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Lead-acid cell performance prediction using pattern recognition analysis

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Lead-acid cell performance prediction using pattern recognition analysis

Petesch, Robert Maurice, M.S.

San Jose State University, 1992

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Ann Arbor, MI 48106

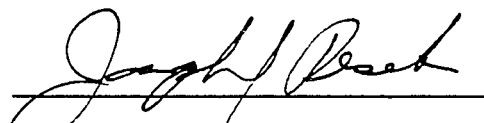# LEAD-ACID CELL PERFORMANCE PREDICTION USING PATTERN RECOGNITION ANALYSIS

A Thesis Presented to the Faculty of the
Department of Chemistry
San Jose State University
In Partial Fulfillment of the Requirements for the Degree
Master of Science

by
Robert M. Petesch
August, 1992
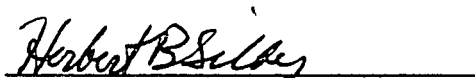
APPROVED FOR THE DEPARTMENT OF CHEMISTRY

Dr. Sam P. Perone

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APPROVED FOR THE UNIVERSITY

ABSTRACT

LEAD-ACID CELL PERFORMANCE PREDICTION USING PATTERN RECOGNITION ANALYSIS

by
ROBERT M. PETESCH
Research Advisor: Dr. Sam P. Perone

Pattern recognition (PR) was used to correlate lead-acid cell capacity performance with battery fabrication data. Fabrication data consisted of detailed documentation of materials, electrolyte composition, and cell capacities during the manufacture and conditioning of 340 (2080 amp-hr) lead-acid cells. PR was used to determine if fabrication features could be used to classify individual cell performance. Cells were assigned to different performance classes based on capacities determined for a 121-cell subset after 7 years of operation. Training sets were constructed for PR studies, and feature elimination and statistical selection methods were used to develop classifiers which could accurately identify high, low and intermediate capacity cells. Accurate classifiers frequently consisted of electrolyte level measurements and adjustments to the latter at specific stages of fabrication. Accuracies of 95% for high-low and 86% for high-low-intermediate class recognition were obtained using K-nearest neighbor and cluster analysis methods.

ACKNOWLEDGMENTS

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I. Introduction

Multivariate analysis and computerized pattern recognition have been shown to be useful tools in a variety of chemical analyses such as identification of amino acid sequences in polypeptides [1], classification of herbicidal activity for nitrodiphenyl ethers [2] and evaluation of several transition-metal ions as potential chemical ionization reagents [3]. Studies involving fundamental electrochemical measurements, such as those taken in voltammetric determinations [4-7], have been useful in understanding the factors that control electrochemical systems. Knowledge of electrochemical control factors is important in the design of electrochemical cells which can meet stringent demands.

The quest for alternate forms of energy, and energy storage methods, has sparked vigorous research into electrochemical cells. Of particular importance for energy storage applications are cell lifetime and efficiency, and we have investigated pattern recognition for prediction of these properties. The usefulness of pattern recognition has been demonstrated in studies involving the prediction of nickel-cadmium [8] and lead-acid [9, 10] cell lifetimes, based on initial acceptance test data. Results of these studies showed that a multivariate examination of easily measurable properties allowed for the accurate prediction (87-100%) of battery lifetimes. Data collected from fabrication, testing, and operation of lead-acid cells [11] have been examined using cluster analysis to determine if natural subsets of cells with similar performance properties could be identified.

The ultimate goal of our research is to determine and evaluate the information content of electrochemical measurements, and to increase the understanding of chemical and physical processes underlying electrochemical cells. The purpose of this particular study was to determine if electrochemical and other measurements taken during lead-acid cell

fabrication contain the information content necessary for accurate prediction of cell performance during its lifetime. In this work, the performance of a battery cell is equated with its ability to deliver the rated capacity. The ability to distinguish between high and low performing cells is important for allowing prior selection of superior cells and exclusion of problem cells. This becomes particularly important for applications involving remote measurement, space travel or situations involving large energy storage systems where cell failure can be disastrous.

Factors which affect cell performance were determined and evaluated using pattern recognition methods to clarify multivariate relationships among electrochemical measurements taken during cell manufacture. This information was then used to classify individual cells as to their performance capability. This present work is related to another investigation that was conducted by our research group concerning pattern recognition analysis of lead-acid cell maintenance data for the purpose of lead-acid cell performance prediction [12, 13].

II. Multivariate Analysis and Pattern Recognition

Multivariate analysis can be defined simply as the analysis of a data matrix composed of multiple samples for which several independent features have been measured. Advances in instrumentation and hyphenated techniques have provided the ability to rapidly acquire vast amounts of data for several parameters within a single assay.

The basic premise of pattern recognition is that a multivariate data matrix of measurements on a system under study contains information that allows for the distinct classification of each item subjected to the analysis [14]. Multiple measurements made to characterize each item create a vector in multi-dimensional feature space which is located in the same region of space as other items of the same class.

It is difficult for most people to visualize beyond three dimensions; however, multivariate computational techniques can be used to examine pattern vectors in multi-dimensional feature space and are an invaluable tool in pattern recognition studies. Pattern recognition is used in multivariate analysis to classify items from several measurable features where the class distinction is not obvious from direct examination of the raw data. The computer techniques aid in the detection of groups with similar patterns and in the classification of items based on their proximity to items of known class in multi-dimensional feature space. Additionally, computer mapping techniques can help in the visualization of multi-dimensional feature space in two dimensions.

II.A. Pattern Recognition Methods

There exist many methods for pattern recognition, and much of the mathematical proof and treatment of such problems have been addressed [15-17]. Generally, pattern recognition methods fall into two categories: *supervised* and *unsupervised* pattern recognition [14, 18, 19]. Supervised pattern recognition methods involve the utilization of predetermined class models to enable the classification of individual items or unknowns. A

training set consisting of known items is used to develop suitable classifiers. The classifiers are then tested on a different set of known items, the *prediction set*. Worthy classifiers are then used to predict the class of each unknown item.

In contrast, unsupervised pattern recognition methods assume no prior knowledge of any classes. Unsupervised methods employ cluster analysis or mapping techniques which do not require *a priori* knowledge of the existence of specific classes. Clusters which form in multi-dimensional feature space, or are observed visually upon plotting data in two or three dimensions, are assumed to represent specific classes of items. Direct knowledge of the origins of the raw data and the significance of observed clusters is needed to accurately assess the identity and characteristics of a particular cluster. Some of the more common methods of pattern recognition, which have been used to study electrochemical cells [8-13], are discussed below.

II.A.1. Supervised Pattern Recognition

In supervised pattern recognition, items are classified based on their proximity to defined class models. There are several ways to perform these classifications, and the most common of these are discussed next.

II.A.1.a. Linear Discriminant Analysis

Linear discriminant analysis (LDA) was first developed by the statistician R. A. Fisher [17] as a means for classifying an object as belonging to one of two classes. Essentially, a mathematical discriminant function is sought (using a training set of known-class patterns) which linearly separate the two classes in pattern space (Figure 1). Each item in the *i*th class can be described by a linear combination of feature elements, X_1, X_2, X_3 ... , X_N, which when multiplied by a weight vector, w_1, w_2, w_3 ... , w_N, w_{N+1}, yields a pattern vector located in the spatial region for class *i* [15, 17].

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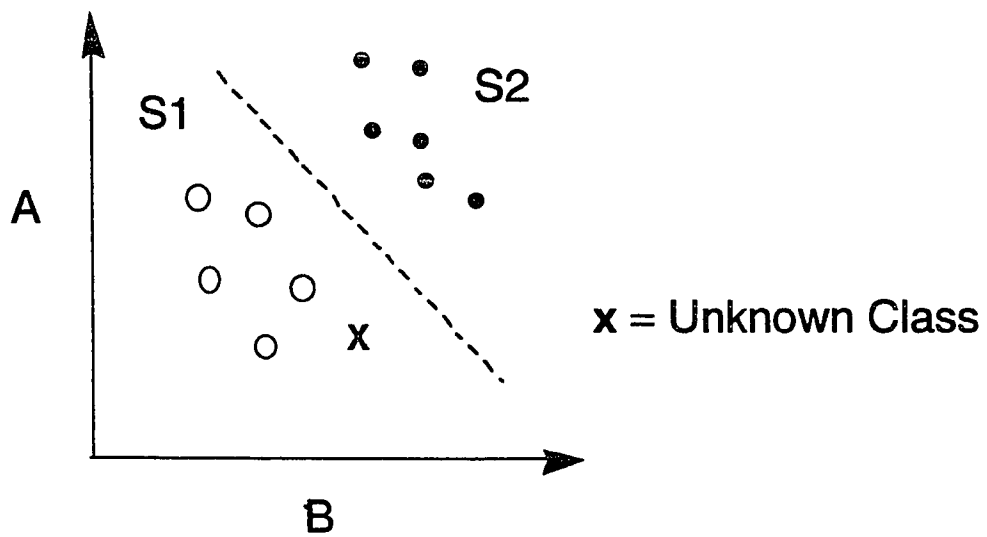
Figure 1. Linear discriminant analysis of unknown item X. A plot of feature A versus B produces two distinct groups, classes S1 and S2, which are separated by a linear boundary. The unknown X is located on the side belonging to S1 and hence is assigned as such.

The general pattern vector for class i takes the following form:

$$S_i(X) = \sum_{k=1}^{N} w_{ik} X_k + w_{i,N+1} \quad \text{where } i = 1, ..., m \tag{1}$$

A similar generalized pattern vector, $S_j(X)$, can be written for items in class j. A decision boundary between the regions is defined by eq 2.

$$S_i(X) - S_j(X) = \sum_{k=1}^{N} w_k X_k + w_{N+1} = 0 \tag{2}$$

where $w_k = w_{ik} - w_{jk}$

and $w_{N+1} = w_{i,N+1} - w_{j,N+1}$.

The discriminant function described by eq 2 is a line, plane, or hyperplane which divides feature space into two regions assigned to different classes. The computed value of the discriminant for each pattern is either positive (+) or negative (-) depending on whether the item belongs to one class or the other. LDA methods have been useful for electrical engineering applications which involve pattern recognition [16].

II.A.1.b. Linear Learning Machine

The linear learning machine (LLM) method is commonly used in chemical pattern recognition [12, 14, 18, 19, 17, 20]. The LLM method of classification involves repetitive calculations which seek to find a linear discriminant that can separate two clusters of training set objects in N-feature space. The discriminant function shown in eq 3 is similar to eq 2.

$$S = \sum_{i=1}^{N} w_i X_i + w_{N+1} \tag{3}$$

The discriminant, S, is > 0 on one side of the plane and < 0 on the other. An arbitrary decision plane is selected and each object in a training set is classified based on which side of the plane it is located. If any object is misclassified, the weight vectors, w,

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are altered to adjust the decision plane, and the object is reclassified. This procedure continues iteratively to convergence until all training set objects are classified correctly, or until the LLM reaches maximum classification accuracy. The resulting discriminant function is then used to classify unknown objects. Training time can be extensive with the LLM method, but unknown pattern classifications are fast. Of course the underlying assumption in this method is that the two classes can be separated by a linear discriminant.

Sometimes linear separation is not possible, so one must use discriminants which give the highest possible accuracy, or use a least squares method to find the best line through the two groups. Another option is to define a "dead-zone" between the two groups, i.e. a region between the classes where objects cannot be unambiguously classified (Figure 2). Objects falling on either side of the dead-zone can be classified correctly. If the dead-zone is too large and many objects are within it, it may be beneficial to use a quadratic or other type of function to separate the clusters.

LLM methods have been used to classify and resolve voltammetric data [5, 21, 22] and have been applied in systematic approaches to pattern recognition analysis of chemical data [23]. LLM was found to be useful in screening out ineffective features prior to analysis by other classification methods.

II.A.1.c. K-Nearest Neighbor Analysis

Another commonly used method for making classification decisions is the K-nearest neighbor (KNN) method. This method is useful when no linear discriminant exists that will separate the clusters in a data set. It is also useful for multi-category classifications. The essential premise is that an unknown object X is assigned to the same class as that of its K-nearest neighbors, as illustrated in Figure 3 [15, 16, 23]. According to Patrick [16], similar KNN decision methods have been proposed [Fix and Hodges, 1951; Cover and Hart, 1966] known as the KNN_1 and KNN_2 decision rules.
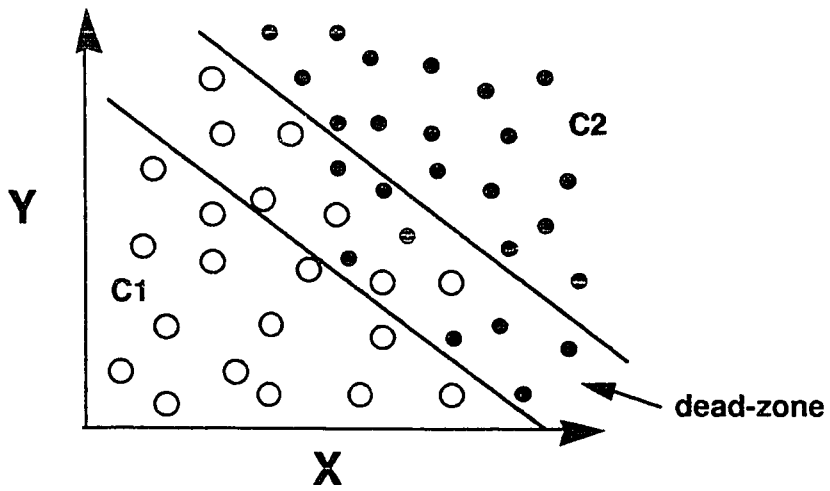
Figure 2. An example of two classes which cannot be separated by a linear discriminant. Designation of a dead-zone between the classes enables the distinction between classifications made outside and those made inside the dead-zone, where classification is ambiguous.
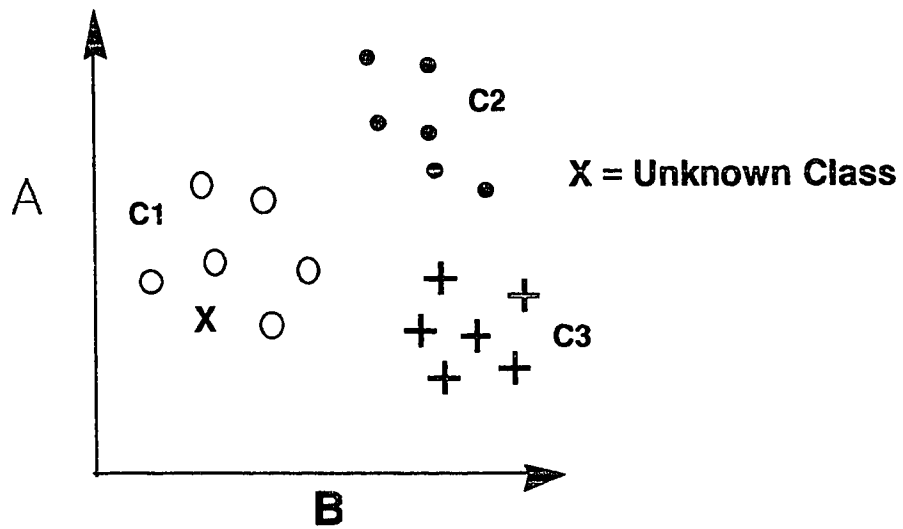
Figure 3. Nearest neighbor analysis of item X of unknown class. Item is classified based on the class of its nearest neighbors of known class. Note that there is no linear discriminant which can separate the classes.

Patrick introduced the third rule, KNN3, which is described above and will be referred to as the KNN method for simplicity. Distances, D_{jk}, between any two objects, j and k, are calculated using the Euclidean distance formula [19].

$$D_{jk} = \sum_{i=1}^{N} \left[(x_{ji} - x_{ki})^2 \right]^{1/2} \tag{4}$$

where x_{ji} and x_{ki} are values for the i-th feature for items j and k. The distance measurements are compared and the unknown is assigned to the class of its K-nearest neighbors. The value of K can be greater than one; however, it is customary to choose an odd number to prevent an equally split vote. If an even number is picked for K, some sort of voting scheme must be used to prevent a split vote [20].

The main advantage of the KNN method is that it can be applied to non-linear classification problems and is suitable for multi-class identifications. There is no inherent training involved. All patterns, known and unknown, are analyzed simultaneously. One disadvantage of the KNN method is that all patterns must be examined for each unknown that is classified. This can result in long computer calculation times, in contrast to the LDA method, where classification is fast. The KNN method also fails to provide a way to screen out features which are less useful than others. Some prior procedures must be followed to determine which are the most effective features for accurate classification (See Feature Selection Methods, II.E). LLM methods may be suited for systematic elimination of features and are often used as a screening tool for dimensionality reduction prior to analysis by KNN.

A variation to the KNN method has been proposed by Pichler and Perone [23] which performs one-dimensional KNN, i.e. examines each feature one at a time, for its ability to classify a training set of known objects. Only those features which are associated with high classification accuracies are chosen to perform multi-dimensional studies. KNN

analysis has been applied to numerous chemical problems including the analysis of voltammetric data [4, 5, 21, 22], the identification of organic compounds [1, 2] and to lifetime [8-10] and performance [12, 13] prediction for battery cells.

II.A.2. Non-Supervised Pattern Recognition

Non-supervised pattern recognition is used to examine data where *a priori* knowledge of specific classes is unknown. Cluster analysis and non-linear mapping methods were used in this work and are discussed below.

II.A.2.a. Cluster Analysis

Cluster analysis is used to determine the existence of subsets in a group of patterns. The mathematical foundations of cluster analysis are very detailed, complex and well established [15, 16], and many techniques have been developed [14, 18, 19, 24-27]. Clusters can occur in a wide variety of shapes [16], and some examples are shown in Figure 4.

Three general steps are involved when performing cluster analysis [24]:

1. The items to be classified are characterized, and the analytical data are collected and preprocessed.

2. The similarity of each object is determined.

3. Clustering algorithms are constructed to enable the development of classifiers which result in meaningful clusters.

It is important to note that computer-based clustering algorithms are generally applicable to multi-dimensional feature space, just like the LLM or KNN supervised learning algorithms. Generally, there are two main types of hierarchical clustering [18]: hierarchical agglomerative clustering and divisive hierarchical clustering. Hierarchical agglomerative clustering is most common and is based on the premise that each object starts

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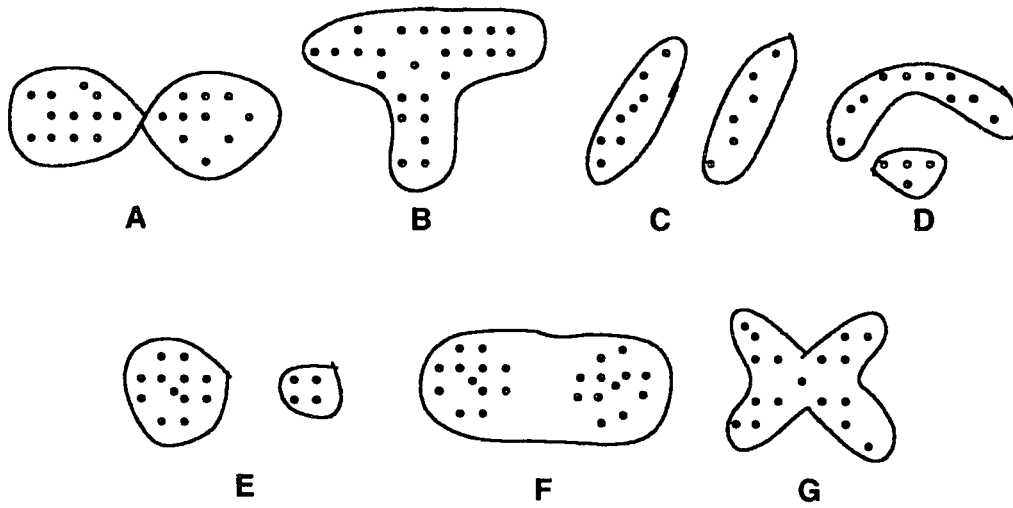
Figure 4. Examples of cluster types: (A, B) Bridges between clusters. (C) Parallel non-spherical clusters. (D) Linearly parallel clusters. (E) Unequal cluster populations. (F) Cluster with a hole [actually two clusters]. (G) The X.

as a cluster generating nucleus. The radius is iteratively increased by a fixed length to include neighboring objects or clusters which contain a smaller number of objects. This process is repeated until each of the smaller clusters progress to successively larger and fewer clusters. Agglomerative methods involve what is known as the SAHN technique.

S stands for "sequential" algorithm.

A stands for "agglomerative" where objects start out as single nuclei and are progressively built into larger clusters.

H stands for "hierarchical" meaning that each ascending level is composed of fewer clusters than the preceding level.

N stands for "non-overlapping", i.e. objects can never be assigned to more than one cluster centroid at a time.

Divisive hierarchical clustering is less common and essentially starts with all objects grouped into one large cluster and proceeds with iterative divisions into progressively smaller clusters. A third type of clustering is known as non-hierarchical clustering. A set of objects is divided into the most likely clusters and the distance between objects and the centroid of each cluster is used as criterion for the assignment of each object to a neighboring cluster [14]. The basic assumption is that similar objects will occupy the same region of feature space. The procedure is continued until convergence, i.e. until all objects have been assigned to a cluster.

Assignment of an object to a specific cluster is usually based on the distance between the two. There are several distance methods to choose from. The most popular is the Euclidean measurement which was previously described in eq 4. Non-hierarchical clustering methods usually involve the following steps [14]:

1. Select initial clusters.

2. Determine distances between objects and centroids.

3. Locate or assign each object to nearest centroid.

4. Compute new centroids and repeat to convergence.

Cluster analysis has found application in a variety of analytical chemistry problems such as GC-MS identification of organic esters [1], evaluation of transition metal ions as chemical ionization reagents [3] and in electrochemical cell studies [8, 11, 13]. Additionally, Massart and Kaufman [24] have discussed in detail the application of cluster analysis in analytical chemistry.

A fourth type of cluster analysis is simply "visual" detection. However, this requires that the objects be represented in 2- or 3-D feature space. When larger numbers of features are required for separation, visual cluster analysis is not directly applicable. Nevertheless, mapping techniques are available to display multi-dimensional space in two dimensions, as described below.

II.A.2.b. Non-linear Mapping

Non-linear mapping (NLM) is a method for plotting data which reduces N-dimensional feature space to two dimensions [14] and is illustrated in Figure 5. The NLM method, sometimes referred to as multi-dimensional scaling, essentially attempts to preserve inter-point distances in converting N-D to 2-D space. Several methods have been proposed, but most operate on the same principle by iterative minimization of the mapping error, E, which can take many forms [15, 18], one of which is

$$E = \sum_{i < j}^{P} [(d_{ij} - d_{ij}^*)^2 / d_{ij}] \qquad (5)$$

where d_{ij} = the original inter-point distance in N-dimensional space

d_{ij}^* = the new inter-point distance in 2-dimensional space

and P = the total number of patterns
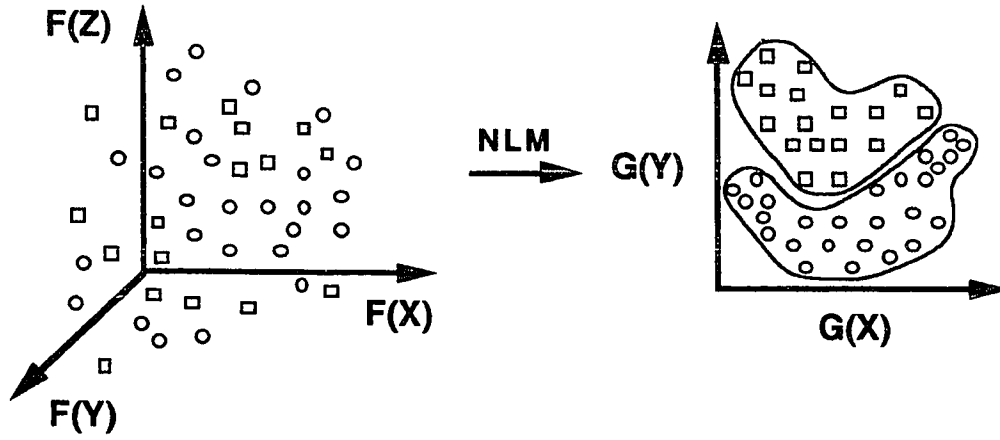
Figure 5. Non-linear mapping (NLM) is used to reduce multi-dimensional space to two dimensions. The example above illustrates the reduction of 3-D space to 2-D using NLM.

Some forms of the mapping error function are referred to as the stress function, but the principle is the same. The mapping error equation proposed by Sammon [28] is similar to that above but contains a weighting factor which can weight the N-dimensional term by different amounts relative to the 2-D term. Sammon's method was subsequently modified by Kowalski and Bender [29] and is expressed below.

$$E = \left\{ \sum_{i<j}^{P} [(d_{ij} - d_{ij}^*)^2 / d_{ij}] \right\} \left(\sum_{i<j}^{P} d_{ij} \right)^{-1} \tag{6}$$

While the NLM method is very powerful for transforming and viewing multi-dimensional space in two dimensions, it suffers from the large amount of computer time needed to execute the transformation. It is prudent to utilize feature selection methods first to eliminate ineffective features and limit the NLM treatment to as few features as possible.

The NLM method has been used in many analytical chemistry applications [1, 3, 21, 22, 30] and is the only display method used as frequently as principal components analysis [24]. NLM is particularly useful in our work for the evaluation of fabrication features for lead-acid cells [11-13].

II.B. Feature Selection Methods

Feature selection is important and ideally will result in a minimum number of features being chosen so as to achieve the highest possible classification accuracy. A reduction in the number of features is sometimes referred to as a reduction in dimensionality. Feature reduction results in a smaller data matrix and subsequently much less data to process; therefore, processing time is reduced. Another advantage to eliminating unnecessary features is that the latter may contribute considerable "noise" to the multivariate data matrix, and may make it more difficult to distinguish among different classes. Elimination of unwanted, noisy features can render classification easier by reducing the degree of class overlap in N-D space.

Another practical consideration is that feature reduction results in only the most important measurements being taken and thus, a reduction of the physical measurement time and effort involved. This, of course results in lower expenses incurred for a given assay. Several feature selection techniques exist, but common methods used for this study are described briefly below.

