0	2.9	7.3	2.6	25,535.4	28,754.8	27,635.1
6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	4.0	3.0	3.3	2.0	5.1	1.5	1.560.3	1,538.7	1,526.0
7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1.8	2.5	1.2	2.3	6.1	1.1	9,156.7	10,742.5	10,330.4
8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1.6	1.8	1.3	1.1	5.4	3.1	11,568.6	13,508.6	12,824.1
9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	2.0	3.3	1.5	3.1	5.6	1.7	151.6	30.2	49.2
10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	6.4	1.9	2.3	4.8	9.5	3.1	279.1	37.0	57.8
11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	3.4	3.8	1.6	3.4	6.9	1.9	348.6	25.7	35.4
12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	7.4	1.7	2.6	4.7	7.3	1.7	287.0	33.4	47.5
13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	4.0	4.9	2.0	3.9	10.5	2.6	379.9	44.9	59.5
14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	0.9	1.1	0.8	0.6	4.9	1.7	74.1	12.3	25.3
15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1.2	3.0	1.0	2.3	7.9	2.4	161.1	35.1	53.1
16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	0.5	2.3	0.8	0.7	7.8	2.2	131.4	35.3	49.3

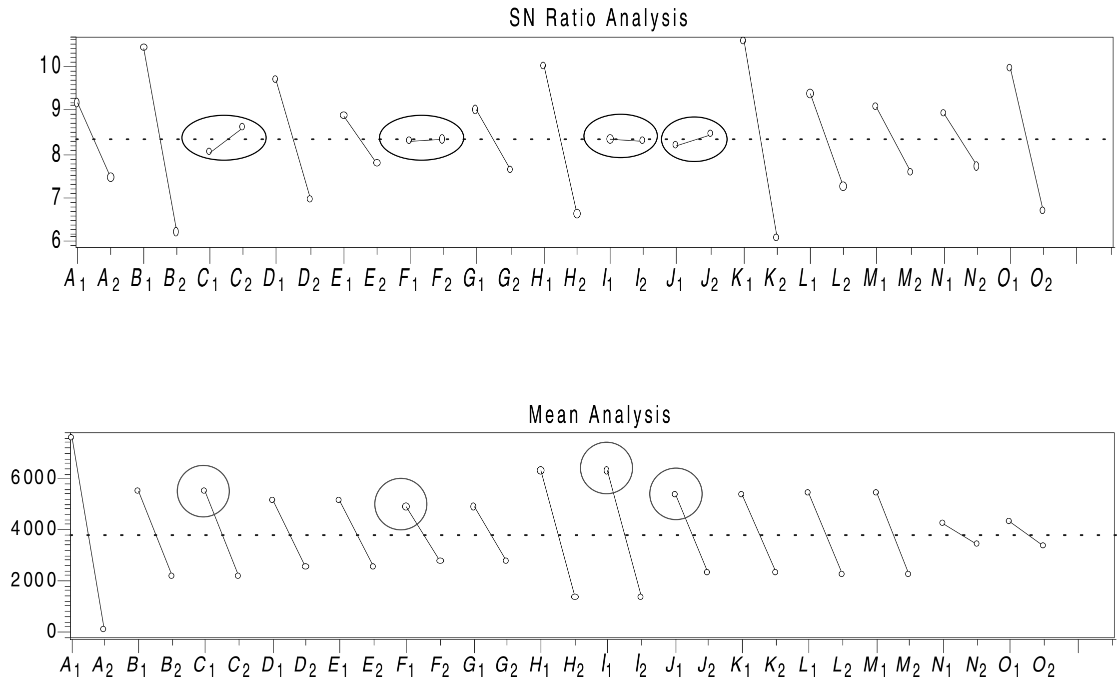

Figure 7
SN and means response charts

the traditional one-variable-at-a-time approach. The method also identified some alternative variables that contributed more to discrimination than did the traditional "favorites."

MTS allows discrimination of even very subtle differences due to aging, thereby allowing detailed feedback on product performance. If continued studies support these preliminary findings, the excellent discrimination will allow product optimization based on significantly shorter tests. Full-length test exposures could then be confined to the product confirmation and validation stages. Robust engineering evaluations for sensor product optimization are ongoing. By applying MTS to characterize sensor performance, the MD can confirm improvements in aging response over time (Figure 8).

