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ANALYSIS OF PIEZOELECTRIC STRUCTURAL SENSORS WITH EMERGENT COMPUTING TECHNIQUES

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Introduction

The purpose of this project was to try to interpret the results of some tests that were performed earlier this year and to demonstrate a possible use of emergence in computing to solve IVHM problems. The test data used was collected with piezoelectric sensors to detect mechanical changes in structures. This project team was included of Dr. Doug Ramers and Dr. Abdul Jallob of the Summer Faculty Fellowship Program, Arnaldo Colon-Lopez - a student intern from the University of Puerto Rico of Turabo, and John Lassister and Bob Engberg of the Structural and Dynamics Test Group. The tests were performed by Bob Engberg to compare the performance two types of piezoelectric (piezo) sensors, Pb (Zr_{1-1} Ti_x) O_3, which we will label PZT, and Pb $(Zn_{1/3}Nb_{2/3})O_3$-PbTiO, which we will label SCP. The tests were conducted under varying temperature and pressure conditions. One set of tests was done by varying water pressure inside an aluminum liner covered with carbon-fiber composite layers (a cylindrical "bottle" with domed ends) and the other by varying temperatures down to cryogenic levels on some specially prepared composite panels. This report discusses the data from the pressure study. The study of the temperature results was not completed in time for this report.

The particular sensing done with these piezo sensors is accomplished by the sensor generating an controlled vibration that is transmitted into the structure to which the sensor is attached, and the same sensor then responding to the induced vibration of the structure. There is a relationship between the mechanical impedance of the structure and the resulting electrical impedance produced in the in the piezo sensor. The impedance is also a function of the excitation frequency. Changes in the real part of impendence signature relative to an original reference signature indicate a change in the coupled structure that could be the results of damage or strain.

The water pressure tests were conducted by pressurizing the bottle on a test stand, and running sweeps of excitations frequencies for each of the piezo sensors and recording the resulting impedance. The sweeps were limited to 401 points by the available analyzer, and it was decided to perform individual sweeps at five different excitation frequency ranges. The frequency ranges used for the PZTs were different in two of the five ranges from the ranges used for the SCP. The bottles were pressurized to empty (no water), 0psig, 77 psig, 155 psig, 227 psig in nearly uniform increments of about 77psi. One of each of the two types of piezo sensors was fastened on to the bottle surface at two locations: about midway between the ends on cylindrical portion of the bottle and at the very edge of one of the end domes. The data was collected in files by sensor type (2 cases), by location (2 cases), by frequency range (5 cases), and pressure (5cases) to produce 100 data sets of 401 impedances.

After familiarization with the piezo sensing technology and obtaining the data, the team developed a set of questions to try to answer regarding the data and made assignments of responsibilities. The next section lists the questions, and the remainder of the report describes the data analysis work performed by Dr. Ramers. This includes a discussion of the data, the approach to answering the question using statistical techniques, the use of an emergent system to investigate the data where statistical techniques were not usable, conclusions regarding the data, and recommendations.

Project Questions to Answer

The questions and summary answers are listed below. The first four questions (in bold) were assigned to Dr. Ramers to investigate. Time did not permit the direct analysis of the data for question 4b. However, approaches to this task already exist that are based on monitoring changes in the imaginary part of the impedance. One technique was discussed in the course presented at MSFC by Los Alamos Dynamics [1], a company specializing in structural dynamics and mechanical vibration consulting.

1) Is there a significant difference in the information provided between the PZT and SCP sensors with the given tests?

Yes, the SCP type sensor appears to be more sensitive and a better discriminator of pressures, but additional testing is needed.

2) Which bands are needed to characterize the PZT and SCP signal?

The results correspond to the literature. The higher frequencies are better. For the better SCP, the 180 – 190kHz frequency band was the best at discriminating between the test pressures.

3) Is there an adequate parsimonious characterization of the piezo signal?

The nonparametric metrics, which reduce a set of impedances comparisons to a single number, are parsimonious. The readings of Re(Z) at 30-50 contiguous excitation frequencies provided good results. A granularity of 400 Hz between frequencies was sufficient for the SCP sensor in the 180 – 190 kHz range to provide good discrimination between the test pressures.

4a) What are metrics that can be used for detecting change in the PZT signal indicating strain?

Of the four metrics tested [2], the Root Mean Square Deviation and the Mean Absolute Percentage Difference performed well and were better than the two covariance based metrics at discriminating between the test pressures.

b) What are methods and metrics that can be used to determine if the PZT is operating correctly? – <u>SEE REFERENCE ABOVE FOR KNOWN METHOD</u>

5) What are the appropriate procedures for attaching PZTs to structures and attaching leads to PZTs?
   a) How does surface area contact affect sensitivity of signal?
   b) How does quality and type of bond have an effect on the nature of the signals?
   c) Does gradual degradation (or changes) in the bonding material have and effect on the nature of the signal?

6) In general, how do we size the sensor (length, width, thickness)?

Discussion of the Data for the Composite Bottle

Because impedance is a function of frequency, each set of five sweeps over the different frequency ranges really constitute ***one*** sample. Each of four experiments was conducted with a location-sensor type combination for which one sample was taken at each of the five pressure levels. One trace (all five frequency ranges) at each level is one sample (see Figure1 for example). Table 1 below summarizes the experiments. A consequence of the lack of multiple samples is that statistical techniques may not be used to answer several of the questions.

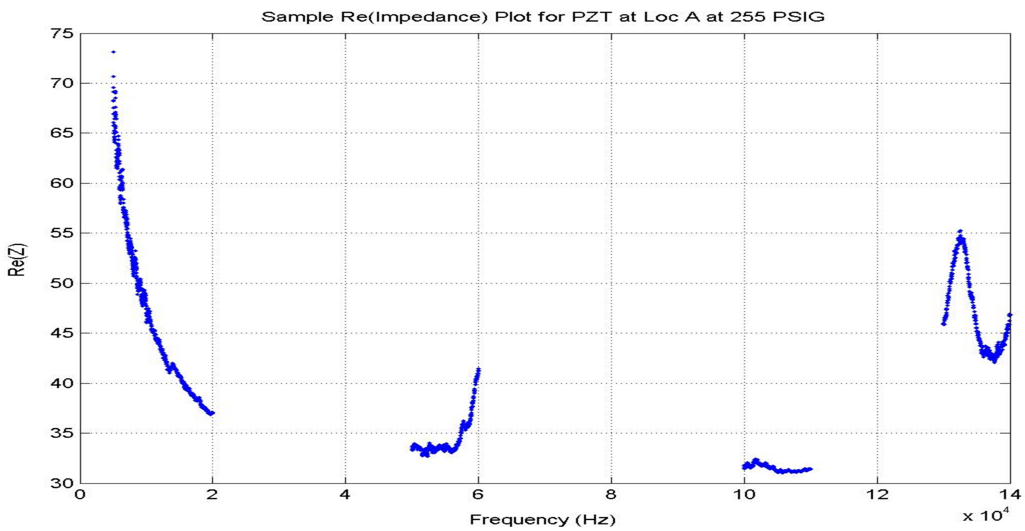


Figure 1 PZT Re(Z) at Location A (Center) Sample

Number of Samples

			Pressure Level			
Sensor	**Location**	**Empty**	**0psig**	**77psi**	**155psig**	**227psig**
Pzt	A	1	1	1	1	1
Scp	A	1	1	1	1	1
Pzt	B	1	1	1	1	1
Scp	B	1	1	1	1	1