II.B.1. Correlation Analysis

Correlation analysis involves calculating the linear correlation coefficient for each pair of features in a multivariate data matrix. The Pearson correlation coefficient ($R_{a,b}$) between features a and b, for n items, is defined as follows [14]:

$$R_{a,b} = \{\Sigma \ [(X_{ia} - \overline{X}_a) \cdot (X_{ib} - \overline{X}_b)]\} \ / \ [\Sigma \ (X_{ia} - \overline{X}_a)^2 \cdot \Sigma \ (X_{ib} - \overline{X}_b)^2]^{1/2} \quad (7)$$

X_{ia} and X_{ib} are the respective values of features a and b for item i, and $\overline{X}_a$ and $\overline{X}_b$ are the respective means of the values for features a and b. Summations are taken for all values of i ranging from 1 to n. The correlation coefficient, as defined in eq 7, lies within the range of +1 to -1. Values of R equal to zero imply that features from set A have no correlation to features from set B. Positive values indicate a positive correlation between two features, and negative values represent a negative correlation. R values equal to +1 or -1 indicate that there is a perfect correlation between the two feature sets. Negative correlations can sometimes be difficult to interpret, and while negative correlations suggest dissimilarity, this is not always true [31]. Therefore, the square of R is sometimes used to eliminate any negative value. R^2 would then range from 0 to +1.

Generally, high correlation values indicate feature pair similarity and one or other of the two features can sometimes be eliminated from the feature set. Elimination of highly correlated features results in a condensation of features with mutually large R values into a smaller set with statistically equivalent information. However, elimination of highly correlated features does not always avoid a loss of information. This is especially true if

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the distribution of the measured values of a given feature are non-Gaussian or if the effectiveness of a feature is dependent on the presence of another feature.

For example, assume feature A is highly correlated with feature B, but the effectiveness of C depends on the presence of feature B. Elimination of feature B based on its high correlation with feature A might actually result in a lower overall classification accuracy, due to the loss of synergistic interactions between features B and C. Therefore, it might be better to retain all three features for the analysis.

II.B.2. Fisher Ratio Analysis

The Fisher ratio is used to determine the ability of a feature (i) to distinguish between two different classes. Essentially, for a binary classification problem the Fisher ratio is given by eq 8.

$$F_i = (m_{1i} - m_{2i})^2 / (V_{1i} + V_{2i}) \qquad (8)$$

The difference between the mean values (m_i) of feature i, for different classes 1 and 2 is squared and compared to the sum of the variance, V_i, for both classes. Values of the Fisher ratio, F_i, for a chosen feature can vary widely depending on the distribution of the values within each class. If the means 1 and 2 are nearly equivalent or equal, values of F_i will be quite small or equal to zero. Likewise, a large variance V_i for one or both classes can result in small Fisher ratios. As the distribution of values within each class narrows, or as the means get further apart, the Fisher ratio becomes larger. First, the Fisher ratios are calculated for each feature in a data matrix. The data set is then reduced in size by retaining features with larger ratios and rejecting those with smaller ratios.

II.B.3. Univariate Discriminating Power

The univariate distribution of values for a given feature can often provide insight on the ability of the feature to discriminate between classes [14, 32, 21]. The univariate

discriminating power is determined for each feature, and features which provide a high degree of discrimination are selected for further study.

Figure 6 illustrates individual feature values with a single dimension vector. The univariate plot shown in Figure 6a indicates what appears to be two classes of items. However, knowledge of the class of each item could lead to the results as shown in Figure 6b. In this case each class of items contains an outlier, causing an overlap in the sets.

Knowledge of the class identity for each of the items within the feature set can significantly affect the interpretation of the results. Histograms are another, more sophisticated way of visualizing univariate data. Histograms allow visualization of the relative proportions of the number of items having a particular value. Histograms are discussed later in more detail.

Another method for measuring univariate data consisting of two classes involves the calculation of the ratio of the difference in the means of a given feature for two classes, 1 and 2, to the combined standard deviation of the two sets of features.

$$R = |X_1 - X_2| / (S_1{}^2 + S_2{}^2)^{1/2} \tag{9}$$

Comparison of eqs 8 and 9 show that the quantity R in eq 9 is simply the square root of the Fisher ratio. Thus, substituting V for S^2 in eq 9 gives

$$R = |X_1 - X_2| \div (V_1 + V_2)^{1/2} = (F)^{1/2} \qquad \text{or} \quad R^2 = F \tag{10}$$

Both F and R have similar properties in that they become larger as the distance between the average location of each class widens, and as the items within each class cluster together. Of course, values of R^2 will be more sensitive to changes in the means and standard deviations of each class. R and F ratios are useful for discerning the discriminating ability of individual features, but they do not reflect any feature to feature interactions. The rejected features may still be valuable for other feature group combinations and should not be exempt from further investigation by other methods.
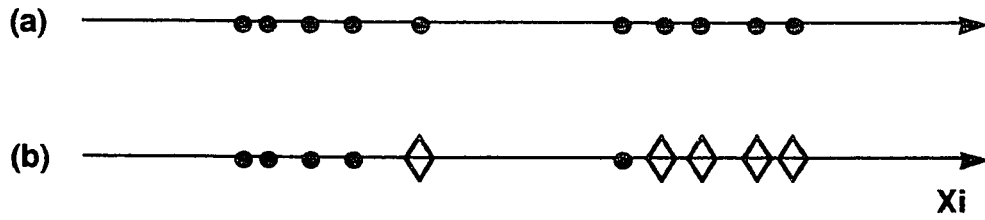
Figure 6. Univariate plots where plot (a) represents what appears to be two distinct groups. This would likely be the conclusion if the class identity of each item is unknown. Plot (b) illustrates what the distribution of items might really be if it were known that there are two distinct classes, represented by • and ◊ .

II.B.4. Statistical Distributions

Often it is useful to group data into classes and group the measurements made for each class [14]. Data which are organized this way can be described graphically with a histogram (Figure 7). $F(x_i)$ is a measure of the relative frequency of occurrence of a measurement in the interval Δx_i. The probability of a measurement occuring within any interval Δx_i is the product of $F(x_i) \cdot \Delta x_i$. If large numbers of measurements are taken on infinitesimally small intervals of x, then the distribution of $F(x_i)$ is represented by a smooth, continuous curve. The area under the curve is just the integral of $F(x)$ for all values of x, which equals 1, the total probability for the occurrence of values of x.

$$\int_{-\infty}^{+\infty} F(x)dx = 1 \tag{11}$$

The function in eq 11 is referred to as a continuous random-variable probability density function. When a continuous variable distribution is normal or normal-like, the values are distributed evenly about the mean in decreasing frequency as the distance from the mean increases. When the data are standardized, a special normal curve results (sometimes referred to as a z-curve) where the mean equals zero and the z_i are in increments equal to one standard deviation [32, 33] (Figure 8).

When a group of random variables consist of a finite number of values, or a countable sequence of an infinite number of values, the variable is known as a discrete variable. The probability function of a set of discrete variables can be depicted graphically as shown in Figure 9. The probability of a discrete variable Xi having a particular value is $P(Xi)$. Similar to continuous distributions, the total probability, i.e. the sum of all $P(Xi)$ equals 1.

$$P(X \leq Xn) = \sum_{i=1}^{n} P(Xi) = P(X1) + P(X2) + P(X3) \ldots P(Xn) \tag{12}$$

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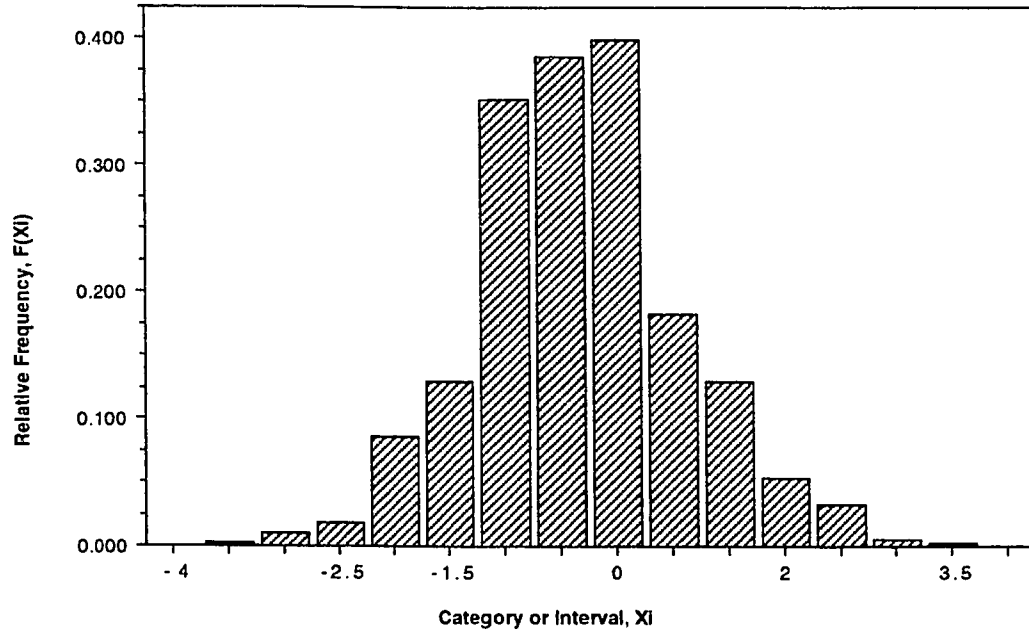
Figure 7. A histogram distribution of items having a relative frequency F(Xi) in the interval Xi. The distribution is not symmetrical throughout the entire interval defined by i = 1 to n.
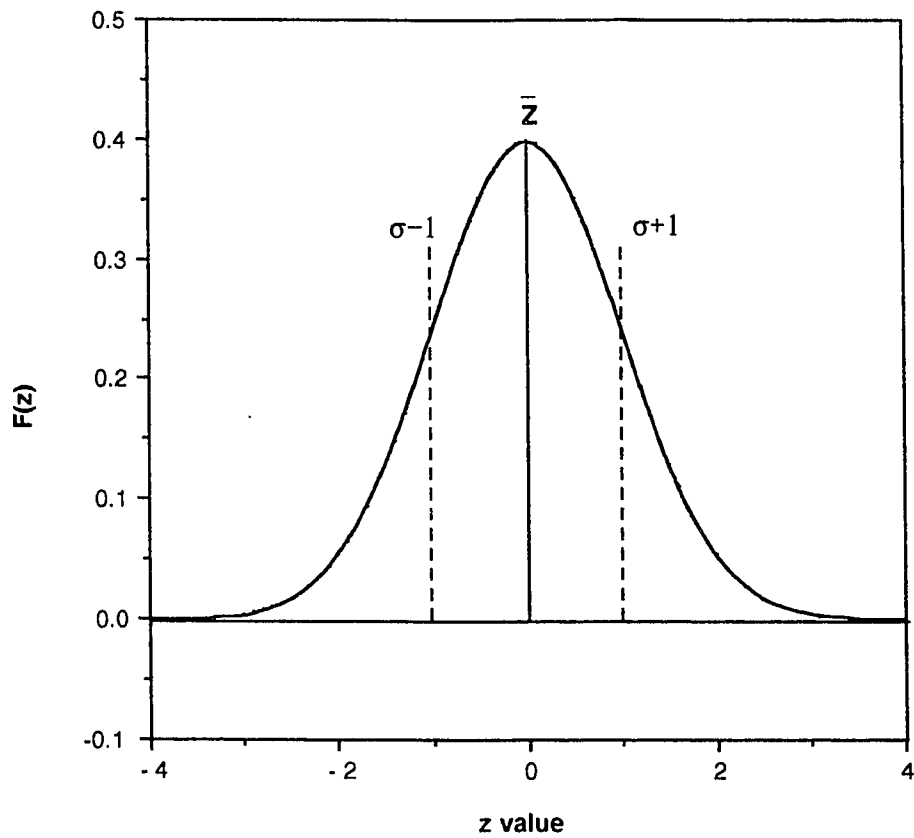
Figure 8. An illustration of a symmetrical continuous probability distribution of the number of items n having a particular value z. Items having values lying within ±1 standard deviation are present in greater numbers as z approaches the mean, but diminish in numbers at the extremes of the distribution, in this case outside ± 1 standard deviation from z.
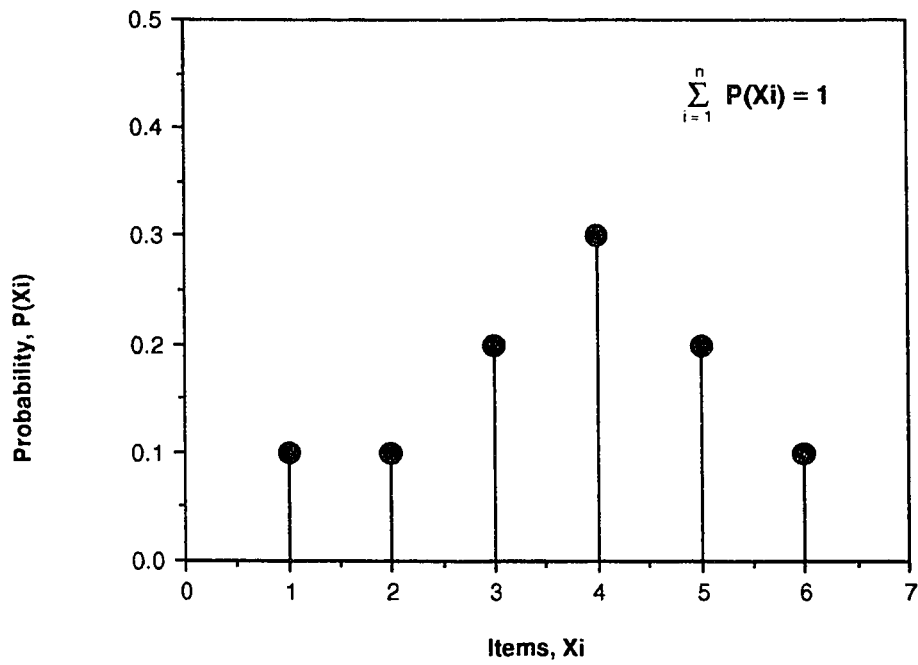
Figure 9. A probability density function composed of discrete variables, Xi. The summation of P(Xi) for all values of i equals unity.

or $\displaystyle\sum_{i=1}^{n} P(Xi) = 1$ (13)

When a particular feature is composed of X_i patterns belonging to more than one

class, class-conditional probability density curves can be constructed to determine the

ability of the feature to discriminate between classes. Ideally, features with high

discriminating ability result in a bimodal distribution of X_i values for each class (Figure 10)

with a minimum amount of overlap. A large difference between means $\mu 1$ and $\mu 2$, and a

small variance within each peak, the less overlap, α, and the greater the discriminating

ability of the chosen feature.

II.B.5. Systematic Selection

Systematic feature selection, while not very scientific, can often provide fruitful

results and should not be overlooked. Smaller feature groups are randomly chosen from

either the original data matrix or from feature groups obtained through other feature

selection methods. The selection can be completely random and non-biased, or specific

feature groups believed to contain useful features can be selected. Other feature selection

methods are often applied to the final feature groups selected by this arbitrary, trial-and-

error method [19]. Systematic feature selection methods have been shown to be effective

in theoretical and experimental studies of overlapped voltammetric data [21, 22].

II.B.6. Sequential Feature Elimination

Sequential feature elimination involves the arbitrary deletion of a feature after a given

feature set is evaluated for classification accuracy. If elimination of the feature results in a

drop in the overall classification accuracy with subsequent pattern recognition analysis, the

feature is added back into the feature set. If the classification accuracy is not degraded or is

improved by removing the feature, then the feature remains excluded from the feature set.

Regardless of the outcome, another feature is then selected to be deleted from the feature
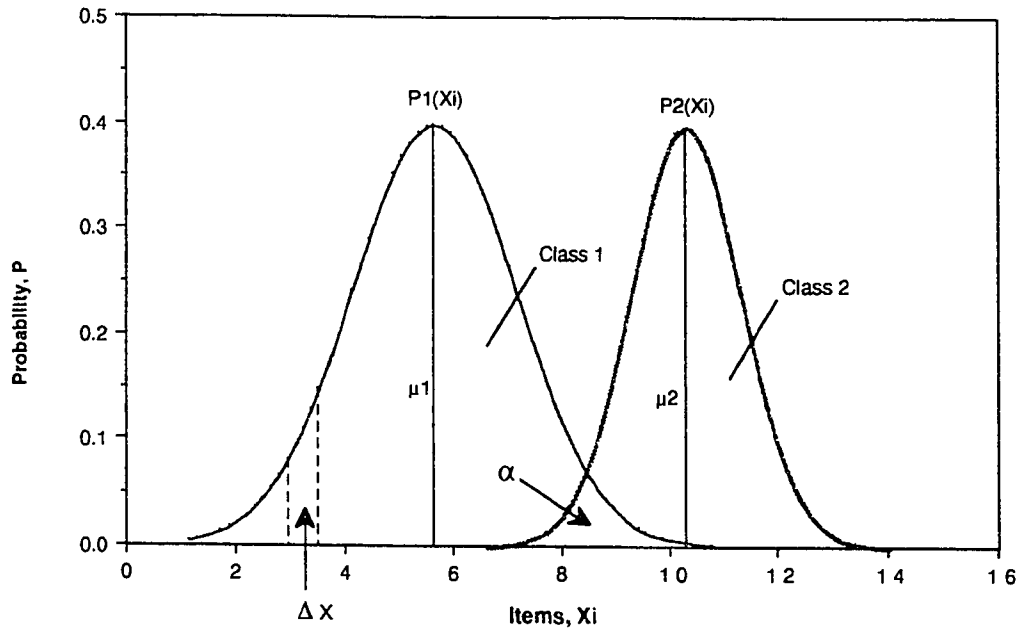
Figure 10. Probability density curves illustrating the ability of feature i to differentiate classes 1 and 2. The probability that an item belonging to class m has a value for feature i in the interval ΔX is $P(Xi)m \cdot \Delta X$.

set, and a subsequent evaluation of the effect of its deletion is done. This procedure is continued until no further deletions are allowed, and the maximum classification accuracy is achieved with minimum features. The order in which the features are examined can change the outcome of the results. The subject of sequential feature analysis and how it applies to pattern recognition and linear learning methods has been treated in detail [17].

The advantage of using sequential elimination methods are that they can be applied to feature groups which have been selected by any other means and can be used to develop other feature groups which may be useful. Computerized sequential methods provide an automated way of establishing the relative importance of each feature and have been shown to be effective in many applications [12, 13, 21-23].

III. Battery Description and Background

III.A. Properties and Construction

The typical lead-acid cells used for this study are much like those found in automobiles. They consist of negative and positive electrodes which are made of sponge lead and lead peroxide, respectively, and are immersed in an electrolyte of sulfuric acid and water [34] (Figure 11a).

A typical cell is represented by:

$$Pb(s) \mid PbSO_4(s) \mid H_2SO_4(aq) \parallel PbSO_4(s), PbO_2(s) \mid Pb(s)$$
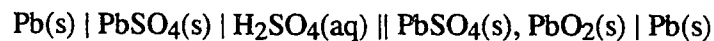
and the cell (a) and half-cell (b and c) reactions are:

(a) $Pb(s) + PbO_2(s) + 2H_2SO_4(aq) \longrightarrow 2PbSO_4(s) + 2H_2O$ Cell Reaction

(b) $Pb(s) + SO_4^{-2}(aq) \longrightarrow PbSO_4(s) + 2e^-$ Negative Electrode

(c) $PbO_2(s) + 4H^+(aq) + SO_4^{-2}(aq) + 2e^- \longrightarrow PbSO_4(s) + 2H_2O$ Positive Electrode
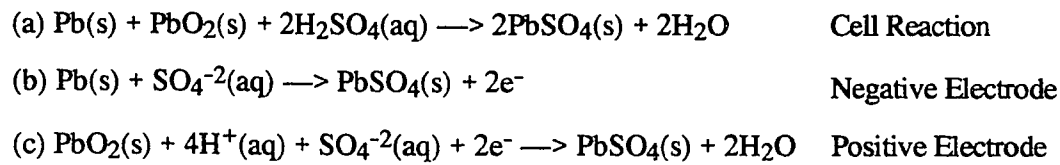
Electrochemical storage cells do not actually store electrical energy. Actually, they convert electrical energy applied to the electrodes into chemical energy; the *state of charge* of the cell refers to the percent of the total available capacity. When a load is placed on the charged cell, the chemical energy is converted, or discharged back into electrical energy.

A fully charged cell has an open circuit voltage just slightly greater than 2 volts (2.06 V), and may be as high as 2.10 to 2.70 V when being charged. The specific gravity, or density of the electrolyte relative to water, is usually between 1.20 and 1.29 at the highest state of charge. A cell constructed this way delivers a 2-volt potential regardless of size; however, size does affect the amount of current (measured in amperes) that a cell can deliver.

When a cell is discharged, the electrodes each react with the sulfuric acid electrolyte to form a lead sulfate coating (Figure 11b). As the sulfuric acid is consumed, the specific

(A) Charged Cell

− 2.06 V +

Electrolyte
Sulfuric Acid
and
Water

Sponge Lead
(Negative Plate)

Lead Peroxide
(Positive Plate)

Maximum Acid Content

(B) Discharging Cell

− ←—LOAD—→ +

< 2.06 V

Decreasing
Sulfuric Acid

Increasing
Water

Sponge Lead
(Decreasing)

Lead Peroxide
(Decreasing)

Increasing Lead Sulfate on Plates

(C) Discharged Cell

− +

~1.75 V

Minimum
Sulfuric Acid

Maximum
Water

Sponge Lead
(Minimum)

Lead Peroxide
(Minimum)

Maximum Lead Sulfate on Plates

(D) Charging Cell

Battery Charger
− +

− ~2.33 V +

Increasing
Sulfuric Acid

Decreasing
Water

Sponge Lead
(Increasing)

Lead Peroxide
(Increasing)

Decreasing Lead Sulfate on Plates

Figure 11. Physical chemical states of a typical lead-acid cell.

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gravity gradually approaches that of water (1.00) and the cell voltage drops to zero volts when completely discharged. Cells are not usually discharged below about 1.7 V to prevent irreversible damage to the electrodes (Figure 11c). Thus, the *nominal capacity* of a cell is the charge delivered (in amp-hr) from a fully charged state to a 1.7 V cell voltage. In practice, lead-acid cells are usually required to deliver a small fraction of their actual capacity before recharging. In fact, cells discharged to a 1.7 V cutoff are described as undergoing *deep discharge*.

The discharged cell can be recharged by applying a charging current (in reverse direction of the discharge current) across the electrodes (Figure 11d). The lead sulfate coated electrodes react with water to produce sulfuric acid and each electrode is restored to its original state. The cell voltage gradually increases back to 2 volts, and the specific gravity increases as more sulfuric acid is formed.

Single cells are not sufficient for large power requirements and several cells are often connected in series to increase the battery voltage. Therefore a 36-volt overall requirement would need a battery consisting of 18 serially connected cells at 2 volts per cell. The capacity of a battery is measured in ampere-hours (amp-hr) and is defined by the total charge that the battery can provide before its voltage drops below a specified cut-off value. It is dependent only on the size of the cells and is independent of the number of cells connected in series. Battery capacity can also be expressed in kilowatt-hours, which is the product of the average voltage per cell and the amp-hr rating of the battery. Battery capacity measured this way is dependent on the size and number of cells in the system.

Battery construction is quite detailed and, for the sake of brevity, will only be summarized here. Generally, a cell is constructed from lead alloy grids which have been impregnated with a paste made of lead oxide (PbO) or a combination of the former with lead sulfate ($PbSO_4$) to form a plate [34, 35]. Grids which will be positive are made

thicker than those which will be negative since charge and discharge cycles are more detrimental to the positive plates. The pasted plates are carefully dried and cured under strict tolerances of humidity and temperature. The cured positive plates are wrapped with protective, porous fiberglass and are grouped alternately with negative plates to form an element. The alternating positive and negative plates are separated by porous electrically insulating material to prevent contact between plates but allow free flow of electrolyte. Ultimately, the completed element is assembled into a protective casing; at this point the cells have no electrical characteristics and no capacity.

To energize the battery, a low-rate *forming charge* is applied for a specified time under a controlled battery temperature level. The forming charge produces the positive and negative polarity of the corresponding plates in the cell. The lead oxide and lead sulfate are converted to lead dioxide in positive plates and to elemental lead in negative plates. Water is consumed during the formation process and sulfuric acid is formed. The relevant formation reactions could be represented as follows:

Positive Plate: $PbO(s) + PbSO_4(s) + 3H_2O(l) \longrightarrow 2PbO_2(s) + SO_4^{-2}(aq) + 6H^+(aq) + 4e^-$

Negative Plate: $PbO(s) + PbSO_4(s) + 2H+ + 4e^-(aq) \longrightarrow 2Pb(s) + SO_4^{-2}(aq) + H_2O(l)$

Net Reaction: $PbO(s) + PbSO_4(s) + H_2O \longrightarrow Pb(s) + PbO_2(s) + H_2SO_4(aq)$
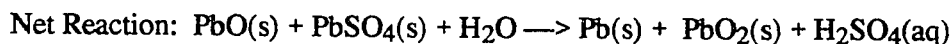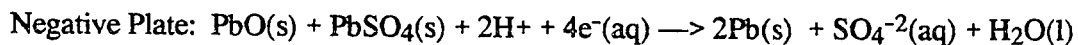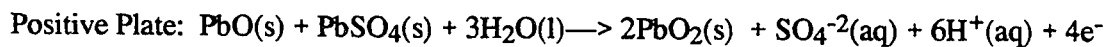
The forming charge also helps to establish the amp-hr capacity of each cell, which will depend on the final amounts of lead and lead dioxide and the specific gravity of the electrolyte. If several cells are connected in series, the forming charge is applied until all cells have reached the rated capacity. This process is called *formation equalization*. Some cells reach capacity sooner than others during formation equalization and undergo a short period of overcharging while the other cells catch up.

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III.B. Fabrication Features

Cell material changes, measured and recorded at the time of fabrication, are summarized in Table 1. It should be noted that no effects on cell performance due to material changes were expected, as all materials met specifications. However, unsupervised cluster analysis studies [11] showed that groups of cells with different materials had different properties.

TABLE 1

FABRICATION MATERIAL CHANGES FOR LEAD-ACID CELLS

Subset	Circuit	Cells	Grid	Paste
a	1	1-15	old	old
b	1	16-80	old	new
c	2	81-160	old	new
d	3	161-218	old	new
e	3	219-240	new	new
f	4	241-320	new	new
g	5	321-340	new	new

Subset a: Pasted plates from inventory.
Subsets b, c, and d: Plates freshly pasted on grids from inventory.
Subsets e, f, and g: Newly cast grids and freshly pasted plates.