Future Evaluations

Although this project proved excellent feasibility in terms of its approach to discriminate performance, much remains to be done to extend the study and consider other variables for better understanding and implementation. The number of sensors in the reference group limited this study. It would be desirable to increase this sample size to allow consideration of many more output characteristics. Additionally, alternative test parameters, which may influence sensor output response during the test, should be considered. Future evaluations that consider more test parameters should ideally comprehend any bias introduced by the test, thereby identifying true product differences.

Implications of Study

Many ideas have evolved as a result of this study. The first key finding is related to detecting small changes in signal output through MTS. With this detection method, shortened tests (to save time and money) should suffice to understand aging trends and optimize designs. Further, rather than supplying our

Table 5
SN and means response tables

	SN Response														
				V_{min}[a]	V_{max}	V_{ampl}	LR_{Time}	RL_{Time}[a]						Position	
	A	***B***	***C***	***D***	***E***	***F***	***G***	***H***	***I***	***J***	***K***	***L***	***M***	***N***	***O***
Level 1	9.2	10.4	8.0	9.7	8.9	8.3	9.0	10.0	8.4	8.2	10.6	9.4	9.1	8.9	9.9
Level 2	7.5	6.2	8.6	7.0	7.8	8.4	7.6	6.7	8.3	8.5	6.1	7.3	7.6	7.7	6.7
Delta	1.7	4.2	0.6	2.7	1.1	0.1	1.4	3.3	0.1	0.3	4.5	2.1	1.5	1.2	3.2
Rank	7	2	12	5	11	15	9	3	14	13	1	6	8	10	4
	Means Response														
Level 1	7614	5486	5481	5161	5161	4903	4907	6297	6292	5324	5331	5452	5450	4267	4275
Level 2	36	2165	2170	2490	2489	2748	2743	1354	1358	2327	2319	2198	2200	3383	3376
Delta	7578	3321	3311	2671	2672	2156	2164	4943	4934	2997	3012	3254	3250	884	899
Rank	1	4	5	11	10	13	12	2	3	9	8	6	7	15	14

[a] V_{min} and RL_{time} are traditional metrics for performance characterization.

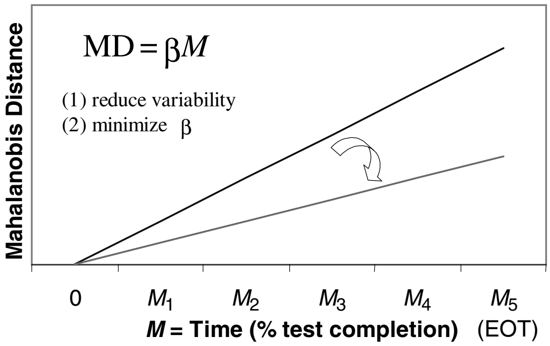

Figure 8
Used in conjunction with product optimization, MD can confirm improvements in aging response over time

product engineers with more than 100 data variables related to a waveform, the MD distance could help them make decisions during product development evaluations.

This study used existing data with no new experimental tests needed. The study points out the potential of its application, as no new test procedures are required, with the exception of additional data calculations, demonstrating the power of appropriate data analysis.

Acknowledgments We would like to recognize Mike Holbrook and Kimberly Pope of Delphi for sharing their expertise in Taguchi methods and MTS studies; also Bob Stack of Delphi for recognizing the role that these tools can play and allowing us time to devote efforts applying them; and finally, thanks to Shin Taguchi, of American Supplier Institute, who enthusiastically teaches and encourages the application of these methods at Delphi. Application of these techniques at Delphi will assure product and marketplace leadership.

Reference

S. Teshima, T. Bando, and D. Jin, 1997. A research of defect detection using the Mahalanobis–Taguchi system method. *Journal of Quality Engineering Forum*, Vol. 5, No. 5, pp. 169–180.

This case study is contributed by Stephanie C. Surface and James W. Oliver II.