Sample Frequency Sweeps (kHz):
401 points ea. Range

Pzt	**Scp**
5-10	50-60
10-20	100-110
50-60	130-140
100-110	180-200
130-140	250-250

Table 1 Summary of Experiments and Samples

However, some interpretations of the data can be made through qualitative examination of the data and through use a factor analysis for experiments with one trial at each level. Analysis experiments were also conducted using evolutionary programming techniques that provided answers as reasonable heuristics for this particular set of data. Qualitative analysis of the data and the factor analysis are discussed in the next section and the evolutionary computing analysis is discussed in the section after.

Qualitative and Factor Analysis of Available Data

Which bands are needed to characterize the sensor signal?

This essentially questions which frequency ranges provide more discriminatory power. The literature, and the model relating impedance to frequency, suggests higher frequencies more sensitive [3]. Each line in each plot in Figure 2 is the real part of the impedance at a pressure level. The plots seem to indicate, in accord with the literature, that the higher frequency result in more distinct separation of pressure related signals.

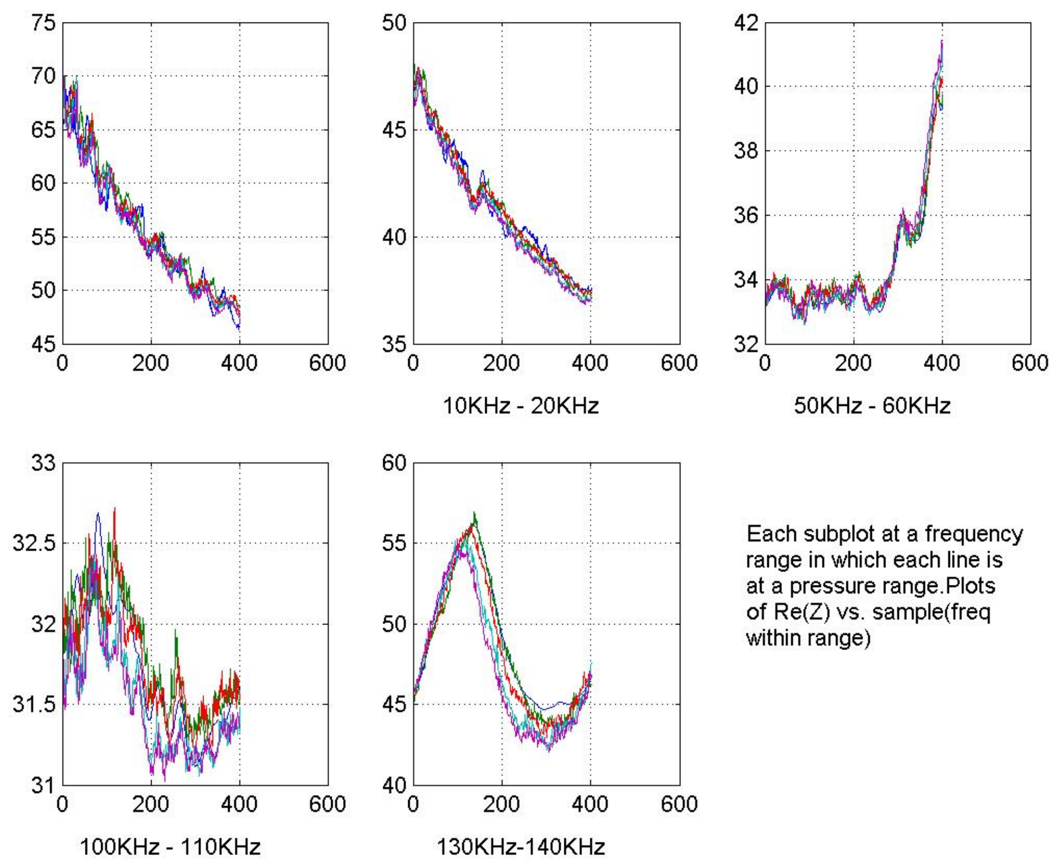


Figure 2 Subplots by Frequency Range for a PZT Type

To help verify this, an analysis of variance test was conducted to see if the mean impedance for each pressure level were the same in each band. If they were, then the band did not discriminate pressures well. However, this statistical test is not valid, because the mean impedance is calculated using the impedance for each frequency in the band, but the impendence is a function of frequency so the observations are not independent samples. Regardless, the ANOVA indicated that if the samples had been independent, the higher frequency bands were better discriminators, particularly bands 4 (110-110kHz) and band 5 (130-140 kHz) for the PZT.

Is there a significant difference in the information provided between the PZT and SCP sensors with the given tests?

A factor analysis using the Root Mean Square Difference (RMSD) metric was used for this analysis. The RMSD metric is calculated as the sum of the squares of the difference between a trace of interest (e.g., at a specific pressure) and a reference trace. The appropriate state for the reference trace the Re(Z) of the bottle filled with water at 0 psig. The Re(Z) for the empty bottles was not used as a reference because the bottle is a different structure with and without water. The mechanical properties that influence mechanical impedance are significantly different for a full or an empty bottle. The metric reflects the change in electromechanical impendence in the sensor, which should be related to the change in mechanical impendence of the structure to which the sensor is attached. The RMSD was calculated for the full 802 frequencies in bands 4 and 5 to get a qualitative indication and order of magnitude of the metric value. The Re(Z) for bands 4 and 5 were chosen because they appear to discriminate between the pressures more than the lower frequency bands do, and measurements were made in the these ranges for both the PZT and SCP type sensors. The results are shown in Table 3. Comparative traces for bands 4 and 5 are shown in Figures 3 and 4.