Battery cell fabrication features for this study include 13 electrochemical and physical measurements taken at various stages of production (Table 2). Feature 1 (SG2) is the specific gravity of the cell prior to formation equalization. The amount of acid added during formation equalization is represented by Feature 2 (EQWF). Cell formation equalization often involves several charge/discharge cycles to condition the cells.

Measurements can be made on the cell at different stages of a cycle. Two such measurements are the specific gravity (Feature 3, SG4) and the amount of acid added (Feature 4, EQWC) prior to the fifth equalization cycle. Feature 5 (ASHP) is a measure of the final acid adjustment before shipping, and Feature 6, RELFRMA, is a transformation which is calculated by dividing the EQWF by the difference between the total weight of the cell after formation equalization (FINLWT) and the dry weight of the cell before the addition of acid (DRYWT, Feature 11). Feature 7 (SHPSLFA) represents the total acid in the cell as shipped.

Each cell was subjected to a test involving 5 charge/discharge cycles. Feature 8 (AVSB) is the average specific gravity before cell discharge for all 5 cycles. The capacity of each cell was measured for each cycle and Feature 9 (AVCAP) represents the average capacity. The average specific gravity after each of 5 discharge cycles is represented by Feature 10 (AVSA) and Feature 12 and 13 are the maximum capacity (MXCAP) and maximum specific gravity (MXSA), respectively, over the 5 test cycles.

III.C. History

It is important to note that the manufacturer of the batteries has performed all experimental procedures relating to battery fabrication and capacity testing, as well as all measurements for each feature being studied. This research originally began in June 1983 with the construction of 340 large lead-acid cells by GNB, Inc., located in Kaukakee, Illinois [36]. Each cell was assigned a number and information about fabrication materials

TABLE 2

FABRICATION FEATURES OF LEAD-ACID CELLS

ID #	Feature	Description
1	SG2	Specific gravity prior to formation equalization
2	EQWF	Acid added in formation equalization step
3	SG4	Specific gravity prior to 5th cycle equalization
4	EQWC	Acid added (equalization) before 5th cycle
5	ASHP	Final acid adjustment before shipping
6	RELFRMA	EQWF ÷ (FINLWT - DRYWT) where FINLWT = total weight of cell after formation equalization
7	SHPSLFA	Total acid in cell as shipped
8	AVSB	Average specific gravity before discharge (5 cycles)
9	AVCAP	Average capacity over 5 test cycles
10	AVSA	Average specific gravity after discharge (5 cycles)
11	DRYWT	Cell weight before acid addition
12	MXCAP	Maximum capacity over 5 test cycles
13	MXSA	Maximum specific gravity over 5 test cycles

and measurements were recorded. The cells were arranged in series into four circuits of 80 cells each and a fifth circuit of 20 cells, for a total of 340 cells. These circuits were labeled 1 through 5 and the cells in each were conditioned by operating the cells for 5 or more charge/discharge cycles.

A total of 324 cells were constructed into 6-cell modules (54 in all) at the Battery Energy Storage Test (BEST) Facility operated by Public Service Electric and Gas Co. for the Electric Power Research Institute (EPRI). Acceptance tests were conducted and completed in December 1983. Requirements were that the cells deliver 500 kW for 1 hour at a capacity limit of 1040 amp-hr. A 5-hour discharge of 2080 amp-hr was to deliver at least 1.2 megawatt-hour of energy. The battery was given an eight year warranty. Modules were tested as 3 parallel strings (labeled A, B, and C) of 18 serially connected modules each and as a single string of all 54 modules. Two-hundred periodic test cycles were performed over a 4-year period for a variety of industrial applications. Periodic maintenance and capacity tests were performed during that time and a database was assembled from the data measurements.

The battery was shipped to Stateville, North Carolina in the Fall of 1987 and installed at Crescent Electric Membership Corporation (CEMC), a local area power plant. Since then the battery has functioned as a peak-shaving device, discharging at a minimum of 200 kW for 3 hours and at a maximum power of 500 kW for 1 hour. Several capacity tests have been performed on a selected subset of 121 cells since installation at CEMC. Capacity testing is performed by taking each of the selected cells through 5 charge/ discharge cycles at a load of 450 or 900 amperes until they reach a voltage cutoff level of 1.7 volts. Capacity tests were performed in March 1989, April 1990 and September 1991. The September 1991 event was a full capacity test, monitoring all cells. As of July 1991, only one cell (# 241) has been excluded due to low capacity [11, 37].

IV. Experimental Methods

IV.A. Instrumentation, Database and Software

Three IBM/AT compatible computers were used for all data storage, manipulation and pattern recognition studies. Each contained a minimum configuration of 1 megabyte (MB) RAM (random access memory) and a 20 MB hard disk. Two computers were equipped with 286-type microprocessors, running at 4 and 12 megahertz (MHz), respectively, and the third used a 386/12 MHz microprocessor equipped with an 8087 math coprocessor. Each computer contained copies of the database composed of GNB battery fabrication data and capacity testing data. Database management and spreadsheet software programs called SYMPHONY™ (Lotus Corp.) and QuattroPro® (ver. 3.0; Borland International) were used to perform all statistical computations on the database.

All experimental results were analyzed using the same three IBM PC's and software listed above plus a Macintosh IIcx equipped with Excel® spreadsheet software (ver. 3.0; Microsoft Corp.) and Cricket Graph™ graphing software (ver. 1.2; Cricket Software, Inc.). Pattern recognition software programs were written "in house" using a compiled BASIC programming language (Microsoft Corp.) and were used to perform all multivariate analysis and pattern recognition procedures.

IV.B. Procedures

IV.B.1. Database Information

The raw GNB battery fabrication and test data for all 340 cells are summarized in Appendix A. The fabrication features were discussed in Section III.B and defined in Table 2. Each feature was assigned a number for convenience. Although capacity tests have been performed annually for the last three years, only the capacity data from the test performed on April 3, 1990 were used for this study. This was because ~7 years had

passed since manufacturing, and this marked the beginning of the final phase of cell life (the last year of the warrenty period). Only 121 of the 323 cells operating at CEMC were monitored for their capacity. The test was performed under a 450-amp discharge until the cells dropped to an average cut-off of 1.7 volts. Results of the test are listed for each cell in Appendix B (by increasing % capacity, corrected for temperature).

It is desirable to have a maximum number of patterns relative to the number of monitored features of interest. The ratio of number of patterns to features should be ≥ 3 to keep the results statistically valid [19], and measurements must be taken with enough sensitivity to allow for a detectable degree of variance in the data. Otherwise, the feature may not have any effect on the ability to discern different classes.

IV.B.2. Data Preprocessing

Multivariate data measurements are often presented as a data matrix (Figure 12) in which each row represents a different sample, and each column represents the data for a given measurement for each sample. When structured in this manner, it is often most useful to examine the relationships between samples within each column. However, multivariate data can rarely be analyzed in its raw state, and some type of preprocessing is usually necessary [18]. Preprocessing of raw data is important in order to preserve or enchance the information content for further analysis. For example, preprocessing may involve computing key characteristics (i.e., peak heights, widths, areas, ratios, etc.) or it may involve numerical transformations (time domain converted to frequency domain).

Preprocessing frequently involves scaling of the data. Otherwise, measurements for a given feature may be left significantly greater or smaller in magnitude than neighboring features, and may lend an unrealistic weight to a feature set and its variance. Scaling can be performed on measured features for a given sample (rows) and on individual features for a collection of samples (columns).

FEATURES OR VARIABLES

$$
\begin{array}{c c c c c c c}
 & 1 & 2 & 3 & \bullet & \bullet & c \\
1 & X_{11} & X_{12} & X_{13} & \bullet & \bullet & X_{1c} \\
2 & X_{21} & \circ & \circ & \circ & \circ & \circ \\
3 & X_{31} & \bullet & \bullet & \bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
r & X_{r1} & \bullet & \bullet & \bullet & \bullet & X_{rc}
\end{array}
$$

ITEMS OR EXPERIMENTS

Figure 12. Graphical representation of a multivariate data matrix. Rows represent individual items or experiments. Individual features or variables are presented in columns for each item.

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Scaling of feature sets (or rows) helps preserve the relative geometrical distances between feature sets. These distances are sometimes referred to as Euclidean distances. It is especially important to maintain the relative geometry of feature sets when subjecting the data to a reduction of dimensionality; otherwise, inaccurate evaluations of the inter-feature relationships might occur.

One popular way to transform data is to normalize it. This involves scaling the measurements to a constant total, usually 100%. The method has limitations in that for some cases, normalization can result in a minimization or loss of variance. An example of this is shown in Table 3. Features F1, F2, and F3 are presented in raw and normalized form for patterns A and B, where features are normalized so that the sum of all features for each sample equals 1.

Table 3
Raw and Normalized Data Sets

Sample	Raw Data			Normalized Data		
	F1	F2	F3	F1	F2	F3
A	50	100	50	0.25	0.5	0.25
B	9	10	1	0.45	0.5	0.05

Note that each feature set for the raw data contains a large variance; however, normalization of the features for each sample results in a loss of the variance observed for F2. In situations such as the latter, it may not be wise to normalize the data if subsequent analysis depends on there being a reasonable degree of variance within each feature.

Scaling down a column or feature set is usually performed to reduce all feature sets to the same range of values. *Standardization* is a way of normalizing each feature set, so that normalized feature values are expressed relative to the inherent variance in each variable. One method of accomplishing this is to *autoscale* the measurements within a column. The

autoscaled value (Xa) is calculated as the difference between the raw data item, Xr, and the mean of the feature column ($\overline{X}$) divided by the standard deviation, s, of the column.

$$Xa = (\overline{X} - Xr) / s \tag{14}$$

Caution is advised when autoscaling data where the relative noise for highly intense measurements is less than that for low intensity peaks; standardization can actually increase the noise in the data.

The choice of scaling methods and the decision of whether or not to scale the data is often a subjective choice, and each data set must be examined carefully before applying a scaling method. For this work, all capacity values were normalized to the rated capacity of 2080 amp-hr and the data measurements were autoscaled for each feature.

IV.B.3. Definition of Class Boundaries

The class of a particular item may be a qualitative property that is known *a priori*. For example, a chemical compound may belong to one of various structural or functional groups (alcohols, ketones, aliphatics, aromatics, *etc.*). For our work, however, the class of each item is based on some quantitative property (*e.g.*, cell capacity). The definition of class boundaries can be performed using different criteria in evaluating the quantitative property of choice (figure of merit). One method assumes that a distribution of this property follows a continuous probability function, one form of which is the Gaussian distribution [32] (Figure 13).

The number of items, Y, that have a value of X_i are assumed to fall symmetrically about a mean $\overline{X}$. Items which lie at the extremes of the distribution are considered to be of different classes. Items that lie to one side of an arbitrary boundary, such as one or more standard deviations from $\overline{X}$, are assigned to a different class from those items lying on the other side. For example, objects that lie outside 1 standard deviation to the left of $\overline{X}$ could be classified as class 1, and those positioned outside 1 standard deviation (σ) to
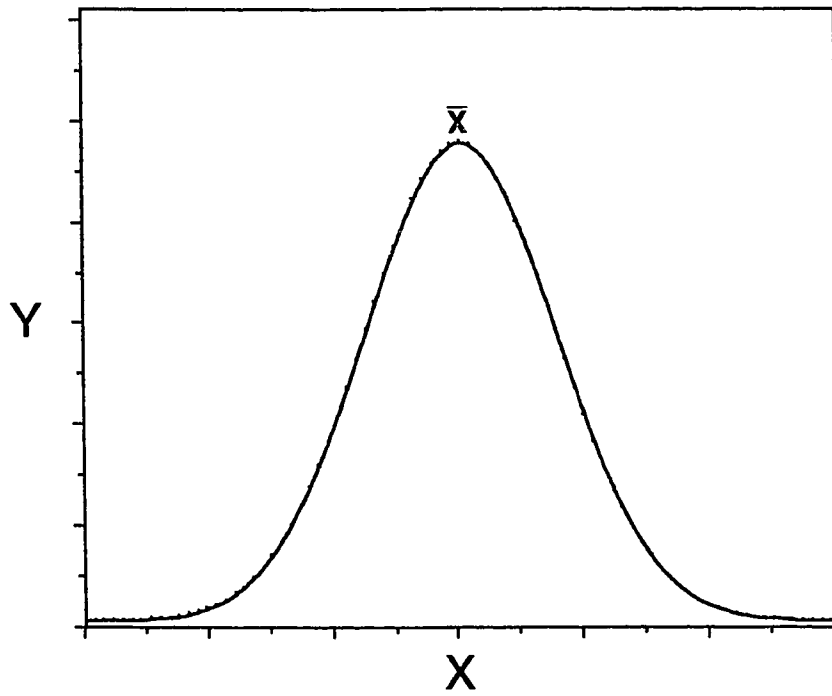
Figure 13. A Gaussian distribution curve. Y is the response for value X. $\overline{X}$ is the average of all values of X.

the right of $\overline{X}$ could be labeled as class 2. The intermediate items falling within ± 1 σ of $\overline{X}$ could be classified as a third class, 3.

Another method for viewing the distribution is the histogram approach. The number of items n having a particular value X_i are plotted as shown in Figure 14. The distribution of items along the x-axis may not be Gaussian, but the class criterion is similarly based on where the item falls within the distribution. The boundaries that separate classes can be set using the natural breaks or minimums that occur between clusters in the distribution of the data.

Capacity values from the 1990 capacity test were used to determine the class assignment of the corresponding patterns (cells) in the fabrication database. The nominal capacity for each cell is 2080 amp-hr, and measured values are expressed as a percentage of this value. High capacity cells were assigned to Class 1, low capacity cells to Class 2 and intermediates to Class 3. All capacity test cells were sorted from lowest to highest capacity (Appendix B). The average capacity, $\overline{X}$, was computed for all 121 cells as well as the standard deviation, σ. High capacity cells were defined as those with capacities greater than ($\overline{X}$ + σ) and low capacity cells as those with capacities less than ($\overline{X}$ - σ). Intermediates were defined as those cells with capacity values within the range ($\overline{X}$ ± σ). For the 1990 capacity test cells, $\overline{X}$ equals 101.5%, and σ equals 2.8%. Using this criterion (the standard deviation classification method, STDEV) the class assignments were as follows:

Class 1; 17 cells, capacities > 104.3%

Class 2; 22 cells, capacities < 98.7%

Class 3; 82 cells, capacities ≥ 98.7% but ≤ 104.3%

A histogram distribution of the 1990 capacity data is shown in Figure 15. Capacity values have been rounded off when assigning cells to a particular category on the

43
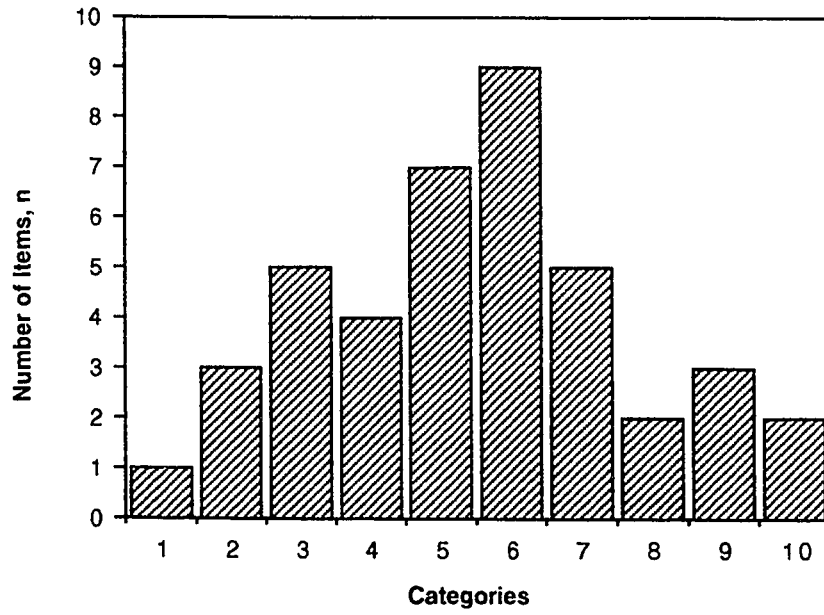
Figure 14. A histogram distribution of categories consisting of n-number of items each.
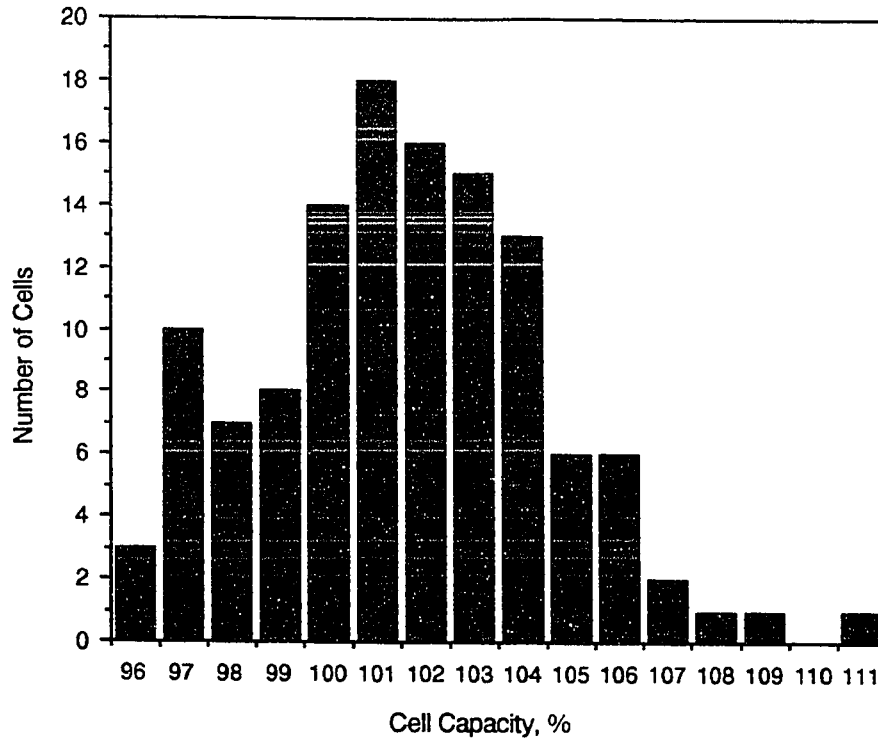
Figure 15. Histogram distribution of cell capacity data collected by CEMC on April 3, 1990.

graph. For example, cells labeled with a capacity of 101% represent capacity values which range from 100.5% to 101.4%.

The training set for the 2-class problem was constructed with Classes 1 and 2. The 3-class study also used the same cells/classes as for the 2-class problem plus about one-third of the cells from Class 3. Thus, the training set for the 2-class problem contained 17 Class 1 cells and 22 Class 2 cells for 39 cells total, and the 3-class training set contained the same 39 cells plus an additional 20 cells from Class 3 for a total of 59 cells. The other 62 intermediate cells (Class 3) were designated as the "Prediction Set " for the 3-class problem. The remaining 219 cells (340 - 59 - 62 = 219) were assigned to the "Unknown Set", designated Class 0.

IV.B.4. Feature Selections

After the raw data are accumulated and preprocessed, the assembled database is examined using different feature extraction methods. Individual features and feature groups are chosen based on statistical, mathematical, and systematic selection methods. Features are considered useful for pattern recognition if they exhibit a large amount of variance or for their ability to accurately distinguish between two or more classes.

Groups of fabrication features were selected from those presented in Appendix A based on selection criteria outlined in Section II.B. Feature groups were selected by correlation methods, Fisher ratio analysis, relative standard deviations, arbitrary selection and sequential feature elimination.

Fabrication measurements were examined using correlation analysis, and features were eliminated to provide a set containing only poorly correlated features. Selected feature groups were then tested for their ability to accurately classify cells belonging to the training set.

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Fisher ratios and relative standard deviations were calculated from the training set data for each fabrication feature for both the 2-class and 3-class training sets. Features yielding the largest ratios and relative standard deviations were selected and analyzed for their classification ability. These select feature groups were also subjected to sequential feature elimination.

Systematically chosen feature groups were also examined for their ability to accurately classify cells from each training set. While systematic selection may appear unscientific, it is not practical to investigate all possible feature group combinations from the entire set of 13 features. The number of possible combinations of Z features from a total of M features can be determined using the following formula [23]:

$$M! \div [Z! \, (M - Z)!] \qquad (15)$$

If $M = 13$ features and Z_i represents equally-weighted Features 1, 2, ..., 13, as i is incremented from 1 to M, the total number of all possible feature groups, T, becomes:

$$T = \sum_{i=1}^{M} \{M! \div [Z_i! \, (M - Z_i)!]\} = 8{,}191 \text{ possible feature groups} \qquad (16)$$

When weighted features are taken into account, the possibilities are enormous. Even with the availability of high-speed technology, it is unproductive to examine all combinations.

For our purposes, the various feature selection methods described here proved very satisfactory. Sequential feature elimination was by far the most productive way to discover suitable classifiers. The method has the powerful advantage of being applicable to feature groups selected by any other method. Using this approach increases the likelihood of the evaluation of a large number of the total possible combinations of feature groups.

IV.B.5. Training

The training procedure involved the LOO-KNN (leave-one-out k-nearest neighbor) classification algorithm combined with sequential feature elimination [38]. The procedure

begins with the selection of a particular feature group using methods described above. All data values for the chosen features are autoscaled as described in Section IV.B.2. Then, each pattern is "left out" of the training set and classified using KNN as if it were an "unknown". This procedure is repeated for all patterns in the set and the classification accuracy is determined (overall and by class). In this procedure, training involves the systematic selection of different groups of features for trial classification runs (LOO-KNN), until the optimum feature set is found.

The algorithm also allows the user a choice of whether or not to optimize the feature weights and perform *forward or backward* feature elimination. The forward and backward direction refers to which way through the data matrix the sequential elimination is proceeding. That is, columns of feature data are sequentially eliminated from left to right for forward elimination and from right to left for backward elimination. The entire process can be quite time-consuming depending on the computer speed, the number of patterns and features, and whether feature weight optimization is selected. It is often prudent to select feature weights of "1" for preliminary training sessions. Feature weight optimization is then performed only on those feature groups which are superior classifiers. This results in the use of much less computer time.

IV.B.6. Classification Accuracy

Classification accuracy can be expressed in several ways. The overall accuracy, A, is the ratio of the number of patterns classified correctly, P, to the total number of patterns, P_t, in the set, expressed as percent.

$$A = 100 \, (P \, / \, P_t) \tag{17}$$

The class-specific accuracy, A_c, (expressed as percent) is defined as the number of correct classifications, P_c, for patterns within a specific class, m, divided by the total number of patterns in the class, P_m.

$$A_c = 100 \, (P_c \, / \, P_m) \tag{18}$$

The average accuracy, $\overline{A}$, is the ratio of the sum of the individual class-specific accuracy to the total number of classes, P_n.

$$\overline{A} = (\textstyle\sum A_{ci}) \, / \, P_n \quad \text{for } i = 1, ..., n \tag{19}$$

IV.B.7. Mapping

Feature groups which provided the highest degree of classification accuracy (as determined by training) were then analyzed using a non-linear mapping (NLM) method as described earlier. The NLM procedure autoscales all feature values for each pattern and then seeks to convert the resulting N-dimensional feature space into an accurate representation in 2-dimensions. Sometimes feature groups fortuitously give high classification accuracy when examined with the LOO-KNN training method. NLM plots using these same feature groups and weights often indicate a fortuitous distribution of the patterns such that no real clusters of specific classes exist. This is undesirable because it gives false credence to the accuracy and reliability of the classifier. NLM plots which result in separate clusters of specific classes are an accurate, independent measure of classifier effectiveness. This method was useful as a critical step for identifying feature groups which were not valid for classification purposes, despite fortuitously high accuracy.

IV.B.8. Pattern Reclassifications

If an item is consistently found to be misclassified during the training phase, it may be that the item actually belongs to a different class. NLM plots can often elucidate this, especially if the pattern is always found to reside within a cluster of patterns which belong to a different class. This occurred for the 3-class problem, and it was beneficial to "reclassify" some items, and repeat the training phase over again. As expected, this approach often led to a higher classification accuracy for each classifier than was obtained

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before. Pattern reclassification also yielded classifiers which were comprised of different feature groups than were originally discovered. These groups were then evaluated again by NLM for their validity.

IV.B.9. Predictions

When a collection of classifiers is obtained from the training set, each classifier is evaluated on its ability to accurately identify the class of each pattern contained in the prediction set [15]. The prediction set is ideally composed of patterns which have the same origins as those in the training set, but which are not part of the training set. The accuracy of classification produced by a classifier which has been applied to a prediction set is referred to as the *prediction ability*.

Calculations of classification accuracies for the prediction set are similar to calculations for the training set (eqs 17-19). Testing the prediction ability of the classifier is a way of validating the high classification accuracies obtained from the training procedure. The higher the classification accuracies for both training and prediction studies, the greater the confidence that the data matrix contains the desired information regarding the particular classification in question, and that an analysis of an unknown data set would yield valid classifications. This assumes that data for the unknown items are treated similarly as the training and prediction sets and that the class(es) of the unknown items are real classes which also exist within the training and prediction sets.

If training or prediction procedures yield poor results, then other classifiers must be developed by choosing different feature groups, by including other features not previously investigated, or by transforming the data. Combinations of the above methods may also prove useful. Based on classification algorithm results, the feature groups which appear to have the greatest capacity for distinguishing classes are then used to categorize items of

unknown classification. In this work, the classification decision is made by assigning the unknown item to the same class as its nearest neighbor(s) of known class.

Fabrication feature groups and their weights which gave high classification accuracies and resulted in NLM plots of distinct class clusters were used for the purposes of prediction. No prediction set was available for the 2-class study due to the limited number of cells of high and low capacity. For the 3-class study, the most useful classifiers obtained from the training and mapping procedures were used to classify the Prediction Set and Unknown Set cells.

V. Results and Discussion

V.A. Scope of Investigation

For this study we were primarily concerned about the information content of the fabrication data, i.e. do the data contain the information necessary for the accurate distinction of good and poor performing cells? One of the difficulties, as discussed in IV.B.3, is that class assignments for the training set cells are based on a Gaussian distribution of the cell capacity data. In fact, this is not so; however the distribution is close enough (Figure 15) that the natural breaks and the mean of the distribution are close to the Gaussian results. The Gaussian model is quite adequate for determining whether or not the information content is there. Some erroneous classifications can occur due to the differences between the natural breaks in the distributuion and the boundaries that are assigned based on a Gaussian spread of the data.

Another point of concern is the question of false-positive identifications, especially their frequency of occurrence for each class. If a good performer is falsely classified as a bad performer, it will be excluded from the set and little harm will have been done. However, if a poor performer is misclassified as being good, it will be included with the other good cells and this may lead to disastrous consequences for the battery. Therefore, from the standpoint of false-positives, accurate classification of poor performers is much more critical than that of good performers.

Finally, determination of which groups of features provide meaningful classifiers gives information about the relationships between fabrication features and how they influence the battery system. This information can be used to design experiments to optimize the fabrication materials to produce better batteries.

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V.B. Two-Class Study

A summary of the pattern recognition training results for the 2-class problem is presented in Table 4. Overall and individual class accuracies are listed for each classifier along with the corresponding features of importance. Extensive training was performed on the 2-class training set, and many useful feature combinations were obtained. A summary of only the superior classifiers are shown here (overall accuracy $\geq 92\%$). Many other classifiers were obtained which gave good results, but those in Table 4 are a good representation of the most useful feature combinations.

Table 4 lists each classifier by its feature code which is expressed as a 13-digit number. Each digit, reading from left to right, represents the corresponding feature ID number. The magnitude of the digit represents the weight given to that feature. Features which have a 2-digit weight are enclosed in hash marks. For example, a feature code of F-0004000101004 would represent a classifier composed of features 4, 8, 10 and 13, which correspond to EQWC, AVSB, AVSA and MXSA, respectively (Table 2). Features AVSB and AVSA are each assigned a weight of "1" and EQWC and MXSA are each given a weight of 4. A feature code of F-200/16/040100011 includes features SG2, EQWC, RELFRMA, AVSB and MXCAP (1, 4, 6, 8, 12 and 13), and utilizes a weight of 16 for EQWC.

Each of the promising classifiers was examined by NLM to determine which feature groups actually resulted in a separation of Class 1 and 2 cells in N-feature space. Classifiers were graded as to their quality, and those which gave good results were noted. Feature groups which gave fortuitously high classification accuracies were rejected if their non-linear maps were poor in quality. Mapping errors were used as a measure of how well the 2-dimensional maps represented their N-dimensional counterparts.

TABLE 4

2-CLASS STUDY
SUMMARY OF BEST TRAINING RESULTS

Classifier	% Classification Accuracy Overall/Class 1/Class 2	Features Used
F-0004000101004	95/94/96	4,8,10,13
F-4001100210000	95/94/96	1,4,5,8,9
F-4001120210000	95/94/96	1,4,5,6,8,9
F-4020101100010	95/94/96	1,3,5,7,8,12
F-4001041201000	95/94/96	1,4,6,7,8,10
F-4001010200101	95/94/96	1,4,6,8,11,13
F-2001000100100	92/94/91	1,4,8,11
F-0008000100011	92/82/100	4,8,12,13

Feature ID	Feature	Frequently Observed
1	SG2	✔
3	SG4	
4	EQWC	✔
5	ASHP	✔
6	RELFRMA	✔
7	SHPSLFA	
8	AVSB	✔
9	AVCAP	
10	AVSA	
11	DRYWT	
12	MXCAP	
13	MXSA	

The 2-class training procedures developed many good classifiers which collectively utilized each of the 13 fabrication features. Those classifiers which gave both high classifications and good quality non-linear separations frequently contained one or more of the following features: SG2, EQWC, ASHP, RELFRMA and ASVB. This suggests that measurements of the specific gravity prior to formation equalization and discharge are important for accurate cell classification, as well as acid additions made during formation equalization. The final acid adjustment before shipping, and the ratio of acid added in the formation equalization step to the total acid present in the cell are also important factors for 2-class (high/low) distinction.

Examination of the fabrication database (Appendix A) shows that many poor performing cells have a lower than average value for SG2, AVSB, and AVCAP than do cells which are good performers. Values of EQWC are greater than or equal to zero for poor performers, whereas values for good performers tend to be large and negative (negative acid adjustments correspond to additions of water). Generally, ASHP values are relatively negative in magnitude for poor performers as opposed to positive for most good performers.

The results clearly suggest that acid adjustments during the formation cycles are crucial to performance capability. Cells which have lower than average specific gravities before dishcarge and demonstrate low capacity performance during testing will likely be poor performing throughout their lifetimes. Also suggested is that addition of acid, rather than water, during the EQWC step may result in premature formation of lead sulfate on the plates and result in lower capacities [34].

When mapping, cells 105 and 109 always appeared as outliers, together in their own cluster and far away from all other cells (Figure 16). Values for SG2, AVSB, AVCAP, EQWC, and ASHP are more deviant for these two cells than for other cells. Because the

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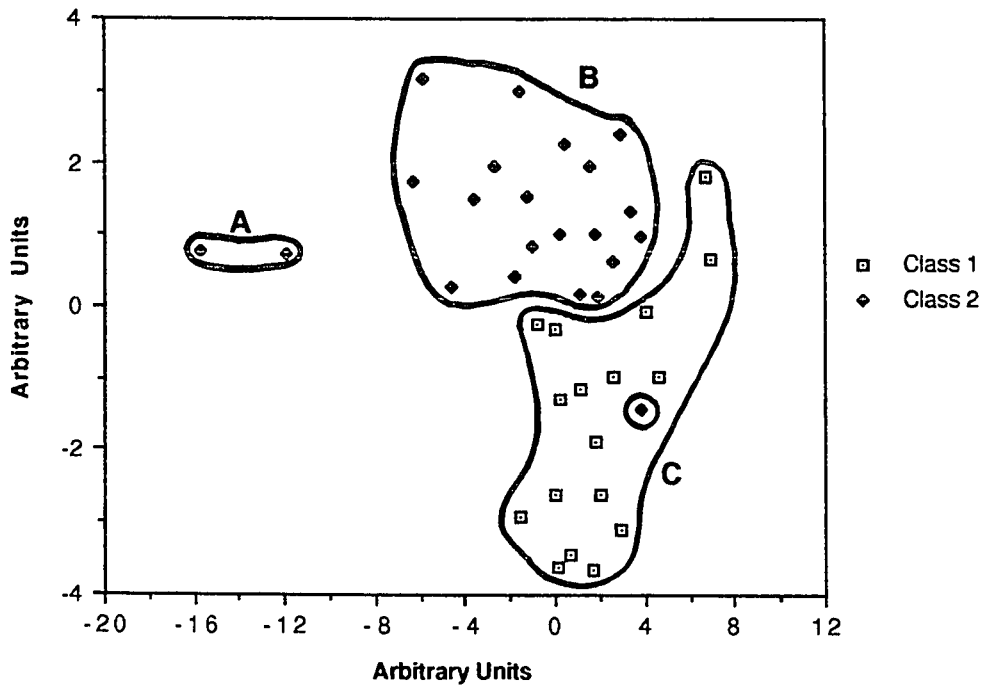
Figure 16. Non-linear mapping (NLM) of five-dimensional feature space for fabrication data; 2-class Training Set cells. STDEV classification criteria. A: Class 2, cells 105 and 109. B: Class 2 cells. C: Class 1 cells with Class 1 false-positive cell 225. Features: SG2, EQWC, ASHP, AVSB, AVCAP.

inclusion of cells 105 and 109 distorted the NLM and pattern recognition analysis results, subsequent NLM's and pattern recognition classifiers were graphed without cells 105 and 109. The classifier used to generate this map yielded an overall accuracy of 95% for the 2-class Training Set cells.

Representative non-linear maps from the 2-class study (less cells 105 and 109) are depicted in Figures 17 and 18. Each map was generated from two different classifiers each yielding 95% overall accuracy, just as for the map in Figure 16. Individual class accuracies were 94% for Class 1 and 95% for Class 2 (96% if cells 105 and 109 are included). The maps in Figures 16-18 illustrate the effective separation of Classes 1 and 2 into distinct regions of N-space.

The map in Figure 17 was generated from the 6-dimensional classifier F-4001041201000, which corresponds to features SG2, EQWC, RELFRMA, SHPSLFA, AVSB and AVSA. Three distinct clusters are produced. Cluster A consists of all Class-1 cells plus one Class 2 cell (#225). Most of the Class 1 cells in Cluster A (13 out of 17) are from Circuit 4. It is interesting to note that all of the Class 1 cells from Circuits 3 and 4 in Cluster A were fabricated with plates consisting of new grids and new paste (Refer to Table 1).

The Class 2 cells are divided into two clusters, B and C. Cluster B is composed of cells from Circuits 2, 3 and 4, while Cluster C is exclusively composed of cells from Circuit 1, which were fabricated from old grids and new paste. Many of the cells in Clusters B and C were found to correspond to cells which have been observed to expand, thus causing the battery casing to swell [26]. Five cells have actually separated between the jar and lid, but the cells are still in service since they continue to function well.

The observations for features SG2, EQWC, RELFRMA, and AVSB were the same as those noted above for good vs. poor performing cells. The SHPSLFA values tended to
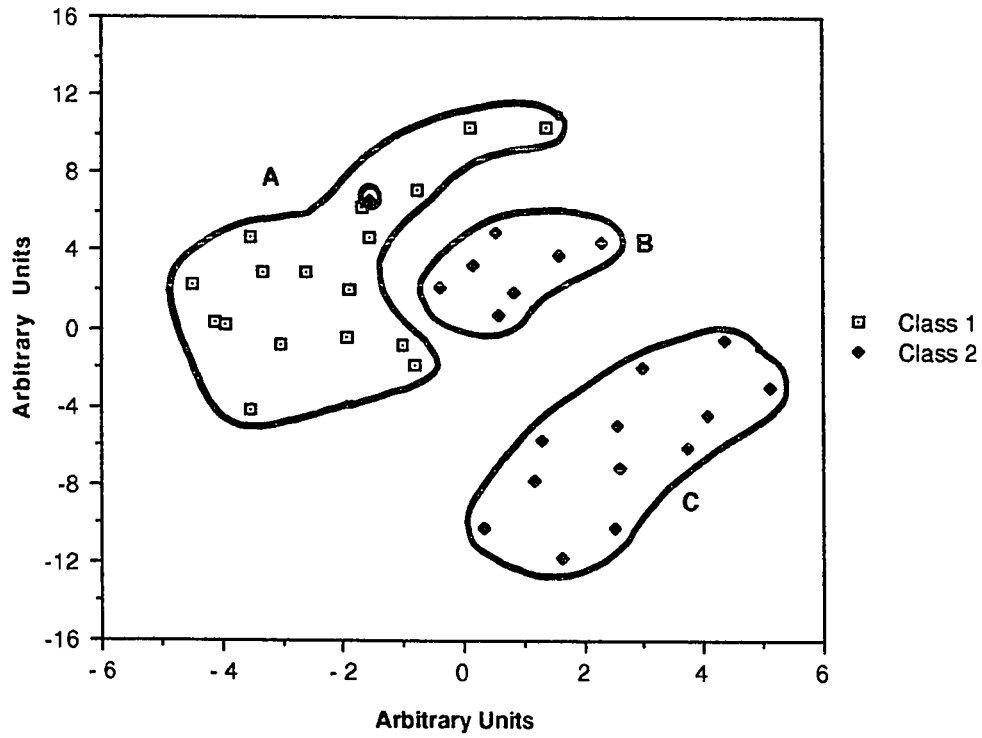
Figure 17. Non-linear mapping (NLM) of six-dimensional feature space for fabrication data; 2-class Training Set cells (less cells 105 and 109). STDEV classification criteria. A: Class 1 cells, Circuits 3 and 4, new grids/new paste. B: Class 2 cells, Circuits 2-4, old grids/new paste and new grids/new paste. C: Class 2 cells, Circuit 1, old grids/new paste. Features: SG2, EQWC, RELFRMA, SHPSLFA, AVSB, AVSA.
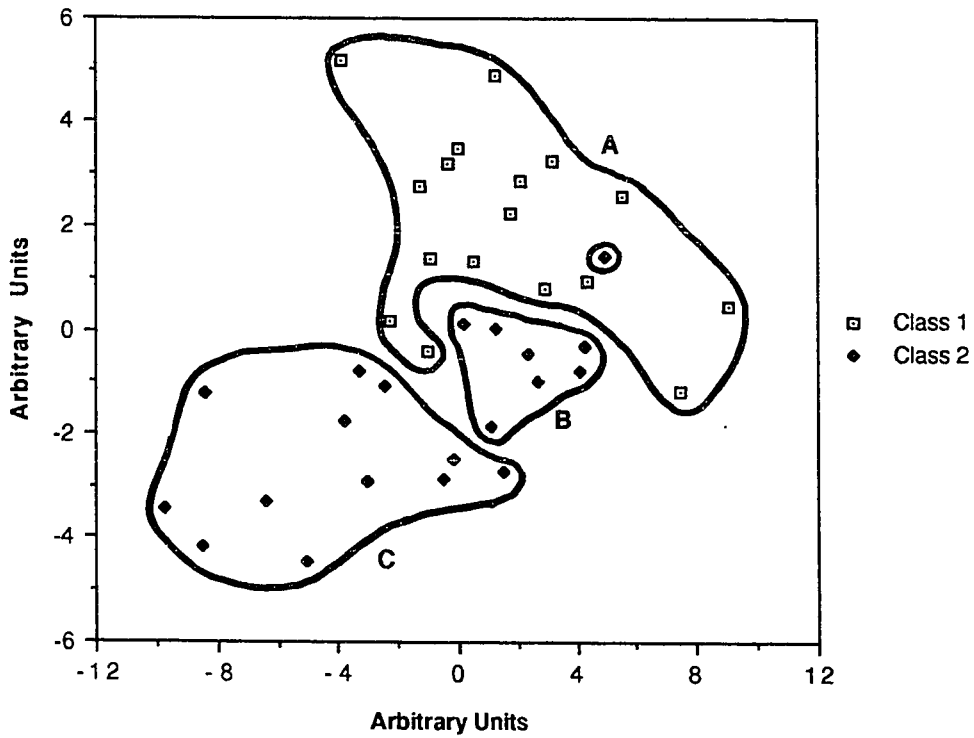
Figure 18. Non-linear mapping (NLM) of six-dimensional feature space for fabrication data; 2-class training set cells (less cells 105 and 109). STDEV classification criteria. A: Class 1 cells, Circuits 3 and 4, new grids/new paste. B: Class 2 cells, Circuits 2-4, old grids/new paste. C: Class 2 cells, Circuit 1, old grids/new paste. Features: SG2, SG4, ASHP, SHPSLFA, AVSB, MXCAP.

be lower for poor performers than those for good performers, and good performers generally had lower AVSA values than poor performers. The map in Figure 18 is an example of less well-defined clusters in spite of a 95% overall classification accuracy. The classifier is composed of features SG2, SG4, ASHP, SHPSLFA, AVSB, and MXCAP. Observations made for SG2, ASHP, SHPSLFA, and AVSB continued to hold true for the observed clusters of Class 1 and 2 cells. Class 1 cells are dispersed more; however, the cells are still the nearest neighbors to other Class 1 cells, and may actually be small isolated clusters. Cluster C is composed exclusively with cells from Circuit 1, whereas Cluster B contains cells from Circuits 1 through 4. It may be that B and C are really one large, dispersed cluster for this particular classifier, the fourth listed in Table 4.

Values for SG4 and MXCAP are lower than average for poor performers and are higher than average for good performers. MXCAP values change remarkably, from 96% average for poor performing cells to 100-105% for good performers. It should be noted though that MXCAP values alone are not sufficient for a high degree of distinction between high and low capacity cells.

A very important aspect of cell classification involves the identification of false positives. False positives are cells which have been incorrectly identified as belonging to the desired class. For the 2-class problem there are two possibilities: Class 2 cells which have been falsely identified as Class 1, and of course Class 1 cells which have been classified as belonging to Class 2. The former case has far greater potential for unfortunate consequences than the latter. Incorrect classification of Class 1 cells simply results in their non-use, whereas Class 2 cells which have been classified as Class 1 would likely (and erroneously) be placed into operation, and could result in undesirable consequences. Class 2 false positive classifications occurred most frequently for cells 146, 236, 239, 243 and 303. More importantly, the most frequently encountered Class 1 false positives were

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cells 225 and 299; cells 91, 228, and 249 were also occasionally identified as Class 1. All

Class 1 false positives were characterized by low capacity values for the 1990 Capacity

Test (Appendix B), but have fabrication data values for one or more of the features SG2,

SG4, EQWC, ASHP, RELFRMA, SHPSLFA, AVSB, ASHP, AVSA, and MXCAP

which are consistent for good performing cells. The results suggest that the cells may have

performed poorly as a cause of something other than that which is represented by the

fabrication data.

Cluster A in Figure 18 was also found to contain cells only from Strings B and C and

none from String A (Section III.C). Cluster B contains cells from all three strings and

Cluster C contains cells only from Strings A and B and none from String C. All cells in

Class 2, Cluster C are from modules 1, 6, 20, and 22 exclusively, and none of the cells in

Clusters A or B are from those stored in these four modules.

Perhaps the most encouraging result obtained from the 2-Class study is that the

battery fabrication data appear to contain the information content necessary for

distinguishing between high and low performing cells. Although the 2-Class classifiers

have not been tested on a prediction set, the NLM maps shown in Figures 16-18 indicate

real class separation which is consistent with earlier independent findings [10-13, 37].

Additionally, the pattern-to-feature ratios are between 7 and 10, which is greater than the

minimum recommended ratio of 3, and whose high value lends statistical validity to the

results [19].

V.C. Three-Class Study

Results from the initial round of 3-class training and mapping are summarized in

Table 5. It is not surprising that the overall and individual cell classification accuracies are

lower than what was obtained from the 2-Class studies. Overall classification accuracy

generally fell between 71 to 75%, and the highest individual accuracies obtained from

TABLE 5

3-CLASS STUDY
SUMMARY OF BEST TRAINING RESULTS

Classifier	% Classification Accuracy Overall/Class 1/Class 2/Class 3	Important Feature Groups
F-0420101000000	75/71/86/65	2,3,5,7
F-0411111000000	72/82/77/60	2,3,4,5,6,7
F-0410121000100	73/71/86/60	2,3,5,6,7,11
F-0420102000000	71/65/86/60	2,3,5,7
F-0041012010120	71/65/77/70	3,4,6,7,9,11,12

Feature ID	Feature	Frequently Observed
2	EQWF	✔
3	SG4	✔
4	EQWC	
5	ASHP	✔
6	RELFRMA	✔
7	SHPSLFA	✔
9	AVCAP	
11	DRYWT	
12	MXCAP	

meaningful classifiers were 82%, 86% and 70% for Class-1, -2 and -3 cells, respectively. Initial training and mapping results indicated that Features 2 through 7, followed by 11 seemed to be the most useful for separating all three classes. Acid adjustments at various fabrication stages (EQWF, EQWC, RELFRMA) the total acid in the cell as shipped (SHPSLFA) and, to a lesser extent, the dry weight of the cell (DRYWT) were found to play an important role in the classification process for training cells classified by the STDEV method.

The 3-class training set contained 59 cells, but only 50 cells could be mapped at any one time since the non-linear mapping program was written for a maximum capacity of 50 patterns. Cells which were always classified incorrectly were identified as aberrant cells and were initially excluded from the mapping data. The maps were plotted, and cells which consistently fell deep within specific clusters were identified and replaced with the aberrant cells after which the maps were plotted again. This step was necessary to determine the relative placement of each of the 59 cells in N-feature space.

Although the absence of the aberrant or non-aberrant cells had some effect on the mapping errors and relative cell placement in pseudo 2-dimensional space, it was very minor. Cells 105 and 109 also appeared as outliers in maps prepared for the 3-class study and were removed to improve map quality. Cells which were most frequently aberrant and the cells which were exchanged with them for mapping purposes are indicated in Appendix C. Aberrant cells and their exchanges for mapping purposes are indicated with a check mark (✓) and all cells which were always classified correctly are marked with a "c".

Maps for two superior classifiers (based on STDEV classifications) are presented in Figures 19 and 20. The map shown in Figure 19 was generated using a 7-dimensional classifier represented by feature code F-0041012010120, which corresponds to features SG4, EQWC, RELFRMA, SHPSLFA, AVCAP, DRYWT AND MXCAP. The

63
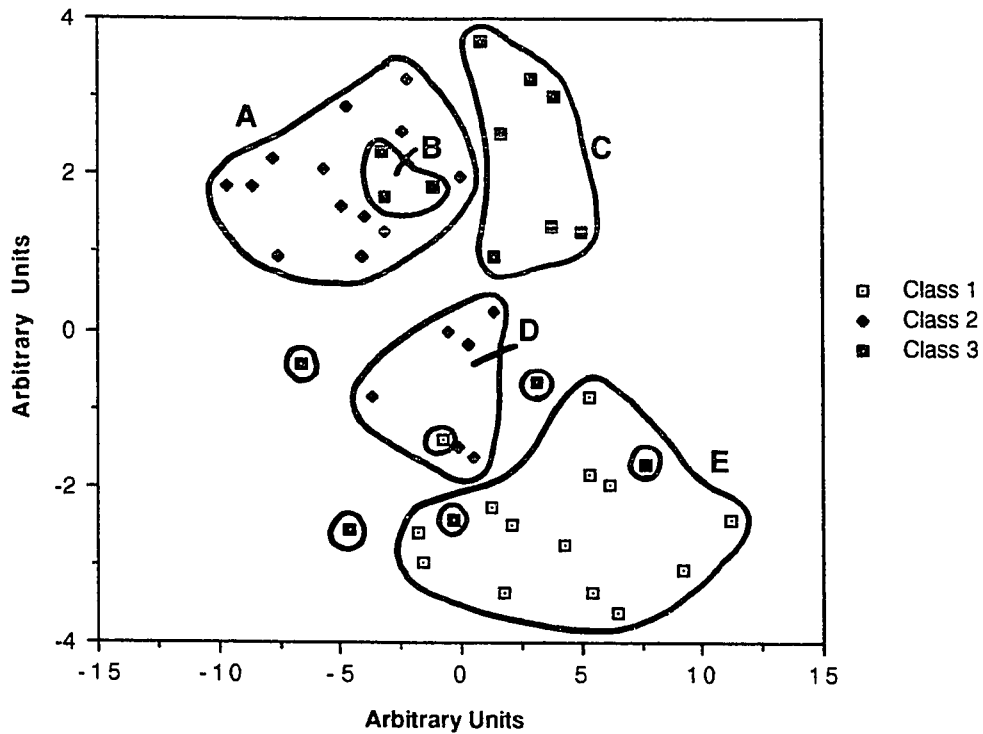
Figure 19. Non-linear mapping (NLM) of seven-dimensional feature space for fabrication data; 3-class Training Set cells (without aberrant cells). STDEV classification criteria. A: Class 2 cells, Circuit 1, old grids/new paste. B: Class 3 cells, Circuit 1, old grids/new paste. C: Class 3 cells, Circuit 2, old grids/new paste. D: Class 2 cells, Circuits 3 and 4, old grids/new paste and new grids/new paste. E: Class 1 cells, Circuits 3 and 4, new grids/new paste. Class 3 cells which are dispersed and individually circled are from Circuits 3 and 4, old grids/new paste (1 cell) and new grids/ new paste (4 cells). Features: SG4, EQWC, RELFRMA, SHPSLFA, AVCAP, DRYWT, MXCAP.
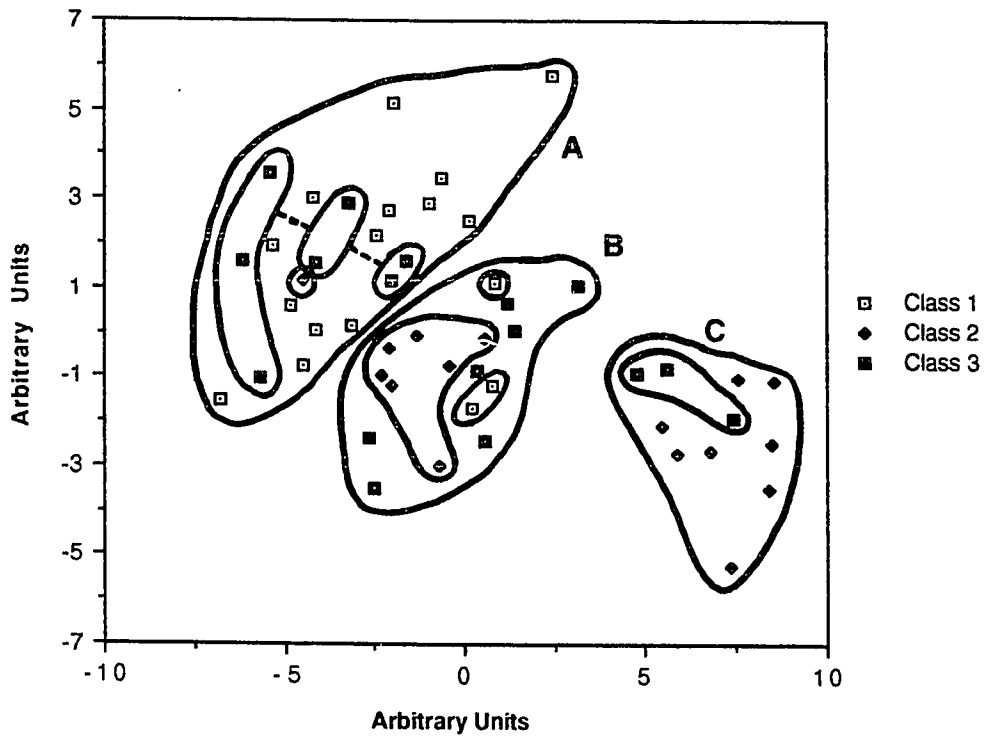
Figure 20. Non-linear mapping (NLM) of six-dimensional feature space for fabrication data; 3-class Training Set cells (with aberrant cells). STDEV classification criteria. Much overlap is observed between classes due to the presence of aberrant cells. A: Primarily Class 1 and Class 3 cells, Circuits 3 and 4, new grids/new paste. B: Mostly Class 2 and Class 3 cells, Circuits 2-4, old grids/new paste and new grids/new paste. C: Class 2 and Class 3 cells, Circuit 1, old grids/new paste. Features: EQWF, SG4, ASHP, RELFRMA, SHPSLFA, DRYWT.

overall classification accuracy was 71% and the individual class accuracies were 65, 77 and 70% for Classes 1, 2 and 3 respectively.