RMSD Bands 4&5		**RMSD for**	
Sensor	**(77-0)psig**	**(155-0)psig)**	**(227-0)psig**
PZT at Location A	1.3991	3.0605	4.0084
SCP at Location A	3.7697	6.5325	8.4372
PZT at Location B	2.4018	15.3351	***85.74***
SCP at Location B	4.5771	12.2303	11.6556

Table 3 RMSD for Bands 4 and 5.

The RMSD metric appears to indicate that the SCP type sensor is more sensitive. For Location A, the RMSD range for the SCP sensor is 4.667 over 155 psi range while it is only 2.6093 over the 155 psi range for the PZT sensor. At location B, that last metric value for the PZT, 85.74, seems inconsistent and may indicate a problem with that sensor. The readings for the SCP sensor at location B appear to be consistent. Examining the traces in figures 3 and 4, we can see that the impedances are lower and relatively flat for the PZT at location B and compared to the corresponding PZT traces for A. The impedances for the lower pressures are also very much lower, and except for the 227 psi trace. Since RMSD is a difference, and the reference was much lower, I suspect a problem with the data from the PZT at location B.

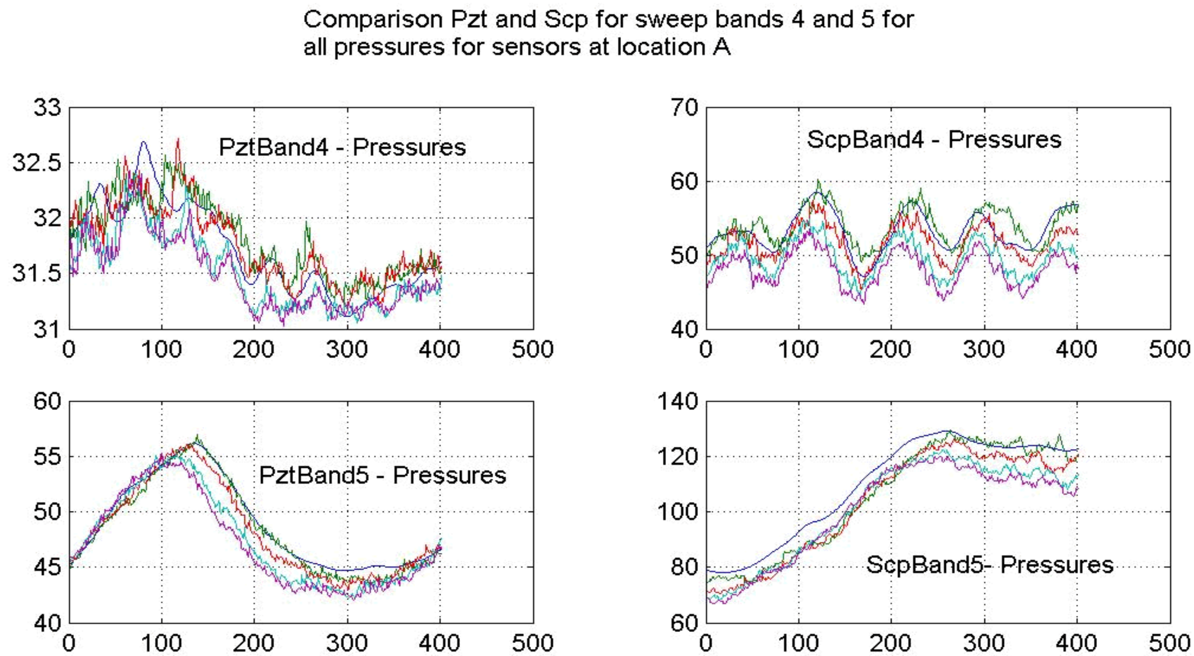


Figure 3 Traces for Location A- Band 4&5

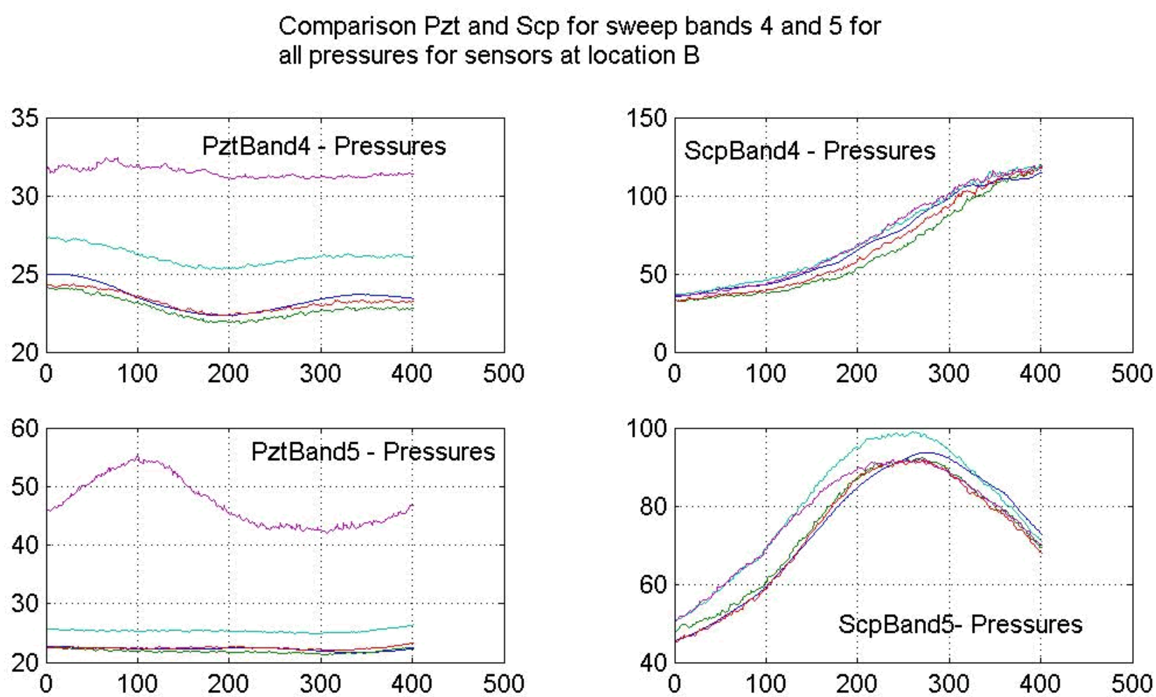


Figure 4 Traces for Location B - Band 4&5

A factor analysis of the above results indicates the same conclusions. The factor plots (Figure 5) comparing the sensors by location show a possible problem at location B. The large increase for the PZT for the high pressure might indicate a problem. Even for the SCP sensor at location B, the increase in RMSD with pressure is not monotonic as it is at location A (see figure 6), indicating a possible problem with the sensor or leads for the SCP at B also. Regardless, these behaviors would not be as desirable for use of these sensors for condition monitoring at location B as the conditions present at location A.