As expected from the training accuracies, the clusters in Figure 19 are not well separated, and there is some degree of overlap. If each of the points from the Class-3 cells were removed from the map in Figure 19, Classes 1 and 2 would very nearly be separable. The overlap is likely due to the arbitrary nature of the boundaries established between the capacity values for Class 3 and those for Classes 1 and 2, within a nearly continuous distribution. That is, the boundaries which have been established using the STDEV criterion may not provide an adequate means of identifying different cell subsets with different properties.

It is interesting to observe that virtually all of the points lying above zero on the Y-axis are from Circuits 1 and 2 and those below are predominately from Circuits 3 and 4. This suggests that differences in fabrication conditions from one batch to another produce real differences in measurable cell properties. Some of the fabrication differences from batch to batch are documented (e.g., material changes, Table 1) and are cited in the figure legends. However, other fabrication changes may simply be associated with a learning curve in the manufacture of these cells. The fact that cells from Circuit 3, which came from two different groups of fabrication materials, have statistically significant differences in capacity [13] suggests that fabrication materials are a determining factor in cell performance, even after 7 years of operation.

Results from the 6-dimensional map in Figure 20 were similar to Figure 19 in that low capacity cells from Circuit 1 are well resolved from the Class 1 cells, but cells from Class 3 are found within each of the three clusters, A, B and C. Cluster B contains cells predominately from Circuits 2 and 3 while Cluster A primarily contains cells with the highest ID numbers, i.e. cells from Circuits 3 and 4 which were made from newer

materials. These observations are supported by a dichotomy of performance observed for the cells from Circuit 3 (Appendix B). The results suggest that measurements during initial cell operation reflect the influence of plate and grid materials, and that these materials, along with other factors, determine cell performance well into battery life.

The histogram distribution of the 1990 cell capacity data (Figure 15) shows that the data do not conform exactly to a Gaussian distribution. Therefore, the boundaries assigned between Class 3 and each of the other two classes, based on the Gaussian σ-value, may not be appropriate. The NLM clusters of Figures 19 and 20 illustrate the existence of subsets of cells with common properties. Unfortunately, these subsets may not reflect only performance differences. However, by first dividing cells into performance subsets by the STDEV criterion, then applying KNN training to find feature sets which separate these classes as well as possible in feature space, the NLM display should illustrate cell grouping reflecting primarily performance differences. Thus, if cell classes are then re-defined based on their observed clustering in performance-based feature space, optimized definition of performance subsets might be achieved.

Table 6 summarizes the results of re-classifying cells based on their consistent occurrence within clusters of different STDEV assigned classes for various feature sets considered good 3-class classifiers (Table 5). Table 6 lists each cell classification based on STDEV criteria and based on the NLM cluster analysis criteria. Remarkably, many of the Class 2 cells were usually classified correctly and very few were reassigned to another class. Many of the Class 3 cells and some of the Class 1 cells were reassigned to other classes. The differences that occur underscore the need for examination of more than one classification system.

After each cell was assigned to the majority class of its nearest or surrounding cluster, the training procedure was repeated on the newly classified cells. As expected, higher

TABLE 6

3-CLASS STUDY
TRAINING SET CLASSIFICATIONS

Cell ID	Class by STDEV	Class by NLM Clusters	Cell ID	Class by STDEV	Class by NLM Clusters
146	1	1	105	2	2
230	1	3	109	2	2
236	1	3	192	2	2
239	1	3	197	2	2
243	1	3	199	2	2
245	1	1	225	2	3
246	1	1	228	2	2
251	1	1	249	2	3
252	1	1	299	2	2
254	1	1	16	3	2
262	1	1	18	3	2
265	1	1	70	3	3
267	1	1	71	3	2
273	1	1	83	3	3
276	1	3	99	3	3
297	1	1	128	3	3
303	1	3	131	3	1
20	2	2	132	3	2
21	2	2	133	3	3
22	2	2	135	3	3
23	2	2	136	3	3
25	2	2	172	3	3
28	2	2	185	3	1
29	2	2	219	3	3
59	2	2	221	3	3
60	2	2	235	3	3
62	2	2	263	3	3
63	2	2	307	3	3
65	2	2	316	3	2
91	2	2			

overall classification accuracy was obtained for each classifier and new classifiers were discovered which were not obtained in the first round of training (Table 7). Overall classification accuracy ranged from 78% to 86%, with greatest improvement obtained for Class 3 cells which increased from a high of 70% for classification boundaries determined by STDEV criterion to 81% using NLM. The use of NLM classification criteria also produced high accuracies for Class 1 and Class 2 cells (85% and 92%, respectively).

Reclassifications based on NLM clusters resulted in the frequent appearance of features SG2, EQWF, EQWC, ASHP and RELFRMA. So, in addition to features and classifiers which were initially found to be important, SG2 was also found to be a useful feature. The classifiers chosen for the NLM assigned cells are able to separate cells on the basis of their fabrication materials. This observation is based on the formation of clusters which contain cells exclusively from a particular circuit, or cells which are made from the same fabrication materials. Representative maps for the reclassified cells are shown in Figures 21 and 22 and depict very good separation of the three NLM-based classes of cells.

A thorough analysis of all useful classifiers generated by 3-class training and mapping showed that the cells most frequently identified as false positives for Class 1 were cells 133, 135, 225, 263 and 299. Cells 225 and 299 were also the most frequent Class 1 false positives encountered during the 2-Class studies. Examination of the data in Appendix A showed no obvious reason for the continuous incorrect classification of these cells. This suggests that the cells were fine during manufacture, but were likely in poor condition at the time the 1990 capacity tests were performed. Examination of capacity slope trends [13] for each cell indicates that many cells have changed their capacity levels over the years. Cells which originally possessed low capacities gradually increased in capacity over the years (1983 to 1990), whereas high capacity cells actually lost some

TABLE 7

3-CLASS STUDY
SUMMARY OF BEST TRAINING RESULTS
AFTER NLM RECLASSIFICATIONS

Classifier	% Classification Accuracy Overall/Class 1/Class 2/Class 3	Important Feature Groups
F-0201010000000	78/69/80/81	2,4,6
F-0/16/11110000000	85/77/92/81	2,3,4,5,6
F-1420110100010	81/85/84/76	1,2,3,5,6,8,12
F-1001020001000	81/77/88/76	1,4,6,10
F-0110010000000	86/85/92/81	2,3,6

Feature ID	Feature	Frequently Observed
1	SG2	
2	EQWF	✔
3	SG4	✔
4	EQWC	✔
5	ASHP	
6	RELFRMA	✔
8	AVSB	
10	AVSA	
12	MXCAP	

70
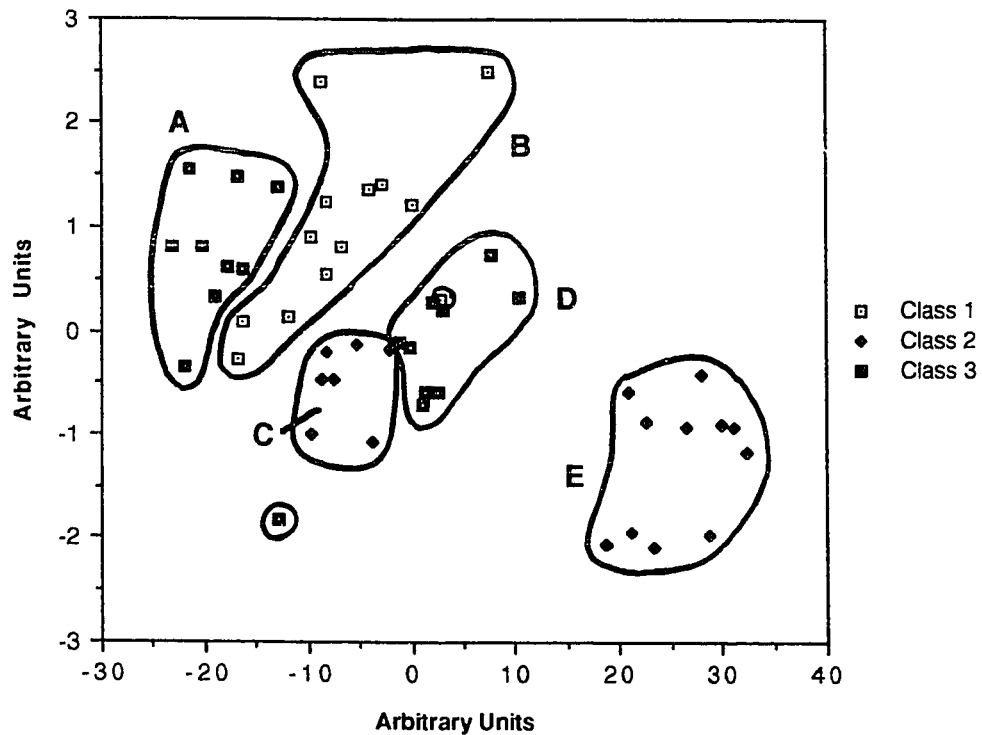
Figure 21. Non-linear mapping (NLM) of five-dimensional feature space for fabrication data; 3-class Training Set cells (with aberrant cells, without exchange cells), NLM cluster classification criteria. A: Class 3 cells, mostly Circuits 3 and 4, new grids/new paste. B: Class 1 cells, primarily Circuit 4, new grids/new paste. C: Class 2 cells, mainly Circuits 2 and 3, old grids/new paste. D: Class 3 cells, Circuits 2 and 4, old grids/new paste and new grids/new paste. E: Class 2 cells, Circuit 1, old grids/new paste. Features: EQWF, SG4, EQWC, ASHP, RELFRMA.

71
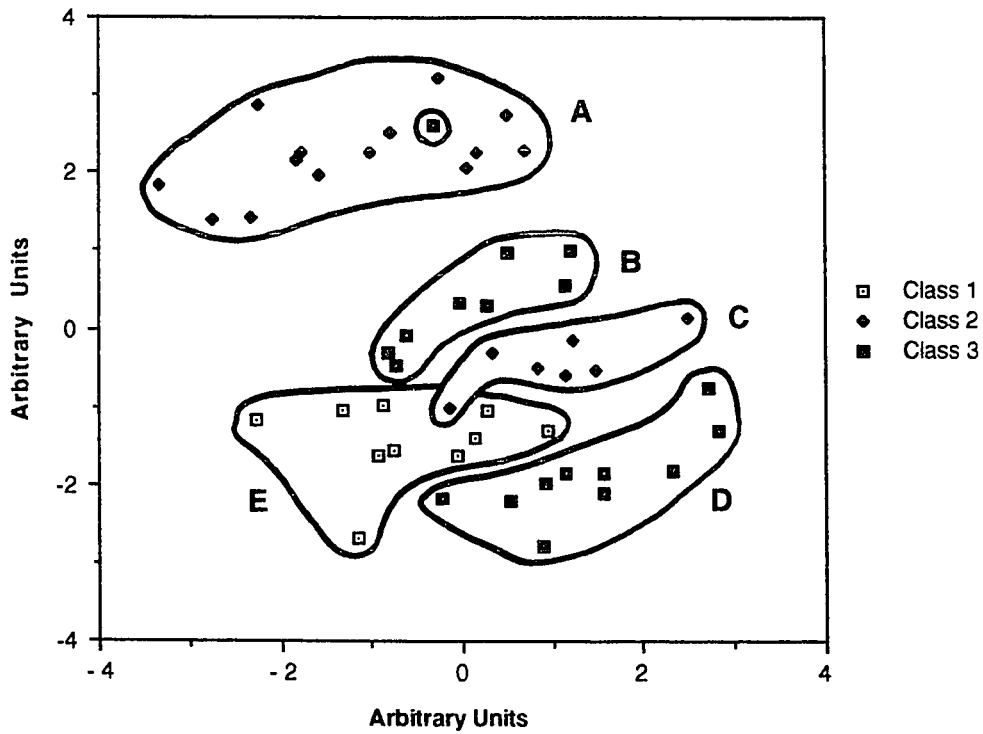
Figure 22. Non-linear mapping (NLM) of five-dimensional feature space for fabrication data; 3-class Training Set cells (with exchange cells, without aberrant cells), NLM cluster classification criteria. A: Class 2 cells, Circuit 1, old grids/new paste. B: Class 3 cells, primarily Circuit 2 (old grids/new paste) and Circuit 4 (new grids/new paste). C: Class 2 cells, mainly Circuit 3, old grids/new paste. D: Class 3 cells, mostly Circuits 3 and 4, new grids/new paste. E: Class 1 cells, Circuit 4, new grids/new paste. Features: SG2, EQWF, EQWC, ASHP, RELFRMA.

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capacity over the same time period. This supports the suggestion that cells can markedly change in performance after manufacture.

Feature groups which afforded the most accurate training results were used to perform prediction studies on the remaining Class 3 cells which were not part of the training set. Individual cell classifications for each classifier and each method (STDEV and NLM) are presented in Appendix D. Classes which were most frequently chosen are listed for each method and for both methods considered equally. Cells which underwent a split-vote have both assigned classes listed, separated by a slash (solidus). This information is summarized in Table 8, where the class is assigned using the best training feature groups from each of the criteria for a total pool of 10 classifiers. Cell classifications utilizing the best training classifier from each type of classification treatment are also presented.

Prediction "accuracy" was generally poorer than expected (max. ~48%). However, the large number of apparent misclassifications may be attributed to the arbitrary STDEV criterion used to assign all of the Predication Set cells to Class 3. It is possible that a Class 3 designation for many of the cells in the prediction set is incorrect, and that the NLM-trained classifiers provide a more accurate assignment of cells to subsets with overall common properties.

The same best feature groups were also used to classify the remaining 219 cells assigned to unknown Class 0. Due to the large number of cells, only summarized predictions are shown in Table 9, while detailed prediction results are presented in Appendix E. Results show that the assigned classes are again consistent with expectations given the knowledge of fabrication material changes made during manufacture. Most cells made early (those will smaller ID numbers) tend to be assigned to Class 2, which would be expected of cells made with old grids and paste. Many Class 3 designations occur for cells lying in the middle and later part of the database (consistent with old grids and new paste).

TABLE 8

SUMMARY OF CLASSIFICATION RESULTS
FOR PREDICTION SET, CLASS-3 CELLS
USING STDEV AND NLM CLASS-ASSIGNMENT CRITERIA

			Majority Vote Result for Best n Classifiers			Result for Best Training Classifier	
			STDEV	NLM	BOTH	STDEV	NLM
Index	Cell ID	Circuit	n = 5	n = 5	n = 10		
1	2	1	3	3	3	3	3
2	9	"	3	2	2 or 3	3	3
3	12	"	2	2	2	3	3
4	13	"	2	3	2	2	3
5	14	"	3	3	3	3	3
6	15	"	2	3	2 or 3	2	3
7	17	"	3	2	2	3	2
8	24	"	2	2	2	2	2
9	40	"	2	2	2	2	2
10	41	"	2	2	2	2	2
11	64	"	2	2	2	2	2
12	78	"	2	2	2	2	2
13	84	2	3	3	3	3	3
14	85	"	3	3	3	3	3
15	86	"	2	2	2	2	2
16	87	"	2	2	2	2	2
17	90	"	2	2	2	2	2
18	93	"	1	3	3	3	3
19	97	"	2	2	2	3	2
20	101	"	3	3	3	3	3
21	102	"	3	2	3	3	2
22	106	"	1	3	3	3	3
23	129	"	3	3	3	3	1
24	130	"	1	3	1	1	3
25	137	"	2	3	2 or 3	3	3
26	138	"	2	2	2	2	3
27	139	"	3	3	3	1	3
28	140	"	2	2	2	2	3
29	141	"	3	2	3	3	3

TABLE 8 (cont.)

Index	Cell ID	Circuit	Majority Vote Result for Best n Classifiers			Result for Best Training Classifier	
			STDEV n = 5	NLM n = 5	BOTH n = 10	STDEV	NLM
30	142	2	3	3	3	2	3
31	143	"	3	2 or 3	3	3	3
32	145	"	2	3	3	3	1
33	147	"	2	2	2	2	2
34	174	3	2	2	2	3	2
35	177	"	3	2	3	3	2
36	195	"	2	1	2	2	1
37	196	"	2	2	2	3	2
38	212	"	3	3	3	3	3
39	217	"	3	3	3	3	3
40	222	"	3	1 or 2	3	3	3
41	223	"	3	1	3	3	2
42	224	"	1	1	1	3	1
43	226	"	3	3	3	3	3
44	231	"	3	3	3	1	3
45	232	"	1	1	3	3	1
46	233	"	1	1	1	1	2
47	234	"	1	1	1	1	1
48	237	"	3	3	3	1	3
49	238	"	1	3	1	1	3
50	241	4	3	1	1	3	1
51	242	"	2	1	1 or 2	1	2
52	244	"	1	1	1	1	1
53	247	"	3	1	1	1	2
54	248	"	1	1	1	1	1
55	250	"	2	1	1	2	3
56	253	"	2	1	3	2	3
57	266	"	1	1	1	1	3
58	278	"	2	1	1	2	1
59	286	"	1	1	1	1	1
60	294	"	2	1	1 or 2	2	1
61	298	"	1	1	1	1	2
62	319	"	1	3	3	3	3

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TABLE 9

SUMMARY OF CLASSIFICATION RESULTS FOR UNKNOWN SET
USING STDEV AND NLM CLASSIFICATION CRITERIA

Index	Cell ID	Circuit No.	Majority Vote Result for Best n Classifiers			Result for Best Classifier		Unanimous Vote
			STDEV n = 5	NLM n = 5	BOTH n = 10	STDEV	NLM	
1	1	1	3	2	3	3	2	
2	3	"	3	2	3	3	2	
3	4	"	3	2	3	3	2	
4	5	"	3	2	2	3	2	
5	6	"	3	2	2	3	2	
6	7	"	3	2	3	3	2	
7	8	"	2/3	2	2	1	2	
8	10	"	3	2	3	3	2	
9	11	"	2	2	2	2	2	✔
10	19	"	3	2	2	2	2	
11	26	"	2	2	2	2	2	✔
12	27	"	3	2	2/3	3	2	
13	30	"	2	2	2	2	2	✔
14	31	"	2	2	2	2	2	✔
15	32	"	2	2	2	2	3	
16	33	"	2	2	2	2	2	✔
17	34	"	2	2	2	2	2	✔
18	35	"	2	2	2	2	2	✔
19	36	"	2	2	2	2	2	✔
20	37	"	2	2	2	2	2	✔
21	38	"	2	2	2	3	2	
22	39	"	2	2	2	2	2	✔
23	42	"	2	2	2	2	2	✔
24	43	"	3	2	2/3	2	2	
25	44	"	2	2	2	2	2	✔
26	45	"	2	2	2	3	2	
27	46	"	3	2	3	3	2	
28	47	"	2	2	2	2	2	✔
29	48	"	2	2	2	2	2	✔
30	49	"	3	2	2	3	2	
31	50	"	2	2	2	2	2	✔
32	51	"	2	2	2	2	2	✔
33	52	"	3	2	3	2	3	
34	53	"	2	2	2	2	2	✔
35	54	"	2	2	2	2	2	✔
36	55	"	2	2	2	2	2	✔
37	56	"	3	3	3	3	3	✔
38	57	"	2	2	2	2	2	✔
39	58	"	3	2	2	2	2	
40	61	"	2	2	2	2	2	✔
41	66	"	2	2	2	2	2	✔
42	67	"	3	2	2	2	2	
44	69	"	2	2	2	2	3	
45	72	"	2	2	2	2	3	

TABLE 9 (cont.)

Index	Cell ID	Circuit No.	Majority Vote Result for Best n Classifiers			Result for Best Classifier		Unanimous Vote
			STDEV n = 5	NLM n = 5	BOTH n = 10	STDEV	NLM	
46	73	1	2	2	2	2	3	
47	74	"	3	2	2	2	2	
48	75	"	2	2	2	2	2	✔
49	76	"	2	2	2	2	2	✔
50	77	"	2	2	2	2	2	✔
51	79	"	3	2	2	2	2	
52	80	"	2	2	2	2	2	✔
53	81	2	3	3	3	3	3	✔
54	82	"	3	1	3	3	3	
55	88	"	3	2	2/3	3	2	
56	89	"	1	3	3	2	3	
57	92	"	1/2	2	2	3	2	
58	94	"	2	2	2	2	1	
59	95	"	2	2	2	3	1	
60	96	"	1	3	3	3	3	
61	98	"	3	1/2	2/3	3	3	
62	100	"	3	3	3	3	3	✔
63	103	"	2	2	2	3	2	
64	104	"	2	2	2	3	2	
65	107	"	3	3	3	3	3	✔
66	108	"	2	2	2	1	2	
67	110	"	2	2	2	2	2	✔
68	111	"	2	2	2	2	2	✔
69	112	"	2	2	2	2	2	✔
70	113	"	2	2	2	2	2	✔
71	114	"	2	2	2	3	2	
72	115	"	3	1	1	3	1	
73	116	"	2/3	1	1	3	1	
74	117	"	3	2	3	3	3	
75	118	"	2	2	2	2	2	✔
76	119	"	1	3	3	3	3	
77	120	"	3	2	3	3	3	
78	121	"	1/3	2	2	3	2	
79	122	"	2	2	2	3	2	
80	123	"	3	3	3	2	3	
81	124	"	2	2	2	2	2	✔
82	125	"	1	3	3	1	3	
83	126	"	1	3	1/3	3	1	
84	127	"	3	3	3	3	1	
85	134	"	3	3	3	3	3	✔
86	144	"	3	3	3	3	3	✔
87	148	"	2	2	2	2	2	✔
88	149	"	1/2	2	2	3	3	
89	150	"	1	1	1	2	1	
90	151	"	2	2	2	2	2	✔
91	152	"	3	3	3	2	2	
92	153	"	3	2/3	3	3	2	
93	154	"	2	2	2	1	3	

TABLE 9 (cont.)

Index	Cell ID	Circuit No.	Majority Vote Result for Best n Classifiers			Result for Best Classifier		Unanimous Vote
			STDEV n = 5	NLM n = 5	BOTH n = 10	STDEV	NLM	
94	155	2	2	2	2	3	2	
95	156	"	2	2	2	3	2	
96	157	"	1	1	1	1	1	✔
97	158	"	3	3	3	3	3	✔
98	159	"	2	2	2	2	2	✔
99	160	"	3	1	3	3	2	
100	161	3	3	1	1/3	3	1	
101	162	"	1/3	3	3	3	1	
102	163	"	3	3	3	2	3	
103	164	"	3	3	3	3	3	✔
104	165	"	3	3	3	3	3	✔
105	166	"	1	1	1	1	1	✔
106	167	"	3	1	1	3	1	
107	168	"	3	3	3	2	3	
108	169	"	1	3	1	1	3	
109	170	"	2	2	2	3	2	
110	171	"	2	2	2	2	2	✔
111	173	"	3	2	3	2	3	
112	175	"	1	1	1	3	1	
113	176	"	3	2	2/3	2	2	
114	178	"	3	1	3	3	1	
115	179	"	3	1	3	3	2	
116	180	"	2	2	2	2	2	✔
117	181	"	2	2	2	2	2	✔
118	182	"	1	1	1	3	2	
119	183	"	1	2	1/2	2	2	
120	184	"	2	2	2	3	2	
121	186	"	2	3	2/3	2	3	
122	187	"	2	2	2	2	2	✔
123	188	"	2	3	3	3	1	
124	189	"	2	2	2	2	3	
125	190	"	2	3	2	2	3	
126	191	"	2	2	2	3	2	
127	193	"	2	2	2	2	2	✔
128	194	"	3	3	3	3	3	✔
129	198	"	2	2	2	2	2	✔
130	200	"	2	1	2	2	1	
131	201	"	2	3	2	2	3	
132	202	"	3	1	1/3	3	1	
133	203	"	3	1	3	3	2	
134	204	"	3	1	1	3	2	
135	205	"	1	2	2	3	2	
136	206	"	2	2	2	3	2	
137	207	"	2	2	2	2	2	✔
138	208	"	2	2	2	2	2	✔
139	209	"	2	2	2	3	2	
140	210	"	3	1	3	2	3	
141	211	"	3	3	3	2	3	

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TABLE 9 (cont.)

Index	Cell ID	Circuit No.	Majority Vote Result for Best n Classifiers			Result for Best Classifier		Unanimous Vote
			STDEV n = 5	NLM n = 5	BOTH n = 10	STDEV	NLM	
142	213	3	3	2/3	3	3	2	
143	214	"	3	1	1/3	3	3	
144	215	"	2	2	2	3	2	
145	216	"	2	2	2	2	2	✔
146	218	"	3	1	1/3	2	2	
147	220	"	1	3	1	1	1	
148	227	"	3	3	3	1	3	
149	229	"	1	3	1/3	1	3	
150	240	"	3	3	3	3	3	✔
151	255	4	3	3	3	3	3	✔
152	256	"	1	1	1	1	1	✔
153	257	"	1	1	1	1	1	✔
154	258	"	3	3	3	1	3	
155	259	"	3	3	3	1	3	
156	260	"	2	1	1	2	3	
157	261	"	1	1	1	1	1	✔
158	264	"	1	1	1	1	1	✔
159	268	"	1	1	1	1	1	✔
160	269	"	3	1	1/3	3	1	
161	270	"	1	1	1	1	1	✔
162	271	"	3	1	1/3	1	1	
163	272	"	1	1	1	3	3	
164	274	"	2	1	1	2	1	
165	275	"	1	1	1	1	3	
166	277	"	1	2	1	3	1	
167	279	"	1	3	1	1	3	
168	280	"	1	1	1	1	1	✔
169	281	"	1	1	1	1	1	✔
170	282	"	1	3	1	1	3	
171	283	"	1	1	1	1	1	✔
172	284	"	3	2	1	3	2	
173	285	"	2	2	2	2	2	✔
174	287	"	1	2	1	1	2	
175	288	"	3	2	3	3	1	
176	289	"	2	2	2	1	1	
177	290	"	1	3	1	2	3	
178	291	"	2	2	2	1	2	
179	292	"	2	2	2	1	1	
180	293	"	1	1	1	1	1	✔
181	295	"	2	2	2	2	1	
182	296	"	3	2	1	3	1	
183	300	"	2	1	3	2	1	
184	301	"	1	1	1	3	1	
185	302	"	3	1	1	3	1	
186	304	"	2	3	2	2	3	
187	305	"	3	3	3	2	3	
188	306	"	3	3	3	3	3	✔
189	308	"	1	1	1	1	1	✔

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TABLE 9 (cont.)

| | | | Majority Vote Result for Best n Classifiers | | | Result for Best Classifier | | Unanimous |
| | | | STDEV | NLM | BOTH | | | |
Index	Cell ID	Circuit No.	n = 5	n = 5	n = 10	STDEV	NLM	Vote
190	309	4	3	3	3	2	3	
191	310	"	1	1	1	3	3	
192	311	"	1	1	1	3	3	
193	312	"	3	2	3	3	2	
194	313	"	2/3	1	1/2	1	1	
195	314	"	1	1	1	2	3	
196	315	"	1	1	1	3	3	
197	317	"	1	1	1	1	1	✔
198	318	"	3	1	3	3	3	
199	320	"	2	1	1	1	2	
200	321	5	1	1	1	3	1	
201	322	"	1	3	3	1	3	
202	323	"	2	1/2	2	3	3	
203	324	"	1	1	1	1	1	✔
204	325	"	1	1	1	3	3	
205	326	"	3	3	3	3	3	✔
206	327	"	1	1	1	1	2	
207	328	"	1	1	1	1	3	
208	329	"	3	3	3	3	3	✔
209	330	"	2	3	3	3	3	
210	331	"	1	1	1	1	3	
211	332	"	1	1	1	1	1	✔
212	333	"	2	3	3	3	3	
213	334	"	1	1	1	3	3	
214	335	"	3	1	1/3	1	1	
215	336	"	1	1	1	1	1	✔
216	337	"	1	3	1	1	1	
217	338	"	3	3	3	3	3	✔
218	339	"	1	1	1	1	1	✔
219	340	"	3	1	3	3	3	

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Cells which were made later with new grids and paste have many more of the Class 1 designations than any of the earlier cells.

Comparison of the results in Table 9 with class assignments based on 1991 capacity data for 202 common cells showed that the predictions are consistent with the actual cell performance for Class 3 cells (~85% correctly classified); however, the correlations between the predictions and the class assignments (based on 1991 performances) for Class 1 and 2 cells were not as high (~25% and ~20% for Class 1 and Class 2, respectively). The poor correlation is likely due to the changes observed in the performance of the cells over time [13]. Cells which have large capacity slope trends will likely be misclassified when comparing the class assignments based on currently measured performance relative to performance soon after the date of manufacture.

In summary, results from the 3-class studies again indicate that battery fabrication data contain the information necessary to distinguish between high and low performing cells. Identification of Class 3 cells is more difficult. Better classifiers were obtained by reclassifying cells based on their nearest NLM cluster, and the cell-class majority within that cluster, than relying entirely on the STDEV criterion. Many of the useful classifiers were composed of only 4 to 7 features. For 59 total cells, the pattern-to-feature ratio lies somewhere between 8 and 15 which is large enough to permit statistical confidence in the results.

VI. Conclusions

The results of this multivariate pattern recognition investigation clearly illustrate the usefulness of battery fabrication data for predicting lead-acid cell performance. Measurements of specific gravity, acid levels and adjustments to these levels appear to be among the most important for accurate cell classifications. Results showed that high and low performing cells could be distinguished quite accurately, demonstrating clearly that performance prediction information is contained within the fabrication measurements. Attempts to predict three different classes of cell performance were not completely satisfactory. It appears that further work is needed regarding more effective definitions of cell performance classes.

One potential benefit from this work may be the ability to isolate poor cells from good ones which are needed for demanding applications. Another benefit would be the ability to assign better-matched cells to energy storage batteries using long strings, where one "weak link" can bring down the whole string. Finally, the ability to reject cells which will degrade performance, fail early, or require exceptional maintenance, provides a significant economic benefit for large energy storage batteries.

In addition to the benefits related to cell pre-selection, we hope the results of our work will help illustrate how changes in manufacturing procedures might lead to improved quality cells. For example, it is now clear from our work that subtle differences in grid and paste materials have a prolonged effect on performance of lead-acid cells. Knowledge of which fabrication features are the most important may also provide information on the observation and adjustment of these features in an effort to produce superior batteries.

Finally, it may be possible that a combination of fabrication and maintenance data measurements, raw or transformed, may yield even greater classification accuracy, and hence more reliable performance predictions. Such studies are in progress. Ultimately,

these studies will include correlation with cell lifetimes, when the CEMC battery goes through its complete life and cell failure data becomes available.

This work has demonstrated that pattern recognition techniques are useful for prediction of lead-acid cell performance. Pattern recognition and other chemometric techniques will continue to play an important role in electrochemical research and in other chemical applications such as spectroscopy [39-41], chromatography [42-44], biochemistry [45], thermodynamics [46], statistical analysis [47-49], QA/QC [50, 51], environmental testing [52-54], food science [55], and in manufacturing and process control [56-58].

VII. Appendices

A. GNB Fabrication Data

B. 1990 Capacity Test Data

C. Correctly Classified Cells, Aberrant Cells and Replacement Cells

D. Prediction Results for Prediction Set Cells

E. Prediction Results for Unknown Set Cells

APPENDIX A

GNB FABRICATION DATA
FOR 340 LEAD-ACID BATTERY CELLS

CELL NO.	SG2	EQWF	SG4	EQWC	ASHP	RELFRMA	SHPSLFA
1	1.249	1258	1.286	-48	0	11.02	25.06
2	1.245	1274	1.290	-246	586	11.43	25.31
3	1.258	1402	1.290	-246	0	12.49	24.21
4	1.232	1501	1.288	-146	0	13.37	24.43
5	1.248	1570	1.284	0	0	13.47	25.69
6	1.245	1583	1.286	-48	0	14.21	24.46
7	1.260	1429	1.290	-246	0	12.77	24.13
8	1.260	1809	1.293	-398	0	15.35	25.11
9	1.256	1801	1.289	-196	-195	15.02	25.58
10	1.265	1450	1.288	-146	0	14.83	21.24
11	1.253	1287	1.282	0	0	11.00	25.80
12	1.248	1406	1.280	0	220	11.93	26.47
13	1.269	1391	1.281	0	220	12.78	24.49
14	1.254	1766	1.284	0	977	16.94	25.14
15	1.265	1323	1.281	0	757	12.27	25.44
16	1.264	1501	1.283	0	562	13.77	25.28
17	1.251	1668	1.283	0	757	15.77	24.99
18	1.266	1365	1.283	0	708	12.84	25.00
19	1.253	1925	1.283	0	977	18.80	24.73
20	1.266	1583	1.280	0	586	14.89	24.73
21	1.261	1944	1.280	0	391	18.61	23.89
22	1.251	1745	1.280	0	464	16.36	24.54
23	1.236	1900	1.280	0	488	18.31	23.95
24	1.239	2186	1.279	96	49	19.83	24.62
25	1.232	1838	1.276	172	49	16.68	24.79
26	1.261	1456	1.280	0	1270	13.63	26.35
27	1.252	1760	1.282	0	562	16.35	24.98
28	1.242	1520	1.276	172	146	13.60	25.34
29	1.255	1961	1.282	0	146	17.96	24.40
30	1.246	1635	1.269	413	171	14.26	26.56
31	1.246	1934	1.280	0	293	17.85	24.53
32	1.260	1980	1.281	0	342	17.74	25.35
33	1.244	1875	1.279	72	391	17.20	25.06
34	1.248	2022	1.281	0	635	19.49	24.27
35	1.243	1766	1.280	0	537	16.75	24.43
36	1.236	2167	1.277	146	195	20.09	24.53
37	1.230	1904	1.276	147	0	18.94	22.49
38	1.258	1851	1.284	0	220	20.04	20.85
39	1.240	1735	1.274	249	122	18.78	21.18
40	1.248	1992	1.283	0	49	21.53	20.51
41	1.256	1865	1.282	0	98	20.15	20.62
42	1.251	1712	1.280	0	708	17.00	23.76
43	1.251	1823	1.282	0	513	17.12	24.61
44	1.260	1764	1.280	0	220	16.38	24.22
45	1.260	1875	1.283	0	195	16.80	25.03

CELL NO.	SG2	EQWF	SG4	EQWC	ASHP	RELFRMA	SHPSLFA
46	1.260	1848	1.284	0	342	16.14	25.99
47	1.258	1584	1.280	0	488	14.55	25.08
48	1.248	1839	1.281	0	24	16.14	25.18
49	1.252	1702	1.281	0	708	16.14	24.81
50	1.245	1585	1.280	0	659	15.48	24.03
51	1.245	1520	1.279	72	513	14.51	24.39
52	1.263	1787	1.281	0	537	16.01	25.78
53	1.252	1643	1.276	172	659	15.41	25.34
54	1.236	1799	1.273	251	220	16.81	24.63
55	1.246	1620	1.281	0	537	15.12	24.81
56	1.260	1839	1.284	0	513	16.56	25.62
57	1.257	1633	1.280	0	928	15.34	25.52
58	1.245	1749	1.281	0	610	16.24	25.08
59	1.261	1507	1.281	0	757	14.20	25.07
60	1.252	1999	1.279	72	146	17.67	25.42
61	1.237	1797	1.275	223	0	16.25	24.87
62	1.254	1811	1.282	0	562	17.63	23.89
63	1.236	1411	1.275	223	195	12.98	24.88
64	1.250	1801	1.282	0	244	16.89	24.05
65	1.246	1609	1.275	223	415	15.95	23.64
66	1.246	1799	1.283	0	610	17.37	24.18
67	1.250	1806	1.278	121	488	16.69	25.19
68	1.252	1427	1.283	0	586	12.83	25.82
69	1.259	1891	1.277	146	171	17.18	24.96
70	1.260	1834	1.281	0	562	17.06	24.94
71	1.254	1838	1.281	0	732	17.23	25.13
72	1.260	1902	1.281	0	391	17.78	24.45
73	1.262	1733	1.275	223	73	15.99	24.54
74	1.252	1882	1.280	0	659	17.96	24.55
75	1.243	1903	1.277	146	366	17.56	25.02
76	1.236	1866	1.275	223	293	16.80	25.63
77	1.251	1749	1.282	0	269	16.80	23.54
78	1.236	1642	1.275	223	586	15.20	25.60
79	1.252	1770	1.282	0	586	16.68	24.69
80	1.250	1987	1.277	146	439	17.83	25.85
81	1.277	1124	1.287	0	0	10.15	24.41
82	1.288	179	1.288	0	439	1.68	24.44
83	1.270	933	1.288	0	391	8.89	24.00
84	1.283	850	1.286	0	269	7.64	25.12
85	1.268	1257	1.286	0	220	11.01	25.65
86	1.270	582	1.284	0	342	5.42	24.42
87	1.274	574	1.284	0	317	5.26	24.74
88	1.280	260	1.282	137	342	2.15	27.68
89	1.284	708	1.284	0	146	6.17	25.63
90	1.268	544	1.284	0	171	5.06	24.08
91	1.274	524	1.284	0	293	4.81	24.65
92	1.276	590	1.283	137	195	5.26	25.48
93	1.284	655	1.284	0	317	5.80	25.60
94	1.274	185	1.284	0	244	1.69	24.65
95	1.265	557	1.283	137	391	5.18	24.86

CELL NO.	SG2	EQWF	SG4	EQWC	ASHP	RELFRMA	SHPSLFA
96	1.280	636	1.283	137	98	5.64	25.38
97	1.208	3620	1.282	206	278	32.94	25.29
98	1.269	468	1.288	0	464	4.44	24.27
99	1.283	698	1.285	0	220	6.63	23.70
100	1.281	844	1.284	0	98	7.44	25.23
101	1.276	1278	1.287	0	171	11.58	24.71
102	1.269	585	1.285	0	146	5.49	23.80
103	1.284	467	1.284	0	171	4.33	24.15
104	1.234	2284	1.284	0	195	19.63	26.08
105	1.200	5045	1.285	0	-220	43.87	24.86
106	1.279	596	1.287	0	317	5.25	25.75
107	1.292	609	1.288	0	49	5.53	24.41
108	1.285	423	1.285	0	0	3.71	25.13
109	1.180	5696	1.283	0	-220	50.66	24.30
110	1.167	5448	1.282	206	269	49.20	25.46
111	1.171	5955	1.283	137	195	52.88	25.56
112	1.195	5446	1.284	0	73	47.29	25.55
113	1.284	160	1.283	137	98	1.40	25.79
114	1.280	315	1.285	0	122	2.92	24.08
115	1.289	131	1.285	0	293	1.22	24.31
116	1.299	212	1.287	0	146	1.85	25.52
117	1.271	502	1.283	137	0	4.31	25.99
118	1.278	272	1.284	0	171	2.42	25.16
119	1.292	838	1.284	0	342	7.50	25.39
120	1.284	366	1.278	130	49	3.12	26.23
121	1.284	222	1.284	0	49	1.89	26.06
122	1.285	263	1.283	137	146	2.31	25.75
123	1.290	793	1.281	206	0	7.14	24.94
124	1.290	140	1.284	0	0	1.20	25.69
125	1.289	-416	1.284	0	49	-3.61	25.53
126	1.291	-284	1.286	0	98	-2.56	24.70
127	1.291	-294	1.284	0	220	-2.56	25.80
128	1.289	-389	1.288	0	269	-3.32	26.39
129	1.283	-176	1.287	0	244	-1.51	26.30
130	1.284	-77	1.285	0	757	-0.72	25.11
131	1.264	313	1.288	0	464	2.85	25.25
132	1.282	194	1.281	206	415	1.73	26.16
133	1.270	728	1.285	0	-73	6.13	26.01
134	1.289	-361	1.287	0	537	-3.19	26.12
135	1.289	-100	1.287	0	415	-0.95	24.09
136	1.273	1052	1.286	0	0	9.50	24.41
137	1.264	1741	1.287	0	98	15.44	25.08
138	1.279	516	1.284	0	317	4.75	24.66
139	1.289	375	1.286	0	415	3.39	25.33
140	1.289	455	1.284	0	0	4.12	24.34
141	1.269	263	1.283	69	293	2.70	22.25
142	1.252	1126	1.284	0	293	10.41	24.50
143	1.283	535	1.286	0	146	4.90	21.40
144	1.283	1168	1.284	0	342	10.34	25.65
145	1.293	-181	1.288	0	391	-1.63	25.31

CELL NO.	SG2	EQWF	SG4	EQWC	ASHP	RELFRMA	SHPSLFA
146	1.290	-97	1.285	0	342	-0.89	24.90
147	1.263	245	1.284	0	317	2.26	24.55
148	1.283	372	1.283	69	391	3.44	24.86
149	1.283	567	1.283	69	122	5.07	25.10
150	1.279	-59	1.284	0	342	-0.55	24.42
151	1.273	515	1.283	69	146	4.75	24.40
152	1.287	104	1.275	293	73	0.95	24.99
153	1.272	603	1.287	0	732	5.67	25.05
154	1.291	295	1.285	0	659	2.77	24.93
155	1.282	297	1.284	0	488	2.64	25.86
156	1.281	295	1.280	275	195	2.69	25.22
157	1.279	20	1.285	0	171	0.18	25.31
158	1.286	83	1.286	0	317	0.79	23.95
159	1.271	420	1.274	270	195	3.89	24.80
160	1.280	299	1.287	0	439	2.86	24.03
161	1.254	959	1.286	-845	49	8.33	23.63
162	1.257	772	1.284	-960	684	6.72	24.70
163	1.259	841	1.284	-389	293	7.56	24.31
164	1.259	618	1.284	-439	293	5.81	23.12
165	1.256	739	1.282	-293	-73	6.31	24.99
166	1.250	1140	1.293	-790	562	10.95	22.45
167	1.257	885	1.291	-638	0	7.74	23.79
168	1.255	1030	1.281	-243	-269	9.13	23.73
169	1.258	725	1.293	-194	-293	6.46	23.68
170	1.259	561	1.277	100	171	4.92	25.76
171	1.254	896	1.267	559	537	8.39	25.97
172	1.261	653	1.282	-194	-171	5.58	25.00
173	1.265	447	1.282	-145	-146	3.70	25.98
174	1.265	447	1.282	-194	244	4.06	24.41
175	1.269	378	1.288	-536	195	3.16	25.61
176	1.267	442	1.282	-243	-195	3.67	25.58
177	1.267	346	1.287	-437	195	3.06	24.40
178	1.269	234	1.285	-290	244	2.13	24.09
179	1.268	235	1.287	-339	635	2.17	24.54
180	1.268	236	1.281	-145	464	2.14	25.00
181	1.269	234	1.281	-194	0	2.06	24.62
182	1.266	100	1.283	-242	244	0.78	28.32
183	1.275	58	1.283	-144	293	0.53	24.40
184	1.269	378	1.283	-193	49	3.34	24.66
185	1.274	254	1.287	-291	366	2.24	25.14
186	1.260	614	1.270	353	195	5.54	25.62
187	1.273	284	1.279	-15	464	2.60	25.10
188	1.263	565	1.287	-388	293	5.02	24.62
189	1.269	378	1.284	-241	98	3.34	24.62
190	1.264	450	1.273	191	98	4.09	24.90
191	1.264	450	1.284	-290	244	4.10	24.12
192	1.269	234	1.283	-96	244	2.05	25.49
193	1.273	139	1.284	-96	684	1.29	25.07
194	1.273	284	1.272	374	757	2.55	27.02
195	1.280	-140	1.283	-242	855	-1.26	25.76

CELL NO.	SG2	EQWF	SG4	EQWC	ASHP	RELFRMA	SHPSLFA
196	1.269	378	1.280	0	732	3.48	25.58
197	1.265	447	1.280	-145	122	4.01	24.51
198	1.273	139	1.285	-241	488	1.24	25.18
199	1.274	254	1.284	-192	488	2.27	25.29
200	1.274	107	1.283	-291	317	0.94	25.22
201	1.258	714	1.274	-385	0	6.31	24.09
202	1.270	182	1.288	-341	610	1.68	24.48
203	1.268	235	1.288	-341	392	2.08	24.97
204	1.265	447	1.289	-488	391	3.99	24.50
205	1.273	-38	1.281	-145	195	-0.34	24.86
206	1.274	157	1.282	-48	366	1.42	25.00
207	1.267	238	1.284	-144	537	2.20	24.75
208	1.269	349	1.280	0	0	3.19	24.11
209	1.278	68	1.283	-193	488	0.62	24.76
210	1.277	-50	1.282	-194	635	-0.44	25.91
211	1.265	447	1.266	531	293	4.25	25.03
212	1.274	109	1.281	-48	49	0.95	25.16
213	1.268	351	1.277	100	-342	3.07	24.70
214	1.275	-42	1.283	-291	342	-0.39	23.96
215	1.266	396	1.282	-243	732	3.67	24.89
216	1.265	447	1.280	-194	293	4.00	24.86
217	1.268	206	1.291	-638	513	1.78	25.22
218	1.269	155	1.288	-536	513	1.34	25.37
219	1.280	-339	1.283	-391	317	-2.83	26.24
220	1.278	-228	1.285	-290	-122	-1.90	25.60
221	1.275	58	1.277	100	-49	0.50	25.91
222	1.276	-171	1.289	-586	439	-1.51	24.58
223	1.272	140	1.289	-586	146	1.22	24.23
224	1.271	142	1.290	-491	-73	1.20	24.89
225	1.277	-149	1.287	-437	391	-1.29	25.40
226	1.270	95	1.277	52	537	0.84	26.16
227	1.284	-654	1.291	-492	415	-5.67	25.26
228	1.268	284	1.283	-193	562	2.51	25.79
229	1.278	-253	1.289	-488	122	-2.12	25.44
230	1.284	-549	1.282	-194	293	-4.92	24.82
231	1.281	-341	1.289	-537	293	-2.94	25.00
232	1.283	-367	1.290	-587	-146	-3.02	25.16
233	1.279	-257	1.286	-437	98	-2.19	25.13
234	1.280	-140	1.289	-488	0	-1.20	24.57
235	1.279	-309	1.291	-687	439	-2.71	24.62
236	1.278	-256	1.288	-341	0	-2.20	24.94
237	1.283	-368	1.288	-487	342	-3.25	24.62
238	1.284	-395	1.289	-439	98	-3.43	24.67
239	1.275	-204	1.286	-487	317	-1.74	25.54
240	1.274	-90	1.292	-640	293	-0.78	24.74
241	1.266	133	1.290	-838	146	1.13	24.46
242	1.271	-214	1.286	-388	513	-1.86	25.70
243	1.271	-110	1.290	-538	513	-0.94	25.71
244	1.267	343	1.288	-637	146	2.91	24.87
245	1.261	486	1.290	-738	244	3.98	25.80

CELL NO.	SG2	EQWF	SG4	EQWC	ASHP	RELFRMA	SHPSLFA
246	1.267	194	1.288	-487	244	1.60	26.16
247	1.268	205	1.288	-438	342	1.81	24.80
248	1.265	521	1.294	-744	0	4.63	23.15
249	1.263	601	1.284	-144	-146	5.35	24.15
250	1.268	4	1.285	-339	391	0.03	25.39
251	1.271	-110	1.284	-290	195	-0.92	26.19
252	1.268	256	1.289	-587	317	2.11	26.18
253	1.268	206	1.286	-641	146	1.74	25.08
254	1.266	233	1.293	-940	0	1.96	24.18
255	1.265	222	1.271	324	293	1.84	28.02
256	1.259	621	1.293	-890	195	5.13	25.17
257	1.264	657	1.298	-906	439	5.57	25.00
258	1.267	43	1.289	-738	342	0.36	25.41
259	1.266	-21	1.289	-738	439	-0.18	24.99
260	1.262	92	1.284	-682	220	0.77	25.23
261	1.260	579	1.290	-738	98	4.64	26.11
262	1.261	436	1.290	-687	244	3.66	25.31
263	1.264	58	1.290	-687	439	0.49	25.33
264	1.262	446	1.295	-894	195	3.58	25.95
265	1.258	614	1.289	-537	122	5.14	25.41
266	1.263	303	1.290	-687	146	2.53	25.21
267	1.263	99	1.285	-340	146	0.82	26.23
268	1.270	79	1.285	-241	-171	0.65	25.75
269	1.268	255	1.286	-437	73	2.44	22.22
270	1.272	55	1.285	-339	195	0.46	26.31
271	1.270	130	1.290	-788	146	1.09	24.95
272	1.272	-96	1.293	-404	-49	-0.81	24.99
273	1.251	923	1.295	-894	415	8.34	23.36
274	1.264	110	1.283	-391	293	0.93	25.77
275	1.263	354	1.290	-788	488	3.06	24.84
276	1.255	657	1.282	-293	269	5.71	25.33
277	1.265	173	1.282	-444	0	1.38	26.58
278	1.269	-190	1.284	-339	537	-1.66	25.71
279	1.274	-169	1.285	-388	122	-1.39	26.23
280	1.268	155	1.285	-589	49	1.25	26.11
281	1.268	155	1.285	-388	0	1.26	26.18
282	1.272	4	1.288	-586	-73	0.03	25.51
283	1.268	-152	1.285	-388	98	-1.27	25.84
284	1.268	-48	1.280	-48	-98	-0.38	27.17
285	1.262	409	1.282	-393	-73	3.36	25.79
286	1.269	17	1.285	-339	-49	0.14	26.41
287	1.264	313	1.285	-488	269	2.59	26.14
288	1.261	336	1.280	-343	-342	2.61	26.84
289	1.268	305	1.283	-341	0	2.53	25.84
290	1.270	-21	1.285	-388	488	-0.18	25.87
291	1.263	454	1.283	-441	439	3.89	25.72
292	1.266	286	1.284	-489	-49	2.32	26.00
293	1.263	454	1.285	-640	-49	3.62	26.16
294	1.269	217	1.285	-640	-146	1.75	25.64
295	1.269	217	1.280	-293	244	1.84	25.92

CELL NO.	SG2	EQWF	SG4	EQWC	ASHP	RELFRMA	SHPSLFA
296	1.268	255	1.280	-495	98	2.02	26.91
297	1.259	719	1.285	-589	0	5.77	26.15
298	1.273	17	1.285	-488	293	0.14	26.05
299	1.265	373	1.284	-439	122	3.16	25.36
300	1.258	712	1.284	-439	-98	6.05	24.77
301	1.269	-138	1.283	-391	98	-1.12	26.47
302	1.253	883	1.287	-636	146	7.48	24.94
303	1.258	713	1.283	-441	415	6.13	25.59
304	1.247	1143	1.278	-318	122	9.82	25.22
305	1.247	1043	1.280	-393	0	9.04	24.56
306	1.253	882	1.284	-489	146	7.77	24.26
307	1.258	563	1.284	-439	488	5.26	23.70
308	1.271	91	1.284	-192	244	0.73	27.60
309	1.254	687	1.280	-145	-342	5.89	24.65
310	1.270	-124	1.282	-243	146	-1.01	26.86
311	1.270	-73	1.283	-291	146	-0.61	26.27
312	1.263	698	1.276	-54	-122	5.96	25.41
313	1.269	217	1.283	-341	-146	1.83	25.03
314	1.272	-96	1.283	-341	0	-0.81	25.39
315	1.272	-45	1.284	-389	391	-0.38	25.92
316	1.270	179	1.279	-159	-49	1.51	25.72
317	1.260	578	1.286	-589	98	4.74	25.81
318	1.268	155	1.290	-840	317	1.32	24.65
319	1.275	-5	1.290	-840	146	-0.04	24.46
320	1.268	205	1.286	-539	0	1.74	24.80
321	1.274	205	1.292	-495	-49	1.74	24.79
322	1.256	911	1.291	-444	220	8.43	23.32
323	1.268	425	1.287	-243	146	3.77	24.65
324	1.262	660	1.296	-704	195	5.52	25.24
325	1.261	70	1.286	-194	-98	0.63	23.92
326	1.262	660	1.287	-243	122	6.01	23.96
327	1.278	66	1.287	-243	0	0.56	25.34
328	1.277	100	1.286	-194	-586	0.81	25.39
329	1.258	826	1.282	0	-488	7.05	24.76
330	1.260	742	1.287	-243	-244	6.43	24.35
331	1.265	541	1.294	-599	0	4.62	24.48
332	1.255	954	1.294	-599	-98	8.54	23.10
333	1.256	911	1.283	-48	-610	7.96	23.79
334	1.263	620	1.291	-444	0	5.49	23.92
335	1.280	0	1.294	-599	53	0.00	25.46
336	1.280	0	1.292	-495	-171	0.00	25.83
337	1.283	-48	1.294	-599	293	-0.40	26.10

APPENDIX A (cont.)