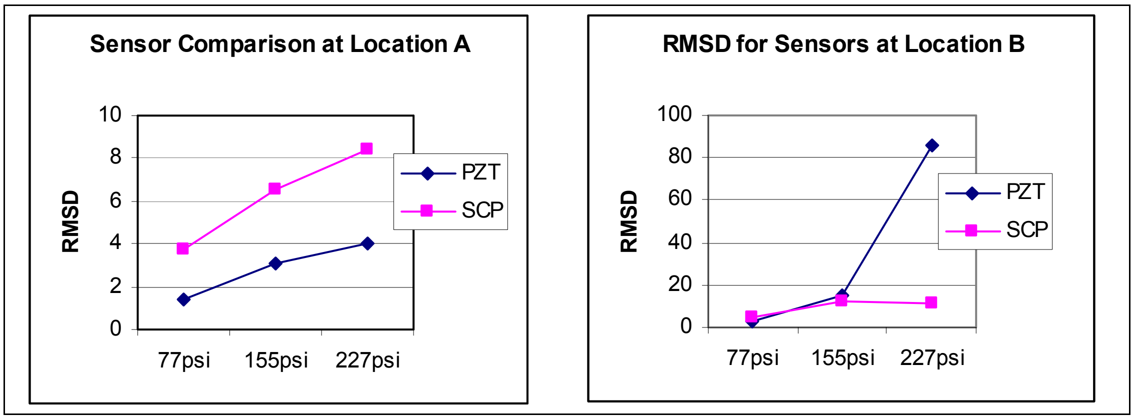


Figure 5 Factor analysis plots for location sensors for pressure levels by sensor

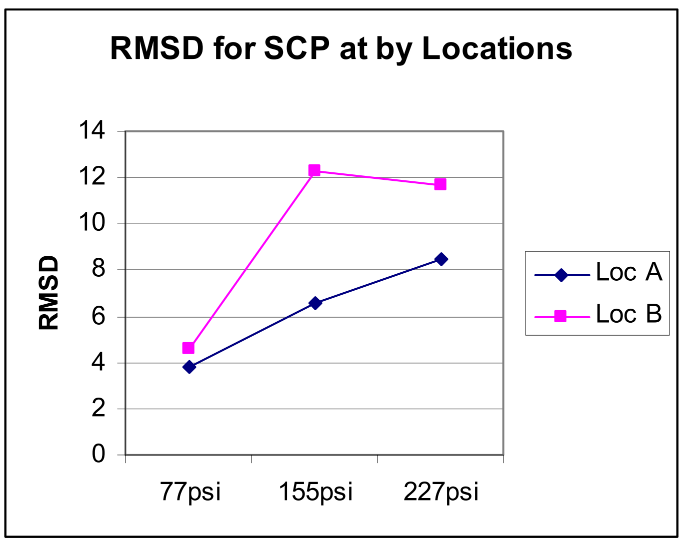


Figure 6 Factor analysis plots for SCP sensor for pressure levels by location

Overall, we could draw no strong conclusions about the sensors or locations. It appears, as expected, that higher frequencies are better. The sensors at location A, though they show more noise, seem to be more consistent. SCP appears to be more sensitive that the PZT. To reinforce the qualitative conclusions made we applied artificial intelligence techniques that facilitate emergence of solutions. The techniques of evolutionary computing and fuzzy logic are useful in situations where there is insufficient data, little is know about the relationships is the data, and there may be ambiguity present I the objectives or measures. These conditions are present in this problem. These techniques allow the emergence of heuristics with regard to the data collected. The approach and results are discussed in the next section.

Evolutionary Computing Analysis of the Data

Introduction

An experiment was conducted using an evolutionary computing (EC) algorithm with a fuzzy logic rule based evaluation (or fitness) function to determine which sensor at which location in which frequency range using which metric would be "best" to differentiate between the effects of pressure. A second EC experiment was conducted to recommend a reasonable resolution needed to obtain reasonable metric readings. This information could be used to compensate for the 401 sample point limit of the impendence analyzer used for the testing.

Evolutionary computing was well-suited to represent the iterative search over the 28,000 possible combinations of variables. It is useful when there is little known about data or relationships in a problem. It has the advantages of conceptual simplicity, parallelism, self-optimization, simultaneous search over wide and complex solution spaces with multiple minima, and the ability to solve problems with no known solutions [4] [5].

In implementing EC we start with a population consists of N sets (called individuals) that each represent an alternative potential solution to a particular problem. For example, each individual could be composed of values for a set of design variables. The variables for each potential solution are varied somewhat randomly, then each individual set is evaluated with a fitness function (basically, an objective function). The solutions are ranked in some way, and then various methods are applied to the ranked set of possible solutions to generate a new population of potential solutions. The characteristics of good solutions are retained. The new solution set is evaluated and the cycle is repeated. The best characteristics of the solution will emerge over several iterations and we have, hopefully, the best solutions. This approach does not guarantee discovery of the unique optimal solution or convergence to a solution at all. It generally does discover good or reasonable solutions for complex problem that cannot be solve with analytic or statistical models when there is insufficient data or the conditions required to calculate statistics.

Fuzzy logic and fuzzy rule based reasoning are appropriate in an evaluation function with evolutionary computing in our current problem. Fuzzy logic and fuzzy expert systems are particularly useful for representing and reasoning about analog processes when the boundaries between variables are not sharply defined and there may be partial occurrences of events. Fuzzy logic is based on fuzzy set theory developed by Zadeh [6] for incorporating vagueness into decision theory. Variable values are characterized by their degree of membership in sets with linguistic values, such as "high stress" or "low temperature," and are reasoned over in parallel with a set of antecedent-consequent rules.

Problem description for EC Solution

The variables used for the first EC experiments were SensorLocationFrequencySet, StartFrequency, BandWidthPct, and MetricID. Each individual solution in the population of solutions contained a set of values for the variables described below.

SensorLocationFrequencySet are indexes to the data organized as it was collected into 20 sets containing the Re(Z) for each of the pressure levels (0psi, 77psi, 155psi, and 227psi) for a sensor(PZT or SCP) at a location (A or B) for one of the five frequency ranges (see Table 1). The variable is an index into which set to use. The way they were organized also represented classes that could be used to evaluate the best sensor and location and indicated in the table below:

Data Set Indexes	**Sensor Type at Location**
1 – 5	PZT at Location A
6 – 10	PZT at Location B
11 – 15	SCP at Location A
16 - 20	SCP at Location B

Table 4 Data set indices for EC

Start Frequency and ***BandwidthPct*** are used to select a sequence of frequencies and corresponding Re(Z) within each of the above data sets. The sample starts at a number from one to 350 of the 401 readings in the data set, and the band width is calculated by taking the indicated % of the samples between the start and the 401st sample in sequence. The calculated bandwidth (BW) is on of the solution evaluation parameters (SEPs).