CELL NO.	AVSB	AVCAP	AVSA	DRYWT	MXCAP	MXSA
1	1.282	91.9	1.146	261.26	96.2	1.151
2	1.285	92.2	1.146	262.58	96.5	1.154
3	1.288	92.6	1.146	261.46	96.7	1.155
4	1.286	92.4	1.146	262.99	96.5	1.155
5	1.286	93.8	1.147	262.28	97.9	1.155
6	1.286	92.9	1.146	265.23	96.9	1.153
7	1.288	93.2	1.145	262.18	97.4	1.154
8	1.290	98.5	1.155	260.05	100.7	1.167
9	1.290	93.6	1.154	263.09	97.8	1.162
10	1.286	97.2	1.147	258.93	99.3	1.158
11	1.286	97.1	1.148	259.23	99.6	1.156
12	1.283	95.5	1.146	257.60	97.3	1.156
13	1.286	95.1	1.143	258.42	97.6	1.155
14	1.286	91.0	1.141	268.48	95.0	1.150
15	1.285	93.1	1.141	260.45	96.9	1.153
16	1.285	92.1	1.145	263.70	96.9	1.155
17	1.286	91.7	1.141	263.91	95.2	1.154
18	1.286	92.8	1.139	260.75	95.9	1.151
19	1.287	92.8	1.141	268.27	96.2	1.151
20	1.284	91.6	1.140	263.60	95.7	1.153
21	1.286	91.2	1.144	266.85	94.4	1.157
22	1.284	93.4	1.142	263.40	96.2	1.156
23	1.283	90.5	1.140	272.54	93.9	1.153
24	1.281	91.9	1.143	272.03	95.9	1.154
25	1.279	90.5	1.144	268.58	94.3	1.153
26	1.284	92.2	1.140	263.19	95.2	1.154
27	1.286	93.0	1.142	263.60	95.7	1.154
28	1.282	92.9	1.141	260.75	95.9	1.150
29	1.289	91.8	1.145	264.92	95.3	1.154
30	1.276	91.5	1.140	257.30	95.3	1.148
31	1.285	91.8	1.143	266.24	95.7	1.153
32	1.285	92.6	1.142	257.71	95.9	1.153
33	1.285	93.2	1.143	261.57	96.4	1.151
34	1.286	91.6	1.139	270.81	94.8	1.147
35	1.283	90.9	1.140	269.19	95.0	1.147
36	1.282	87.9	1.141	272.75	93.0	1.148
37	1.281	90.0	1.140	268.99	95.5	1.147
38	1.286	93.5	1.142	266.44	97.4	1.150
39	1.277	89.6	1.138	268.27	93.9	1.142
40	1.285	92.1	1.145	269.29	95.6	1.151
41	1.286	93.9	1.142	268.37	97.2	1.153
42	1.286	92.6	1.142	265.63	95.6	1.158
43	1.284	91.2	1.142	264.82	95.6	1.148
44	1.284	93.8	1.145	261.06	97.2	1.149
45	1.287	93.2	1.147	261.16	96.5	1.151
46	1.289	95.6	1.149	258.01	98.7	1.157
47	1.286	91.6	1.141	260.96	94.4	1.148
48	1.286	94.3	1.146	260.35	97.4	1.153
49	1.284	91.8	1.140	262.58	95.7	1.147

CELL NO.	AVSB	AVCAP	AVSA	DRYWT	MXCAP	MXSA
50	1.280	89.9	1.136	263.60	94.4	1.142
51	1.278	92.0	1.135	264.41	96.4	1.140
52	1.286	93.7	1.139	262.08	97.1	1.145
53	1.280	91.6	1.138	263.30	96.5	1.142
54	1.276	91.6	1.135	263.09	94.4	1.140
55	1.284	91.8	1.138	260.96	96.2	1.144
56	1.286	93.9	1.143	260.45	97.2	1.150
57	1.285	90.8	1.138	260.25	94.2	1.145
58	1.284	92.9	1.140	260.45	95.7	1.145
59	1.286	91.7	1.136	262.08	95.0	1.140
60	1.280	92.1	1.143	261.98	96.7	1.148
61	1.281	90.8	1.139	262.48	95.6	1.144
62	1.286	91.7	1.137	265.02	96.3	1.144
63	1.277	89.4	1.135	263.50	94.1	1.138
64	1.286	91.3	1.142	262.48	95.3	1.147
65	1.283	89.0	1.136	263.30	93.5	1.141
66	1.281	90.9	1.135	265.13	95.5	1.140
67	1.287	91.7	1.137	262.99	95.3	1.141
68	1.286	93.6	1.139	258.11	97.2	1.144
69	1.281	91.9	1.140	262.48	96.1	1.144
70	1.288	92.8	1.140	264.21	95.4	1.145
71	1.285	91.1	1.140	264.62	94.4	1.156
72	1.288	93.3	1.141	262.28	96.3	1.147
73	1.282	91.6	1.138	262.18	96.3	1.141
74	1.284	89.4	1.136	263.50	92.8	1.141
75	1.285	91.9	1.138	262.58	95.6	1.143
76	1.280	90.6	1.139	264.82	95.3	1.143
77	1.286	93.2	1.141	259.84	96.2	1.147
78	1.281	90.9	1.138	264.31	95.6	1.147
79	1.286	92.0	1.139	265.73	95.3	1.147
80	1.284	92.5	1.141	265.02	96.4	1.147
81	1.286	96.5	1.150	268.56	99.4	1.170
82	1.285	96.9	1.138	263.44	99.5	1.149
83	1.286	95.0	1.142	265.35	97.3	1.152
84	1.284	94.6	1.146	264.75	97.3	1.155
85	1.285	95.1	1.149	265.05	98.7	1.162
86	1.285	93.0	1.140	265.85	95.6	1.149
87	1.281	93.9	1.137	264.24	96.4	1.145
88	1.279	93.4	1.139	262.44	97.0	1.144
89	1.281	95.9	1.147	263.64	99.8	1.156
90	1.280	92.9	1.141	264.04	96.6	1.153
91	1.283	94.5	1.145	264.24	97.9	1.153
92	1.282	90.9	1.144	265.45	96.2	1.149
93	1.282	93.6	1.145	264.65	97.7	1.158
94	1.282	92.0	1.143	266.75	96.0	1.155
95	1.280	91.4	1.142	264.04	95.5	1.152
96	1.280	91.8	1.144	262.74	97.2	1.153
97	1.278	91.5	1.138	265.55	95.5	1.145
98	1.281	90.0	1.138	264.75	94.4	1.147
99	1.284	92.2	1.144	264.04	95.5	1.158

APPENDIX A (cont.)

CELL NO.	AVSB	AVCAP	AVSA	DRYWT	MXCAP	MXSA
100	1.284	91.8	1.150	263.04	96.5	1.171
101	1.284	92.6	1.148	265.75	97.0	1.160
102	1.281	92.7	1.143	264.24	96.8	1.153
103	1.281	91.3	1.137	265.05	95.1	1.145
104	1.281	93.9	1.145	262.64	97.0	1.154
105	1.281	92.4	1.145	264.14	94.2	1.153
106	1.281	93.4	1.143	260.43	96.8	1.152
107	1.284	92.8	1.147	265.35	96.8	1.160
108	1.282	92.9	1.147	266.95	97.9	1.160
109	1.280	88.6	1.143	264.24	92.2	1.154
110	1.278	92.9	1.141	264.04	94.9	1.150
111	1.279	95.2	1.138	261.53	97.4	1.145
112	1.279	96.3	1.148	262.84	99.8	1.154
113	1.281	94.3	1.147	262.64	99.5	1.156
114	1.282	91.3	1.143	265.65	96.3	1.152
115	1.282	90.5	1.145	265.15	95.1	1.155
116	1.282	92.8	1.148	261.84	97.3	1.160
117	1.280	91.8	1.148	266.85	97.7	1.161
118	1.280	92.0	1.148	265.05	96.6	1.160
119	1.281	92.0	1.146	264.85	96.3	1.156
120	1.279	92.7	1.153	266.25	96.8	1.164
121	1.280	92.8	1.147	265.45	97.0	1.150
122	1.281	92.0	1.143	263.34	95.7	1.152
123	1.279	94.8	1.148	263.74	99.5	1.162
124	1.281	94.5	1.148	262.24	98.9	1.165
125	1.282	92.7	1.139	263.74	97.3	1.150
126	1.282	92.0	1.142	260.73	95.5	1.154
127	1.281	93.3	1.142	259.23	96.4	1.149
128	1.284	95.0	1.145	259.73	99.5	1.154
129	1.282	94.3	1.143	258.93	98.5	1.153
130	1.281	92.5	1.135	264.95	96.9	1.147
131	1.285	94.6	1.144	262.14	98.3	1.158
132	1.280	93.2	1.144	263.74	98.5	1.154
133	1.281	94.8	1.148	261.33	98.5	1.165
134	1.285	91.7	1.142	261.74	96.0	1.154
135	1.281	92.3	1.137	264.24	95.6	1.145
136	1.281	93.1	1.142	264.95	97.5	1.150
137	1.282	95.3	1.147	266.75	98.3	1.159
138	1.282	93.8	1.141	267.86	97.7	1.152
139	1.285	94.1	1.142	265.35	98.1	1.153
140	1.281	93.6	1.144	267.86	98.3	1.154
141	1.280	93.6	1.142	266.35	99.3	1.154
142	1.281	95.7	1.142	266.25	99.5	1.154
143	1.281	96.2	1.144	266.55	100.0	1.154
144	1.281	93.1	1.146	263.54	98.5	1.158
145	1.283	93.1	1.144	261.33	98.2	1.155
146	1.281	93.3	1.142	263.04	98.3	1.154
147	1.282	92.8	1.140	265.35	97.8	1.154
148	1.281	92.0	1.139	265.65	98.0	1.152
149	1.281	92.1	1.141	265.25	98.0	1.152

APPENDIX A (cont.)

CELL NO.	AVSB	AVCAP	AVSA	DRYWT	MXCAP	MXSA
150	1.283	91.9	1.144	263.04	97.4	1.155
151	1.280	93.0	1.145	266.75	98.1	1.159
152	1.274	90.2	1.142	263.24	97.4	1.154
153	1.283	92.5	1.143	266.35	97.7	1.154
154	1.281	92.4	1.139	262.64	94.6	1.148
155	1.281	92.6	1.140	262.94	96.6	1.153
156	1.278	89.3	1.141	268.36	94.9	1.149
157	1.282	92.4	1.144	266.75	96.8	1.154
158	1.281	92.5	1.138	267.56	95.7	1.150
159	1.277	93.2	1.140	267.16	97.3	1.154
160	1.282	92.5	1.144	267.76	96.2	1.153
161	1.286	102.3	1.140	265.11	105.3	1.150
162	1.286	98.3	1.134	265.11	100.4	1.145
163	1.282	95.3	1.133	266.65	97.9	1.140
164	1.285	95.6	1.129	266.03	98.2	1.135
165	1.284	96.9	1.139	266.03	100.6	1.146
166	1.286	101.2	1.130	266.75	103.4	1.137
167	1.284	99.6	1.138	263.97	103.2	1.144
168	1.281	95.5	1.136	265.83	100.1	1.138
169	1.282	95.3	1.137	267.16	99.1	1.142
170	1.275	97.5	1.128	265.41	102.4	1.132
171	1.277	92.9	1.129	265.62	97.1	1.135
172	1.283	97.3	1.139	263.46	100.7	1.146
173	1.284	97.4	1.141	261.40	100.3	1.150
174	1.284	95.1	1.135	264.18	97.9	1.142
175	1.286	97.9	1.141	262.02	100.4	1.150
176	1.283	97.3	1.135	262.33	100.3	1.140
177	1.283	96.1	1.132	262.22	98.7	1.136
178	1.284	96.0	1.134	262.22	98.7	1.140
179	1.284	96.3	1.131	263.56	99.2	1.140
180	1.282	95.0	1.132	261.30	98.2	1.138
181	1.281	96.8	1.137	261.40	100.4	1.146
182	1.284	97.9	1.134	259.86	100.1	1.142
183	1.282	96.4	1.131	261.30	98.8	1.138
184	1.282	97.8	1.135	260.06	101.0	1.142
185	1.286	98.5	1.135	259.86	101.8	1.145
186	1.277	95.3	1.129	263.66	98.8	1.133
187	1.280	96.2	1.133	262.02	98.8	1.138
188	1.281	98.6	1.138	263.05	101.1	1.146
189	1.282	96.9	1.140	263.05	100.1	1.147
190	1.283	95.0	1.132	263.66	97.8	1.138
191	1.281	95.6	1.132	264.59	98.2	1.140
192	1.280	96.8	1.134	260.99	99.2	1.140
193	1.282	95.7	1.131	261.61	98.4	1.138
194	1.279	95.7	1.132	261.09	98.5	1.140
145	1.283	93.1	1.144	261.33	98.2	1.155
195	1.283	96.5	1.133	258.93	99.2	1.144
196	1.280	95.8	1.133	263.05	99.0	1.140
197	1.282	96.5	1.134	264.28	99.5	1.140
198	1.284	97.4	1.132	261.92	100.2	1.142

CELL NO.	AVSB	AVCAP	AVSA	DRYWT	MXCAP	MXSA
199	1.282	97.2	1.134	260.99	99.5	1.140
200	1.281	97.4	1.133	261.40	99.7	1.143
201	1.282	96.4	1.135	269.53	100.3	1.147
202	1.284	97.2	1.132	260.27	99.9	1.137
203	1.283	96.2	1.132	262.84	99.1	1.140
204	1.284	97.0	1.137	264.80	99.8	1.143
205	1.282	96.6	1.133	259.86	100.0	1.141
206	1.282	97.0	1.134	261.61	99.7	1.141
207	1.282	96.6	1.133	260.99	99.0	1.142
208	1.281	97.0	1.135	262.53	99.8	1.145
209	1.281	96.9	1.129	260.99	100.1	1.138
210	1.282	96.7	1.133	262.22	99.5	1.142
211	1.274	94.0	1.128	265.00	97.3	1.140
212	1.282	97.1	1.137	261.20	100.3	1.145
213	1.277	96.7	1.135	260.68	100.2	1.142
214	1.281	97.3	1.131	262.22	100.3	1.142
215	1.281	96.6	1.131	260.78	99.1	1.143
216	1.281	96.7	1.136	264.38	99.3	1.149
217	1.284	99.9	1.135	260.89	102.6	1.146
218	1.282	100.3	1.134	261.09	102.5	1.149
219	1.282	100.2	1.134	259.24	103.4	1.145
220	1.281	100.9	1.138	258.52	104.0	1.147
221	1.281	98.9	1.134	258.62	101.4	1.145
222	1.284	100.4	1.134	258.42	102.6	1.149
223	1.284	100.2	1.134	260.37	102.6	1.150
224	1.284	100.7	1.138	261.20	103.3	1.151
225	1.285	100.1	1.135	259.34	102.6	1.146
226	1.284	98.8	1.132	259.55	101.4	1.146
227	1.284	102.0	1.133	258.52	105.9	1.149
228	1.283	99.5	1.131	259.55	102.6	1.140
229	1.286	103.5	1.138	257.59	107.9	1.153
230	1.278	103.3	1.132	259.65	106.2	1.145
231	1.284	103.9	1.134	259.14	107.6	1.149
232	1.284	104.5	1.139	259.55	108.2	1.156
233	1.283	103.1	1.135	260.78	107.4	1.150
234	1.283	103.7	1.138	259.45	107.4	1.152
235	1.286	103.0	1.133	261.09	105.4	1.146
236	1.284	103.8	1.134	261.30	107.8	1.145
237	1.284	102.3	1.133	260.89	106.2	1.152
238	1.282	102.4	1.134	260.47	105.9	1.153
239	1.282	101.6	1.136	259.75	104.5	1.153
240	1.284	101.3	1.136	262.02	104.5	1.155
241	1.290	99.9	1.141	260.20	103.7	1.144
242	1.287	101.0	1.135	259.50	102.6	1.140
243	1.288	102.0	1.137	259.20	104.2	1.143
245	1.288	103.9	1.141	254.40	107.2	1.150
246	1.286	101.4	1.141	256.10	104.1	1.148
247	1.287	103.2	1.134	256.40	104.9	1.140
248	1.288	105.2	1.144	257.10	107.1	1.150
249	1.283	103.2	1.140	257.10	104.4	1.149

APPENDIX A (cont.)

CELL NO.	AVSB	AVCAP	AVSA	DRYWT	MXCAP	MXSA
250	1.286	100.1	1.134	258.00	102.4	1.137
251	1.285	98.8	1.138	256.30	102.4	1.145
252	1.287	103.2	1.142	256.10	106.3	1.152
253	1.285	99.9	1.139	256.80	102.4	1.147
254	1.287	102.3	1.141	255.90	105.2	1.152
255	1.276	97.1	1.134	255.40	100.3	1.143
256	1.288	101.7	1.143	257.40	104.4	1.149
257	1.291	102.2	1.138	257.70	104.9	1.139
258	1.286	100.5	1.138	256.70	103.3	1.140
259	1.286	98.7	1.138	257.30	102.1	1.153
260	1.283	100.2	1.137	258.00	103.0	1.145
261	1.287	100.5	1.145	258.40	103.0	1.153
262	1.289	99.7	1.140	258.00	103.8	1.145
263	1.286	100.6	1.137	259.40	103.5	1.140
264	1.287	101.5	1.142	257.90	104.0	1.148
265	1.287	103.5	1.140	258.20	104.9	1.149
266	1.287	100.2	1.138	256.10	103.2	1.144
267	1.285	100.0	1.137	258.40	103.8	1.140
268	1.286	106.0	1.142	258.60	106.8	1.149
269	1.286	103.3	1.142	268.19	104.8	1.149
270	1.287	102.8	1.140	256.40	104.1	1.144
271	1.288	101.7	1.142	257.20	103.9	1.149
272	1.284	103.4	1.133	259.60	104.4	1.139
273	1.287	99.2	1.135	263.70	102.7	1.138
274	1.283	101.4	1.135	258.50	102.7	1.140
275	1.286	100.5	1.136	257.10	103.0	1.142
276	1.282	100.2	1.135	261.30	105.5	1.139
277	1.283	101.9	1.138	256.00	105.5	1.144
278	1.283	99.8	1.130	258.00	101.4	1.134
279	1.285	103.2	1.137	257.10	104.9	1.143
280	1.286	104.2	1.141	261.30	106.1	1.149
281	1.284	102.9	1.137	258.40	105.9	1.143
282	1.285	102.8	1.139	256.00	107.2	1.143
283	1.284	104.3	1.137	256.40	106.1	1.144
284	1.285	103.8	1.138	253.50	106.4	1.144
285	1.285	100.5	1.137	260.20	103.1	1.144
286	1.284	98.7	1.138	259.10	101.8	1.145
287	1.287	97.4	1.138	256.50	101.5	1.145
288	1.283	97.7	1.142	256.80	102.0	1.152
289	1.286	97.6	1.140	254.60	101.5	1.149
290	1.285	95.7	1.134	254.30	98.9	1.139
291	1.285	95.3	1.134	257.00	99.4	1.138
292	1.285	97.6	1.139	255.10	101.4	1.149
145	1.283	93.1	1.144	261.33	98.2	1.155
293	1.285	98.6	1.142	253.60	101.8	1.150
294	1.286	99.0	1.142	255.10	102.0	1.152
295	1.285	96.7	1.133	256.80	101.5	1.139
296	1.285	100.8	1.139	254.80	102.6	1.147
297	1.284	98.4	1.140	258.10	104.1	1.149
298	1.284	100.5	1.134	254.80	101.9	1.140

CELL NO.	AVSB	AVCAP	AVSA	DRYWT	MXCAP	MXSA
299	1.282	98.4	1.135	257.40	100.8	1.145
300	1.284	98.0	1.137	257.60	103.7	1.143
301	1.284	103.5	1.136	260.60	104.6	1.143
302	1.284	98.5	1.137	258.80	102.9	1.143
303	1.284	95.0	1.133	259.50	99.8	1.140
304	1.282	96.3	1.136	262.10	101.2	1.139
305	1.284	98.0	1.135	259.70	102.9	1.142
306	1.283	96.5	1.137	264.90	100.2	1.144
307	1.283	97.4	1.128	264.80	100.0	1.131
308	1.284	103.1	1.138	254.10	105.0	1.143
309	1.285	100.1	1.135	264.80	103.6	1.140
310	1.285	102.8	1.133	255.20	104.6	1.135
311	1.284	101.4	1.134	256.80	103.2	1.138
312	1.280	99.5	1.135	265.89	102.1	1.143
313	1.286	102.7	1.134	262.10	104.6	1.137
314	1.282	100.6	1.135	261.40	102.4	1.138
315	1.286	101.5	1.133	260.60	103.7	1.137
316	1.283	102.5	1.135	262.80	104.2	1.138
317	1.286	102.3	1.139	259.80	104.3	1.143
318	1.286	103.0	1.134	260.10	106.1	1.138
319	1.285	104.2	1.136	260.20	106.6	1.144
320	1.284	102.3	1.136	262.20	104.9	1.142
321	1.293	104.9	1.155	260.86	107.3	1.162
322	1.289	96.1	1.155	266.38	101.1	1.160
323	1.284	94.7	1.158	262.07	98.8	1.166
324	1.289	98.6	1.160	260.16	102.8	1.163
325	1.288	97.1	1.155	264.08	101.2	1.161
326	1.289	96.5	1.157	263.57	99.0	1.166
327	1.292	101.9	1.152	261.16	104.3	1.154
328	1.290	104.3	1.156	261.66	106.7	1.160
329	1.286	98.3	1.156	262.47	102.4	1.166
330	1.284	97.4	1.152	261.36	101.9	1.160
331	1.292	96.7	1.160	258.95	99.6	1.169
332	1.285	99.6	1.155	267.49	102.2	1.160
333	1.285	98.6	1.155	264.68	102.4	1.165
334	1.289	98.9	1.154	262.17	100.9	1.162
335	1.292	102.3	1.156	257.65	104.7	1.160
336	1.290	102.7	1.156	257.85	104.9	1.160
337	1.293	103.6	1.157	256.84	106.0	1.160
338	1.285	96.6	1.153	263.98	101.3	1.165
339	1.289	102.9	1.150	258.65	104.7	1.153
340	1.286	96.6	1.149	263.98	100.3	1.160

APPENDIX B

BATTERY CAPACITY TEST
CEMC, 450A DISCHARGE, APRIL 3, 1990

START TIME =   09:00   C\SYMPH\CEMDATA
CUTOFF VOLTAGE =   1.7   CAP90SRT.WK1
AH CRRCTN FACTR =   0.994 *(TEMP CORRCTN)

                    07/19/92   [BY % CAPACITY]
                    22:43

SGBR = SP GR BEFORE RAW DATA
SGBC = SP GR BEFORE CORRCTD FOR TEMP
SGAR = SP GR AFTER RECHG RAW
SGAC = SP GR AFTER RECHG CORRCTD
FVLTB = FLOAT VOLTAGE BEFORE DISCHARGE

| | | | | MEASUREMENTS BEFORE DISCHARGE | | |
STRING	MODULE	CELL NO.	FVLTB	SGBR	TEMP	SGBC
A	11	109	2.327	1.284	92	1.289
B	20	22	2.318	1.276	93	1.281
A	11	105	2.313	1.286	93	1.291
B	20	21	2.311	1.276	95	1.282
B	22	60	2.312	1.266	95	1.272
B	20	28	2.328	1.276	93	1.281
B	29	197	2.327	1.276	92	1.281
A	1	25	2.348	1.280	89	1.284
B	22	59	2.307	1.272	95	1.278
B	22	63	2.315	1.270	93	1.275
C	44	249	2.316	1.270	92	1.283
B	29	192	2.353	1.278	90	1.282
A	1	23	2.346	1.270	89	1.274
B	32	225	2.332	1.276	92	1.281
B	22	62	2.318	1.278	93	1.283
B	30	199	2.316	1.272	92	1.277
A	9	91	2.313	1.274	93	1.279
B	32	228	2.326	1.272	94	1.278
B	20	20	2.316	1.276	95	1.282
B	20	29	2.341	1.282	92	1.287
A	6	65	2.315	1.280	91	1.285
C	50	299	2.317	1.272	93	1.277
B	31	221	2.334	1.272	92	1.277
B	29	185	2.332	1.280	92	1.285
A	8	90	2.338	1.282	89	1.286
A	10	102	2.340	1.282	92	1.287
B	22	40	2.336	1.280	92	1.285
A	18	174	2.311	1.272	95	1.278
B	29	172	2.326	1.282	90	1.286
B	19	17	2.341	1.280	91	1.285
B	22	41	2.332	1.282	91	1.287
B	19	15	2.325	1.282	93	1.287

APPENDIX B (cont.)

MEASUREMENTS
BEFORE DISCHARGE

STRING	MODULE	CELL NO.	FVLTB	SGBR	TEMP	SGBC
B	19	18	2.339	1.284	91	1.289
B	29	195	2.318	1.276	94	1.282
B	31	212	2.349	1.278	89	1.282
B	20	24	2.345	1.280	91	1.285
C	48	278	2.311	1.276	95	1.282
C	54	316	2.323	1.280	93	1.285
A	18	177	2.333	1.280	90	1.284
C	54	319	2.340	1.280	89	1.284
A	9	93	2.342	1.276	91	1.281
C	50	298	2.322	1.278	92	1.283
A	6	71	2.309	1.276	92	1.281
A	10	97	2.325	1.280	94	1.286
A	6	64	2.330	1.284	89	1.288
B	29	196	2.319	1.270	94	1.276
B	32	238	2.344	1.282	89	1.286
B	31	219	2.326	1.278	94	1.284
B	27	141	2.333	1.286	94	1.292
B	31	223	2.340	1.280	89	1.284
A	1	12	2.315	1.278	92	1.283
B	26	135	2.347	1.286	90	1.290
B	32	226	2.327	1.282	94	1.288
B	25	130	2.328	1.284	92	1.289
B	31	222	2.330	1.280	92	1.285
A	1	2	2.322	1.280	91	1.285
B	26	136	2.357	1.282	90	1.286
B	24	84	2.327	1.282	92	1.287
C	49	286	2.309	1.272	93	1.277
C	44	250	2.324	1.278	92	1.287
B	19	16	2.316	1.282	95	1.288
C	49	294	2.344	1.284	90	1.288
A	10	101	2.332	1.288	91	1.293
C	42	233	2.339	1.274	89	1.290
B	32	237	2.334	1.286	92	1.291
B	25	132	2.316	1.280	94	1.286
A	8	85	2.349	1.282	89	1.286
A	8	78	2.315	1.276	92	1.281
C	42	231	2.321	1.272	92	1.281
A	10	99	2.310	1.276	95	1.282
C	43	244	2.340	1.286	89	1.288
B	33	241	2.350	1.284	89	1.288
A	8	87	2.313	1.280	92	1.285
B	32	224	2.348	1.280	89	1.284
A	6	70	2.311	1.280	92	1.285
B	27	143	2.324	1.282	94	1.288
A	1	9	2.314	1.286	92	1.291
B	31	217	2.326	1.280	94	1.286
B	24	83	2.341	1.284	91	1.289
B	27	145	2.332	1.286	92	1.291
B	27	147	2.349	1.286	90	1.290
A	1	13	2.327	1.280	90	1.284
C	43	248	2.329	1.280	92	1.291

APPENDIX B (cont.)