MetricID refers to which one of the four nonparametric metrics [ref] to apply to the selected and extracted sample. The four metrics (and the indices) are:

Index	**Metric Label and Name**	**Formula**
1	RMSD root mean square deviation	$\sqrt{\dfrac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N} x_i^2}}$
2	MAPD mean absolute percentage deviation	$\dfrac{100}{N} \times \sum_{i=1}^{N} \left\| \dfrac{y_i - x_i}{x_i} \right\|$
3	COVMETRIC covariance	$\dfrac{1}{N} \times \sum_{i=1}^{N} \left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)$
4	CCMETRIC variance normalized covariance	$\dfrac{Cov(x, y)}{\sigma_X \sigma_Y}$

Table 5 Metrics investigated by EC

All of the metrics are measures of differences between a reference set and a measured set. So the x_i variables represent the reference set values while the y_i values represent the measured set. The value of N is the number of pairs in the sequences that are being compared. The σ_X and σ_Y are the variances of the reference and measured sets respectively

Using the metrics above, the "best" solutions were measured by a fuzzy rule base by considering:

In this problem the first set of computations (shown in Appendix A) were to extract a sequence of impedances for all four pressures (0, 77, 155, 227psig) from the data set and segments identified by the first three variables of each solution. The next calculation is to applying the metric identified by the last variable of the solution (***MetricID***). This calculation results in three numbers that are the metrics value for 0-77psi, 0-155, and 0-227psi. These three numbers are then used to calculate the variables to use in determining the quality of each solution. The criteria used to determine the "best" solutions were:

1) **monotonicity** – metric values increase or decrease consistently with pressure,
2) reasonably **uniform separation** between measures at different pressures, and
3) require **fewer,** rather than more, **measurements** to get reasonable values for a metric.

These criteria were represented by fuzzy variables with membership functions and then processed with a fuzzy rule base to calculate a single quality of solution metric to each individual solution on the population.

The EC system

The EC system used for this analysis was developed by D.L. Ramers over the in 2003 and early 2004, and is described in the recent conference paper [7]. The system was originally developed to study engineering design processes, and consequently the present problem is viewed as the design of measurement system for pressure in the bottle.

A population of 100 individuals was used, and they were varied in parallel over 60 iterations. The resulting track of the fitness statistics and of the population distribution for the 60th generation of solutions is shown in figures 7 and 8 respectively.

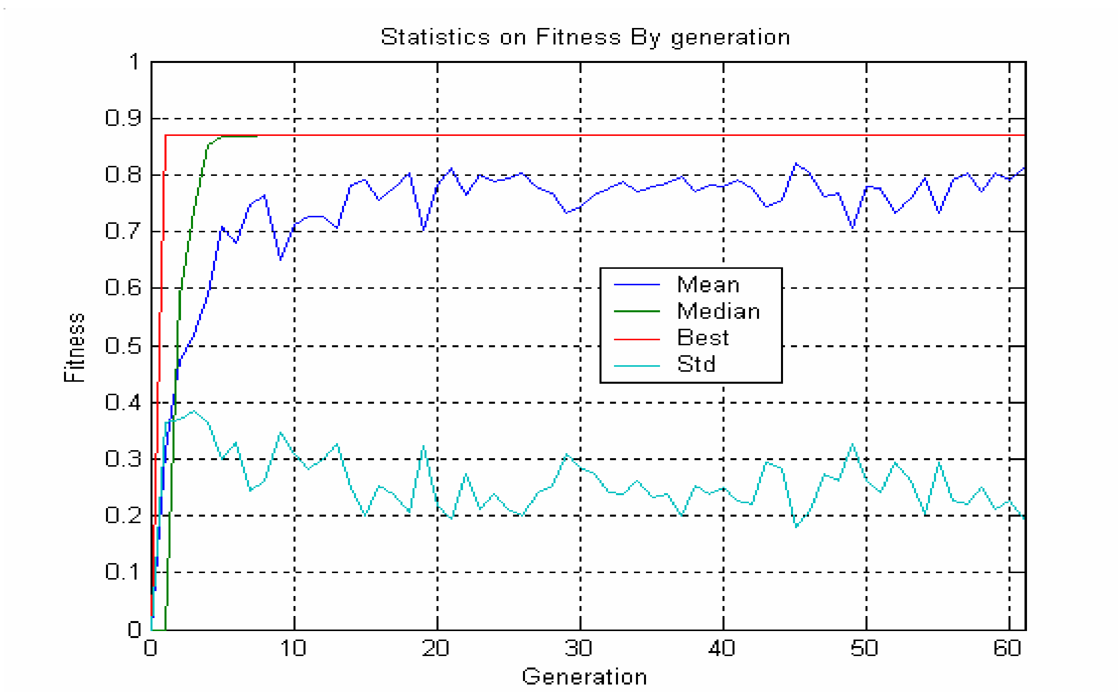


Figure 7 Population fitness progress over 60 generations

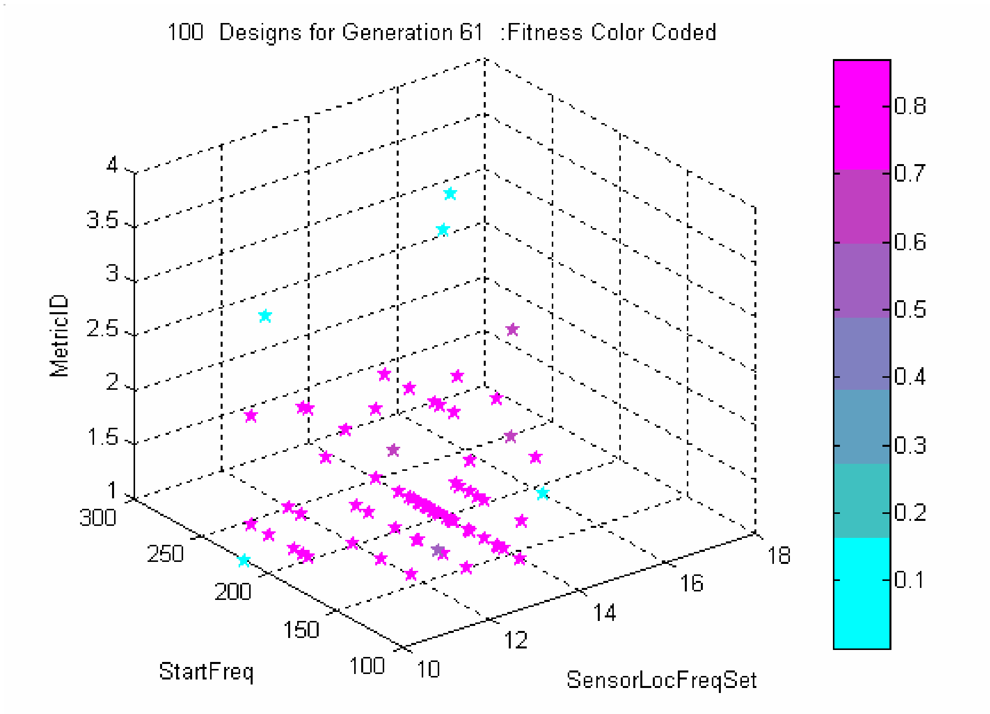


Figure 8 Distribution of alternative solutions of the 60th generation

Discussion of Results

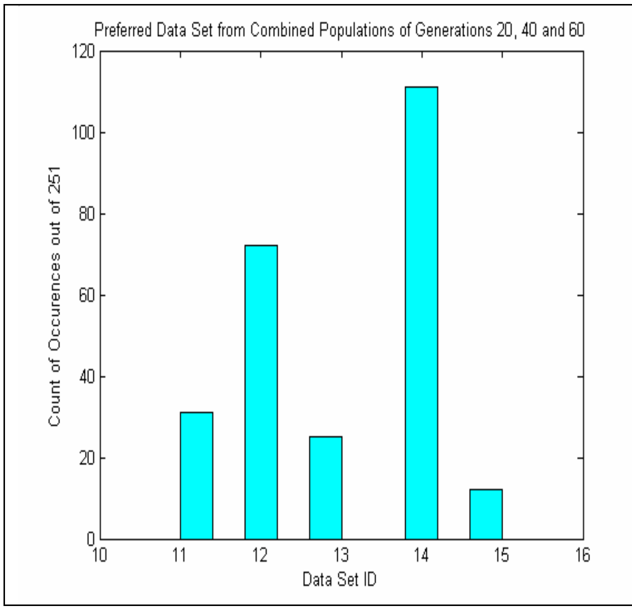
Visual examination of the fitness measures shows that the median population fitness reached the best population fitness by the 10th generation (iteration). The mean and the population fitness remained stable over the following generations, showing the intended and forced randomness used with the EC to continue exploring the solution space. The indicated variation was desirable.

From visual examination of the 60th generation solution values we can draw the following conclusions:

- Data sets 10-15, representing the SCP sensor at Location A gave the best solutions, and
- Metrics 1 (RMSD) and Metric 2 (MAPD) resulted in the best solutions.

The results also indicate that data set number 14, with a frequency range of 180-200 kHz using metric 1 provide the largest percentage of best solutions. It is important the recall that this last population represents the testing and selection of the best solution combinations from roughly 6000 trials.

Histograms of the combined variable values for only the best individuals (all the of the highest possible score) of the 20th, 40th, and 60th generations, a total of 251 out of 300 individuals, were generated to confirm the visually deduced results, and are shown in the figures below.



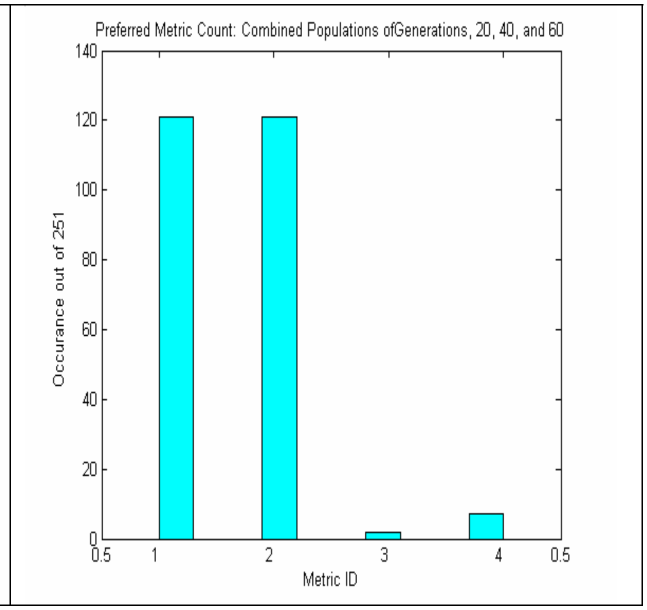


Figure 9 Histogram for Data Sets

Figure 10 Histogram for Metrics

The histogram for the bandwidth (figure 11) indicates that 28 to 52 samples were usually sufficient to give a good indication of pressure with the metrics. The ***StartFreq*** is not analyzed because its significance in not clearly understood. The results merely show that within the set of frequencies, the ones staring between 140 and 220 seemed to provide the best results. Since the purpose of this variable was to see if we could reduce the number of measurements, it seems that the next experiment that deals with the number of uniformly collected sample to collect, will give a better indication of this factor. This experiment is discussed in the next section.

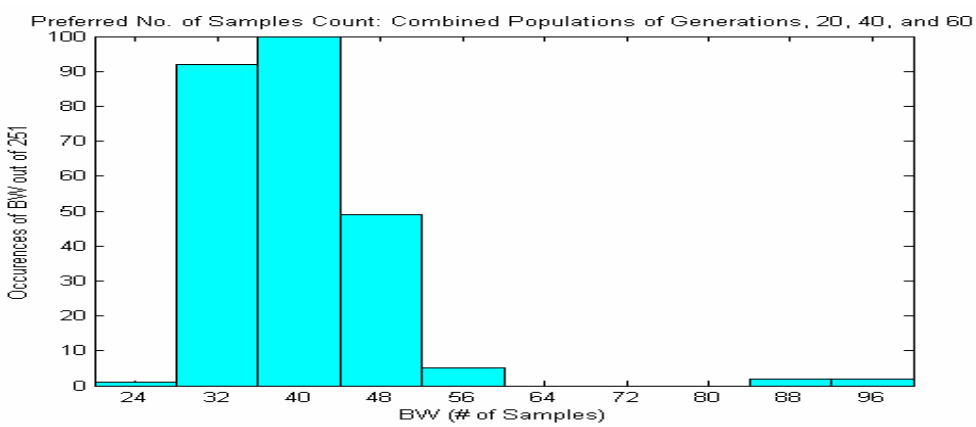


Figure 11 Histogram for Bandwidth

EC Experiment to Determine Sampling Interval

The EC system was modified so that instead of s start frequency and a bandwidth, each complete 401 data set (for a frequency range) would be considered completely but we would vary a sampling interval to take the impedance at every 1, 2, 3, 4 …20th frequency to use for our metric calculation. This means that if we found an adequate quality of pressure differentiation sampling every 10th frequency, we could afford to coarsen the resolution and have the 401 samples that the instrument could measure take over 10 times the frequency range used in the current samples (about 10kHz typically), which might, in turn, give better results.

A population of 100 individuals was used again, and the distribution of final solutions after 80 generations is shown below (figure 12).

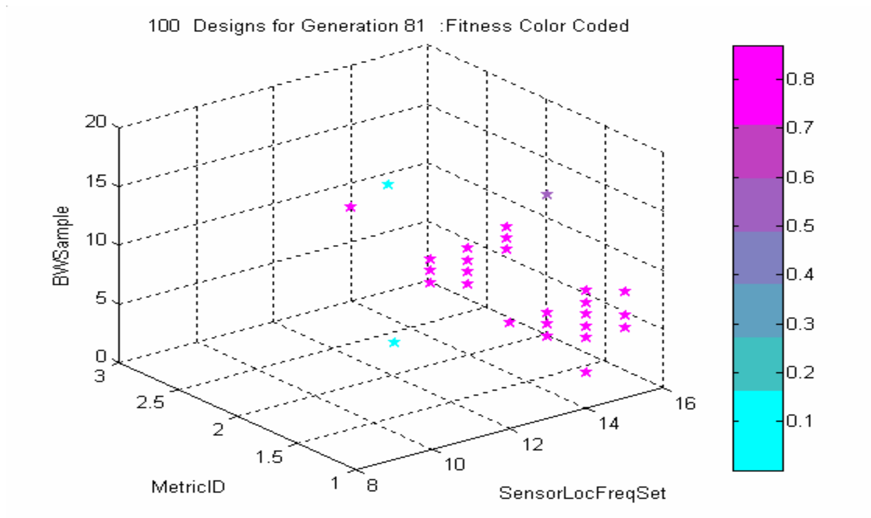


Figure 12 Designs for Last Generation

These results confirm the results of the previous experiment indicating that the RMSD and the MAPD metrics seem to work best, and that data set for the SCP at location A for the higher frequencies, in particularly the 180-200 kHz range, provides the best results for distinguishing pressures thorough the use of the metrics. The histograms below of the distribution of the best scoring alternatives in the final population show these results. They also show that the sampling resolution could be made coarser by a factor of eight (taking impedance at 400Hz instead of every 50 Hz) and still provide good discrimination. This may permit expanding range or frequencies in a single sweep.

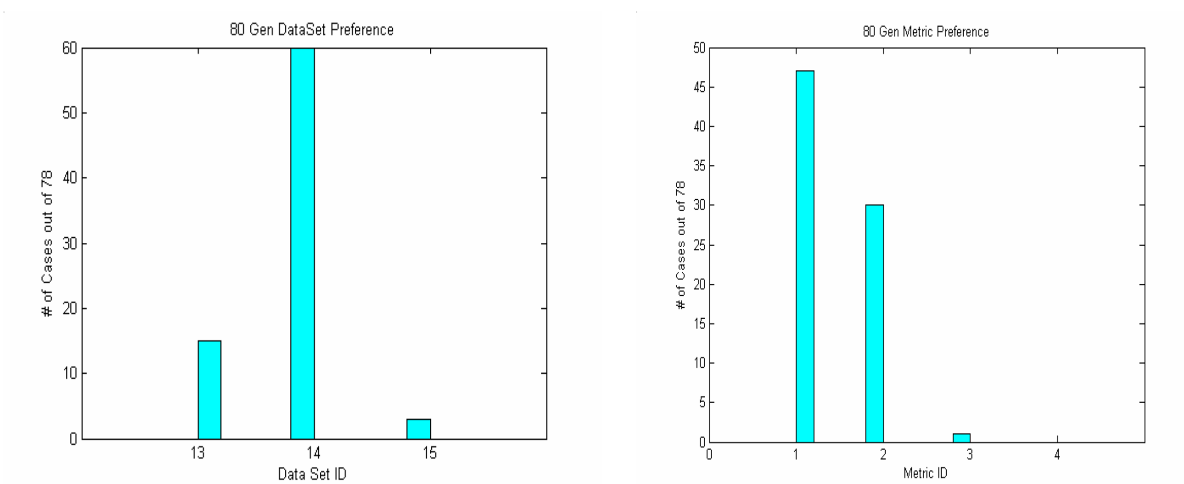


Figure 13 Preferred Data Sets and Metrics in Best of Final Population

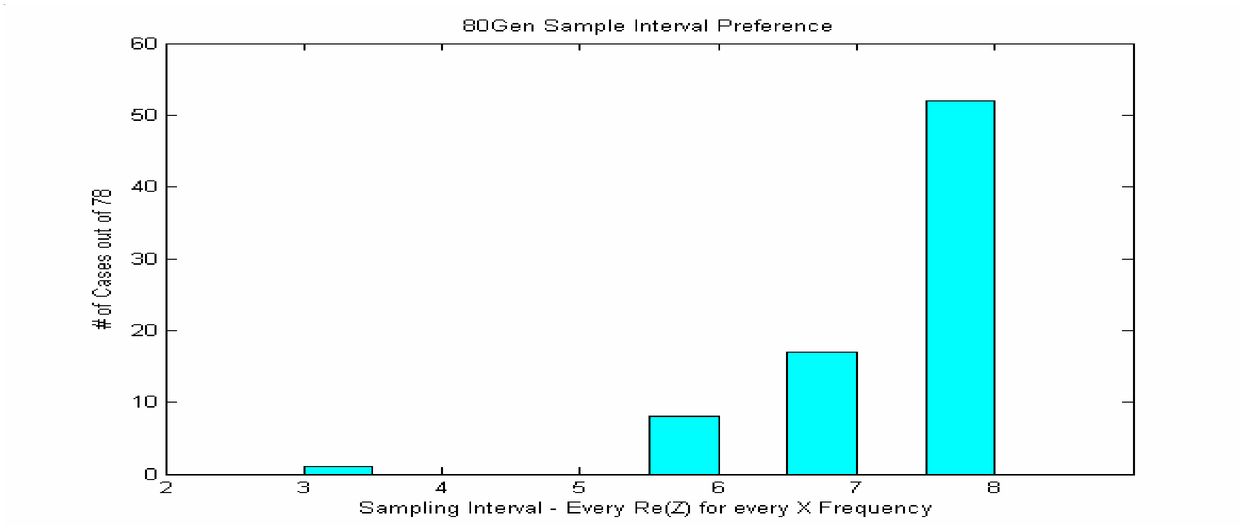


Figure 14 Preferred Sampling Intervals in Best of Final Population

Finally, if we examine the Re(Z) traces (Figure 15) for the four pressures in the preferred data set (set #14) we can see that it does do a good job of distinguishing between the pressures, in particular in the 180-190 kHz range.

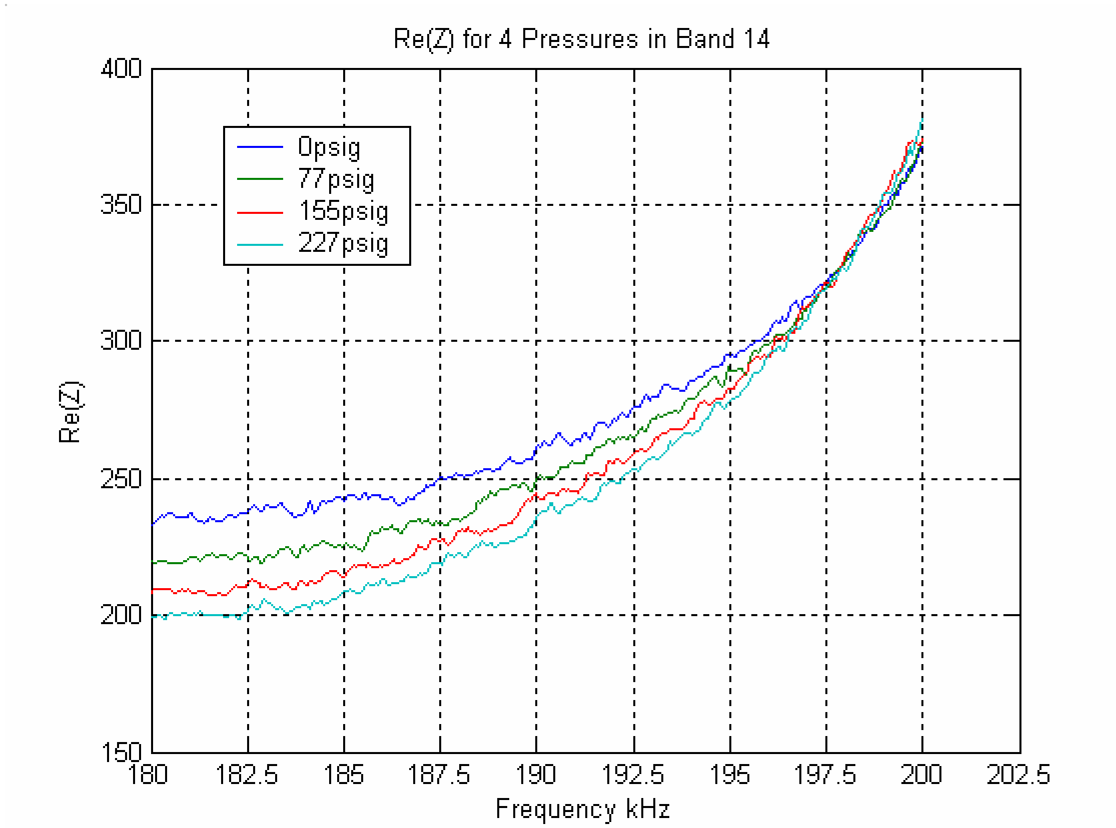


Figure 15 Re(Z) traces for Dataset 14: SCP at location A 180-200 kHz

Conclusions and Recommendations

Though there was insufficient data to perform statistical modeling on the data, we were able to develop reasonable answers to the initial questions that may be used to guide more specific tests. These conclusions are listed below.

- The SCP type sensor appears to be more sensitive and a better discriminator of pressures.

- The location at the center of the bottle provided better data, but there may have been a failure of the sensor systems on the end of the bottle.

- This type of structural impedance testing seems to be more effective at higher frequencies. For the SCP sensor, the best range was 180 – 190 kHz for discriminating between the test pressures.

- The nonparametric metrics are reasonable and parsimonious representations of the signals. In addition, fewer samples over wider frequency ranges may be sufficient for satisfactory pressure discrimination. These conclusions are based on:

    * Re (Z) at only 30-50 contiguous excitation frequencies was sufficient for reasonable metric calculations to discriminate between pressures..

    * A granularity of 400 Hz between frequencies was sufficient for the SCP sensor in the 180 – 190 kHz range to provide good discrimination between the test pressures.

- The Root Mean Square Deviation performed the best and the Mean Absolute Percentage Difference performed well at discriminating between the test pressures. The RMSD metric is reasonable to use in testing.

Another conclusion is that it appears that the EC approach worked very well at providing decision making information in an ambiguous, data and knowledge space problem situation. These conclusions can be considered as ad hoc heuristics. In IVHM it is likely that there will be unexpected situations like the one described, and perhaps emergence though EC may be a way to provide some ad hoc heuristics when fairly quick response time is needed. This approach would not work in a short term real time situations, since there must be at last some time allowed for emergence. However, we may want to have emergence based system that observes for emergence of situations and events on monitored systems, and to develop strategies and information to support decision making. In addition, the EC approach is also a tool that could be used for simulations, as it was in this case, to describe emergent states.

For this problem I have listed my recommendations for further testing and analysis.

1) Conduct a PZT-SCP test with only one of each sensor at one location, the center of the bottle, to determine the best sensor to use and develop its pressure adjustment relation.

2) Run each sample case sweep at a single high frequency range with a 100 to 150 kHz bandwidth for the 401 samples. Convert the results to the RMSD metric and use this as a basis for exploring good starting frequencies before the test.

3) A single sample set should consist of a sweep at each of the pressures of a selected range for each of the two sensors. The pressure range should include the min and max pressures on interest. Conduct tests to develop 6-10 sample sets as described above. This would permit calculation of some small sample statistics. If more confidence is desired, develop more sample sets.

4) Compare the tests and perform statistical analysis the RMSD as the random variable while trying to its relation to pressure and sensor type. The results should indicate the best sensor to use and provide enough information to develop a model relating the RMSD to the pressure for correction purposes.

I will try to analyze the cryogenic data to explore thermal effects on the sensor over the coming year and report back to John Lassiter.

References

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