STRING	MODULE	CELL NO.	MEASUREMENTS BEFORE DISCHARGE			
			FVLTB	SGBR	TEMP	SGBC
B	25	131	2.329	1.286	92	1.291
B	19	14	2.325	1.282	93	1.287
C	43	247	2.317	1.280	92	1.291
B	26	138	2.329	1.286	94	1.292
B	26	140	2.347	1.286	92	1.291
C	51	307	2.310	1.276	96	1.282
B	24	106	2.333	1.282	92	1.287
B	27	142	2.336	1.290	92	1.295
B	25	129	2.345	1.280	90	1.284
C	42	232	2.335	1.272	89	1.292
B	25	133	2.348	1.288	90	1.292
B	24	86	2.342	1.288	91	1.293
C	46	266	2.340	1.280	90	1.286
C	44	253	2.333	1.282	89	1.280
C	46	263	2.310	1.276	95	1.282
C	42	234	2.314	1.278	92	1.287
B	33	242	2.344	1.282	89	1.294
B	26	137	2.328	1.290	94	1.296
B	26	139	2.338	1.290	92	1.295
B	25	128	2.320	1.284	94	1.290
C	42	235	2.307	1.274	94	1.292
B	27	146	2.345	1.286	90	1.290
C	46	267	2.343	1.284	90	1.288
C	43	236	2.331	1.280	89	1.286

APPENDIX B (cont.)

VOLTAGE MEASUREMENTS

DURING DISCHARGE

STRING	MODULE	CELL NO.	10:00 10:00	11:00 11:00	12:00 12:00	12:30 12:30	12:37 12:34	12:41 12:41	13:00 13:00	13:05 13:07	13:10 13:10
A	11	109	1.963	1.920	1.867	1.833	1.823	1.817	1.789	1.779	1.771
B	20	22	1.956	1.914	1.861	1.829	1.820	1.813	1.788	1.777	1.770
A	11	105	1.962	1.917	1.860	1.831	1.823	1.817	1.787	1.779	1.773
B	20	21	1.955	1.909	1.858	1.827	1.818	1.813	1.787	1.777	1.769
B	22	60	1.948	1.907	1.856	1.826	1.818	1.810	1.787	1.777	1.770
B	20	28	1.950	1.908	1.855	1.823	1.815	1.809	1.783	1.773	1.766
B	29	197	1.947	1.906	1.852	1.817	1.811	1.803	1.779	1.768	1.760
A	1	25	1.961	1.919	1.867	1.835	1.827	1.820	1.792	1.782	1.772
B	22	59	1.956	1.908	1.863	1.829	1.822	1.818	1.790	1.781	1.774
B	22	63	1.952	1.911	1.859	1.829	1.820	1.813	1.788	1.778	1.771
C	44	249	1.952	1.908	1.858	1.828	1.820	1.813	1.789	1.779	1.771
B	29	192	1.951	1.908	1.857	1.825	1.817	1.809	1.785	1.773	1.765
A	1	23	1.958	1.921	1.867	1.835	1.826	1.820	1.793	1.782	1.774
B	32	225	1.951	1.909	1.859	1.823	1.817	1.809	1.786	1.778	1.769
B	22	62	1.957	1.916	1.864	1.832	1.823	1.818	1.791	1.781	1.776
B	30	199	1.952	1.906	1.854	1.824	1.816	1.809	1.785	1.775	1.767
A	9	91	1.959	1.916	1.863	1.832	1.824	1.818	1.793	1.783	1.776
B	32	228	1.958	1.915	1.865	1.831	1.824	1.817	1.793	1.783	1.776
B	20	20	1.956	1.914	1.864	1.833	1.825	1.819	1.795	1.785	1.779
B	20	29	1.965	1.923	1.872	1.841	1.830	1.826	1.798	1.788	1.782
A	6	65	1.957	1.914	1.863	1.831	1.824	1.816	1.790	1.781	1.776
C	50	299	1.955	1.915	1.865	1.829	1.822	1.819	1.795	1.784	1.777
B	31	221	1.951	1.908	1.860	1.830	1.822	1.815	1.792	1.781	1.773
B	29	185	1.956	1.910	1.861	1.830	1.822	1.815	1.791	1.781	1.773
A	8	90	1.960	1.917	1.867	1.835	1.827	1.821	1.795	1.785	1.777
A	10	102	1.962	1.921	1.870	1.838	1.830	1.827	1.799	1.790	1.782
B	22	40	1.966	1.925	1.874	1.845	1.836	1.830	1.805	1.794	1.788
A	18	174	1.962	1.920	1.870	1.840	1.832	1.829	1.804	1.794	1.789
B	29	172	1.960	1.915	1.869	1.835	1.828	1.820	1.796	1.786	1.778
B	19	17	1.969	1.926	1.875	1.844	1.835	1.830	1.804	1.794	1.788
B	22	41	1.965	1.923	1.873	1.842	1.833	1.827	1.801	1.792	1.785
B	19	15	1.960	1.918	1.867	1.837	1.831	1.833	1.801	1.789	1.783
B	19	18	1.965	1.923	1.874	1.843	1.834	1.829	1.803	1.793	1.787
B	29	195	1.957	1.915	1.864	1.833	1.826	1.818	1.795	1.787	1.779
B	31	212	1.952	1.918	1.864	1.836	1.829	1.822	1.796	1.787	1.778
B	20	24	1.965	1.926	1.877	1.846	1.838	1.832	1.807	1.798	1.791
C	48	278	1.959	1.919	1.868	1.836	1.829	1.824	1.802	1.790	1.785
C	54	316	1.957	1.915	1.867	1.838	1.831	1.825	1.802	1.791	1.786
A	18	177	1.967	1.927	1.878	1.848	1.840	1.833	1.808	1.798	1.791
C	54	319	1.962	1.922	1.872	1.841	1.834	1.828	1.802	1.792	1.786
A	9	93	1.967	1.924	1.875	1.840	1.836	1.830	1.805	1.794	1.789
C	50	298	1.957	1.916	1.866	1.837	1.830	1.825	1.800	1.790	1.786
A	6	71	1.961	1.920	1.869	1.840	1.834	1.829	1.804	1.792	1.786
A	10	97	1.964	1.920	1.872	1.839	1.834	1.827	1.803	1.793	1.787
A	6	64	1.963	1.923	1.873	1.842	1.835	1.830	1.805	1.796	1.789
B	29	196	1.956	1.914	1.864	1.835	1.828	1.822	1.799	1.788	1.783
B	32	238	1.959	1.919	1.872	1.844	1.837	1.830	1.806	1.795	1.787
B	31	219	1.958	1.917	1.869	1.841	1.833	1.827	1.804	1.795	1.789

APPENDIX B (cont.)

VOLTAGE MEASUREMENTS
DURING DISCHARGE

STRING	MODULE	CELL NO.	10:00 10:00	11:00 11:00	12:00 12:00	12:30 12:30	12:37 12:34	12:41 12:41	13:00 13:00	13:05 13:07	13:10 13:10
B	27	141	1.957	1.914	1.867	1.834	1.827	1.821	1.795	1.789	1.784
B	31	223	1.963	1.922	1.875	1.841	1.835	1.828	1.804	1.795	1.786
A	1	12	1.962	1.919	1.873	1.843	1.835	1.829	1.805	1.797	1.791
B	26	135	1.963	1.921	1.871	1.840	1.832	1.827	1.801	1.783	1.787
B	32	226	1.960	1.919	1.870	1.842	1.835	1.828	1.806	1.797	1.789
B	25	130	1.962	1.918	1.867	1.837	1.830	1.825	1.800	1.791	1.785
B	31	222	1.961	1.919	1.872	1.839	1.832	1.825	1.802	1.792	1.785
A	1	2	1.966	1.926	1.875	1.844	1.837	1.831	1.807	1.798	1.791
B	26	136	1.964	1.922	1.872	1.842	1.833	1.828	1.800	1.794	1.787
B	24	84	1.960	1.917	1.867	1.838	1.829	1.824	1.801	1.792	1.785
C	49	286	1.962	1.923	1.874	1.843	1.836	1.829	1.807	1.798	1.791
C	44	250	1.957	1.917	1.869	1.837	1.829	1.823	1.800	1.792	1.786
B	19	16	1.971	1.927	1.881	1.850	1.840	1.837	1.810	1.803	1.798
C	49	294	1.969	1.927	1.878	1.846	1.839	1.831	1.809	1.800	1.793
A	10	101	1.969	1.928	1.878	1.848	1.840	1.834	1.810	1.801	1.795
C	42	233	1.966	1.927	1.880	1.848	1.842	1.834	1.812	1.800	1.794
B	32	237	1.961	1.920	1.874	1.844	1.834	1.830	1.807	1.799	1.792
B	25	132	1.958	1.916	1.866	1.836	1.829	1.824	1.801	1.789	1.786
A	8	85	1.969	1.927	1.876	1.845	1.839	1.833	1.809	1.800	1.793
A	8	78	1.963	1.922	1.875	1.845	1.836	1.832	1.804	1.800	1.792
C	42	231	1.964	1.922	1.876	1.841	1.832	1.826	1.806	1.796	1.791
A	10	99	1.961	1.920	1.870	1.844	1.834	1.829	1.809	1.799	1.795
C	43	244	1.969	1.927	1.879	1.846	1.837	1.831	1.808	1.799	1.792
B	33	241	1.968	1.928	1.881	1.852	1.844	1.837	1.814	1.804	1.797
A	8	87	1.962	1.922	1.873	1.843	1.836	1.630	1.807	1.798	1.791
B	32	224	1.966	1.925	1.878	1.845	1.838	1.832	1.809	1.799	1.792
A	6	70	1.964	1.921	1.875	1.845	1.836	1.833	1.810	1.803	1.794
B	27	143	1.961	1.921	1.867	1.841	1.835	1.829	1.806	1.799	1.792
A	1	9	1.966	1.926	1.877	1.847	1.839	1.833	1.810	1.799	1.795
B	31	217	1.960	1.919	1.872	1.840	1.834	1.828	1.806	1.797	1.789
B	24	83	1.968	1.930	1.881	1.851	1.843	1.838	1.814	1.804	1.798
B	27	145	1.960	1.918	1.867	1.839	1.828	1.825	1.802	1.791	1.787
B	27	147	1.967	1.925	1.874	1.844	1.836	1.831	1.806	1.799	1.791
A	1	13	1.967	1.926	1.877	1.849	1.842	1.834	1.812	1.803	1.796
C	43	248	1.965	1.923	1.875	1.843	1.837	1.831	1.809	1.799	1.793
B	25	131	1.964	1.922	1.873	1.843	1.835	1.828	1.807	1.799	1.792
B	19	14	1.968	1.928	1.877	1.849	1.842	1.835	1.813	1.805	1.798
C	43	247	1.960	1.919	1.871	1.843	1.835	1.829	1.807	1.799	1.792
B	26	138	1.963	1.923	1.874	1.845	1.838	1.832	1.809	1.800	1.795
B	26	140	1.964	1.922	1.873	1.844	1.836	1.830	1.808	1.799	1.793
C	51	307	1.965	1.927	1.881	1.850	1.844	1.839	1.816	1.808	1.802
B	24	106	1.966	1.924	1.874	1.846	1.838	1.830	1.810	1.801	1.796
B	27	142	1.966	1.924	1.876	1.848	1.838	1.835	1.810	1.800	1.797
B	25	129	1.967	1.925	1.875	1.845	1.837	1.932	1.808	1.797	1.793
C	42	232	1.964	1.927	1.879	1.851	1.841	1.834	1.811	1.805	1.796
B	25	133	1.966	1.925	1.876	1.847	1.838	1.833	1.809	1.801	1.796
B	24	86	1.972	1.930	1.882	1.852	1.845	1.839	1.814	1.807	1.800
C	46	266	1.963	1.923	1.875	1.847	1.841	1.834	1.811	1.803	1.796
C	44	253	1.969	1.929	1.882	1.849	1.843	1.836	1.815	1.802	1.795
C	46	263	1.965	1.926	1.879	1.849	1.841	1.836	1.816	1.806	1.800

APPENDIX B (cont.)

VOLTAGE MEASUREMENTS
DURING DISCHARGE

STRING	MODULE	CELL NO.	10:00 10:00	11:00 11:00	12:00 12:00	12:30 12:30	12:37 12:34	12:41 12:41	13:00 13:00	13:05 13:07	13:10 13:10
C	42	234	1.961	1.919	1.875	1.846	1.843	1.837	1.816	1.804	1.801
B	33	242	1.972	1.932	1.885	1.854	1.845	1.839	1.815	1.808	1.798
B	26	137	1.966	1.924	1.876	1.848	1.840	1.835	1.811	1.804	1.798
B	26	139	1.966	1.924	1.875	1.846	1.838	1.833	1.810	1.802	1.796
B	25	128	1.964	1.921	1.872	1.843	1.835	1.831	1.808	1.800	1.793
C	42	235	1.964	1.925	1.880	1.849	1.847	1.839	1.818	1.809	1.801
B	27	146	1.970	1.929	1.880	1.850	1.842	1.838	1.814	1.804	1.789
C	46	267	1.972	1.931	1.883	1.851	1.845	1.839	1.817	1.807	1.799
C	43	236	1.967	1.930	1.884	1.856	1.849	1.842	1.820	1.811	1.804
C	44	251	1.965	1.925	1.878	1.847	1.841	1.835	1.814	1.805	1.796
B	33	243	1.970	1.930	1.883	1.852	1.846	1.840	1.817	1.809	1.803
C	44	254	1.968	1.929	1.882	1.853	1.846	1.840	1.818	1.809	1.802
C	43	245	1.969	1.929	1.883	1.852	1.845	1.838	1.818	1.811	1.803
C	42	230	1.964	1.925	1.879	1.852	1.848	1.842	1.819	1.810	1.806
B	33	265	1.965	1.925	1.880	1.849	1.842	1.836	1.815	1.807	1.800
C	46	262	1.968	1.930	1.885	1.853	1.847	1.840	1.819	1.813	1.807
C	44	252	1.967	1.928	1.881	1.853	1.847	1.841	1.820	1.812	1.805
B	33	239	1.973	1.934	1.890	1.863	1.855	1.850	1.828	1.821	1.813
C	47	276	1.976	1.936	1.890	1.860	1.852	1.846	1.825	1.818	1.811
C	47	273	1.972	1.932	1.886	1.861	1.851	1.846	1.825	1.817	1.809
C	43	246	1.972	1.931	1.886	1.857	1.850	1.845	1.825	1.816	1.810
C	50	297	1.970	1.931	1.883	1.854	1.848	1.840	1.819	1.812	1.807
C	51	303	1.981	1.941	1.896	1.869	1.862	1.857	1.837	1.829	1.823

APPENDIX B (cont.)

VOLTAGE MEASUREMENTS

DURING DISCHARGE

STRING	MODULE	CELL NO.	13:15 13:16	13:19 13:20	13:24 13:26	13:30 13:30	13:36 13:35	13:51 13:51	TIME TO CUTOFF
A	11	109	1.763	1.753	1.743	1.725	1.710	1.635	04:39
B	20	22	1.762	1.753	1.743	1.728	1.715	1.654	04:40
A	11	105	1.762	1.756	1.744	1.728	1.716	1.655	04:40
B	20	21	1.762	1.754	1.744	1.730	1.719	1.666	04:43
B	22	60	1.764	1.753	1.744	1.730	1.720	1.665	04:43
B	20	28	1.759	1.750	1.741	1.727	1.716	1.664	04:42
B	29	197	1.751	1.742	1.730	1.722	1.714	1.657	04:41
A	1	25	1.766	1.758	1.748	1.732	1.718	1.653	04:40
B	22	59	1.767	1.761	1.752	1.738	1.722	1.676	04:45
B	22	63	1.764	1.757	1.744	1.732	1.720	1.666	04:43
C	44	249	1.762	1.754	1.742	1.733	1.723	1.669	04:42
B	29	192	1.756	1.746	1.734	1.724	1.713	1.649	04:41
A	1	23	1.767	1.758	1.749	1.732	1.719	1.655	04:40
B	32	225	1.760	1.752	1.742	1.732	1.721	1.670	04:43
B	22	62	1.768	1.759	1.748	1.735	1.724	1.669	04:44
B	30	199	1.758	1.750	1.739	1.730	1.720	1.670	04:44
A	9	91	1.770	1.761	1.753	1.739	1.729	1.684	04:45
B	32	228	1.768	1.759	1.748	1.740	1.731	1.683	04:47
B	20	20	1.772	1.764	1.755	1.743	1.732	1.685	04:48
B	20	29	1.774	1.763	1.755	1.741	1.728	1.674	04:45
A	6	65	1.770	1.761	1.751	1.739	1.729	1.682	04:45
C	50	299	1.768	1.763	1.751	1.743	1.735	1.689	04:47
B	31	221	1.766	1.756	1.747	1.736	1.728	1.676	04:46
B	29	185	1.764	1.756	1.745	1.737	1.726	1.678	04:46
A	8	90	1.771	1.763	1.754	1.740	1.729	1.679	04:44
A	10	102	1.775	1.768	1.759	1.746	1.735	1.689	04:48
B	22	40	1.781	1.773	1.763	1.749	1.737	1.684	04:48
A	18	174	1.780	1.774	1.765	1.752	1.740	1.698	04:51
B	29	172	1.769	1.761	1.750	1.741	1.727	1.676	04:47
B	19	17	1.780	1.770	1.764	1.749	1.738	1.688	04:48
B	22	41	1.778	1.769	1.760	1.746	1.735	1.685	04:48
B	19	15	1.776	1.769	1.760	1.747	1.738	1.695	04:50
B	19	18	1.780	1.771	1.761	1.749	1.738	1.690	04:48
B	29	195	1.770	1.763	1.754	1.746	1.738	1.694	04:51
B	31	212	1.769	1.762	1.750	1.742	1.731	1.680	04:47
B	20	24	1.784	1.776	1.767	1.754	1.742	1.692	04:49
C	48	278	1.776	1.771	1.761	1.750	1.741	1.705	04:53
C	54	316	1.777	1.770	1.761	1.752	1.743	1.702	04:51
A	18	177	1.785	1.776	1.768	1.753	1.742	1.691	04:49
C	54	319	1.776	1.769	1.758	1.749	1.740	1.693	04:48
A	9	93	1.781	1.774	1.766	1.752	1.742	1.698	04:50
C	50	298	1.778	1.768	1.761	1.750	1.742	1.702	04:51
A	6	71	1.783	1.773	1.765	1.755	1.742	1.703	04:52
A	10	97	1.783	1.775	1.768	1.756	1.746	1.706	04:54
A	6	64	1.783	1.775	1.766	1.753	1.743	1.697	04:50
B	29	196	1.776	1.766	1.758	1.751	1.742	1.702	04:54
B	32	238	1.780	1.770	1.761	1.750	1.740	1.690	04:50
B	31	219	1.781	1.773	1.763	1.755	1.745	1.703	04:55

APPENDIX B (cont.)

VOLTAGE MEASUREMENTS
DURING DISCHARGE

STRING	MODULE	CELL NO.	13:15 13:16	13:19 13:20	13:24 13:26	13:30 13:30	13:36 13:35	13:51 13:51	TIME TO CUTOFF
B	27	141	1.775	1.769	1.762	1.749	1.740	1.703	04:55
B	31	223	1.779	1.769	1.759	1.749	1.742	1.690	04:50
A	1	12	1.784	1.777	1.769	1.757	1.748	1.707	04:53
B	26	135	1.779	1.771	1.761	1.749	1.740	1.694	04:52
B	32	226	1.782	1.775	1.765	1.757	1.748	1.707	04:55
B	25	130	1.778	1.771	1.763	1.751	1.741	1.700	04:54
B	31	222	1.779	1.771	1.760	1.753	1.743	1.700	04:54
A	1	2	1.785	1.777	1.769	1.755	1.747	1.706	04:53
B	26	136	1.780	1.772	1.763	1.750	1.741	1.695	04:52
B	24	84	1.779	1.772	1.764	1.752	1.743	1.703	04:54
C	49	286	1.783	1.775	1.767	1.759	1.751	1.711	04:55
C	44	250	1.777	1.770	1.760	1.752	1.744	1.706	04:54
B	19	16	1.791	1.784	1.775	1.763	1.754	1.715	04:57
C	49	294	1.784	1.777	1.767	1.759	1.751	1.707	04:53
A	10	101	1.788	1.780	1.777	1.759	1.748	1.707	04:54
C	42	233	1.786	1.778	1.768	1.758	1.749	1.703	04:53
B	32	237	1.783	1.776	1.764	1.758	1.750	1.705	04:55
B	25	132	1.780	1.773	1.760	1.753	1.744	1.709	04:57
A	8	85	1.787	1.780	1.770	1.759	1.749	1.708	04:53
A	8	78	1.786	1.781	1.773	1.761	1.752	1.714	04:56
C	42	231	1.782	1.776	1.765	1.759	1.749	1.709	04:56
A	10	99	1.787	1.780	1.772	1.761	1.752	1.717	04:59
C	43	244	1.784	1.776	1.765	1.758	1.750	1.706	04:54
B	33	241	1.788	1.780	1.770	1.760	1.751	1.704	04:54
A	8	87	1.786	1.779	1.771	1.760	1.751	1.715	04:57
B	32	224	1.784	1.775	1.765	1.758	1.748	1.705	04:54
A	6	70	1.787	1.780	1.776	1.761	1.753	1.716	04:57
B	27	143	1.786	1.778	1.772	1.759	1.750	1.713	04:59
A	1	9	1.789	1.781	1.773	1.763	1.754	1.717	04:57
B	31	217	1.782	1.776	1.766	1.759	1.749	1.713	04:59
B	24	83	1.793	1.785	1.776	1.764	1.754	1.712	04:57
B	27	145	1.782	1.775	1.766	1.755	1.746	1.710	04:58
B	27	147	1.784	1.776	1.769	1.756	1.746	1.704	04:56
A	1	13	1.791	1.783	1.776	1.764	1.755	1.715	04:56
C	43	248	1.783	1.777	1.768	1.760	1.752	1.715	04:58
B	25	131	1.787	1.779	1.772	1.759	1.751	1.714	04:58
B	19	14	1.792	1.785	1.777	1.766	1.756	1.719	04:59
C	43	247	1.784	1.778	1.769	1.761	1.753	1.716	04:58
B	26	138	1.790	1.782	1.774	1.763	1.755	1.718	05:01
B	26	140	1.787	1.780	1.772	1.761	1.752	1.714	04:59
C	51	307	1.794	1.787	1.779	1.771	1.764	1.728	05:03
B	24	106	1.777	1.783	1.775	1.764	1.758	1.719	05:00
B	27	142	1.788	1.784	1.774	1.762	1.756	1.717	05:00
B	25	129	1.787	1.779	1.772	1.760	1.749	1.712	04:58
C	42	232	1.791	1.783	1.773	1.762	1.753	1.714	04:58
B	25	133	1.778	1.782	1.774	1.763	1.755	1.717	04:59
B	24	86	1.795	1.788	1.779	1.768	1.759	1.720	05:00
C	46	266	1.789	1.782	1.773	1.765	1.757	1.719	05:00
C	44	253	1.790	1.782	1.771	1.764	1.755	1.717	04:59
C	46	263	1.793	1.786	1.778	1.770	1.765	1.730	05:04

APPENDIX B (cont.)

VOLTAGE MEASUREMENTS
DURING DISCHARGE

STRING	MODULE	CELL NO.	13:15 13:16	13:19 13:20	13:24 13:26	13:30 13:30	13:36 13:35	13:51 13:51	TIME TO CUTOFF
C	42	234	1.791	1.784	1.775	1.770	1.762	1.723	05:02
B	33	242	1.791	1.784	1.775	1.767	1.757	1.717	04:59
B	26	137	1.792	1.785	1.778	1.767	1.759	1.724	05:04
B	26	139	1.790	1.783	1.775	1.764	1.755	1.720	05:02
B	25	128	1.789	1.782	1.775	1.764	1.756	1.723	05:04
C	42	235	1.794	1.787	1.779	1.770	1.762	1.726	05:04
B	27	146	1.792	1.784	1.777	1.766	1.756	1.719	05:01
C	46	267	1.794	1.786	1.778	1.770	1.761	1.725	05:02
C	43	236	1.797	1.789	1.780	1.772	1.764	1.724	05:01
C	44	251	1.793	1.786	1.778	1.770	1.761	1.729	05:06
B	33	243	1.795	1.788	1.778	1.771	1.765	1.728	05:05
C	44	254	1.795	1.787	1.778	1.770	1.762	1.725	05:02
C	43	245	1.795	1.789	1.780	1.774	1.767	1.734	05:08
C	42	230	1.797	1.790	1.782	1.775	1.768	1.734	05:09
B	33	265	1.794	1.786	1.779	1.772	1.764	1.732	05:09
C	46	262	1.799	1.792	1.783	1.777	1.771	1.737	05:08
C	44	252	1.799	1.790	1.783	1.776	1.769	1.736	05:09
B	33	239	1.806	1.799	1.790	1.784	1.776	1.739	05:09
C	47	276	1.803	1.798	1.787	1.783	1.776	1.742	05:10
C	47	273	1.801	1.795	1.786	1.780	1.771	1.738	05:09
C	43	246	1.802	1.797	1.787	1.782	1.775	1.744	05:14
C	50	297	1.800	1.792	1.782	1.775	1.766	1.741	05:17
C	51	303	1.815	1.810	1.803	1.796	1.790	1.760	05:23

APPENDIX B (cont.)

						END OF DISCHARGE			
						OPEN CIRCUIT			
				Ah	%CAP.	INTERPOLATED TEMP			
STRING	MODULE	CELL NO.	Ah	CORR	CORR	VOLT	SGAR	TEMP	SGAC
A	11	109	2093	1997	96.0	1.932	1.120	95	1.126
B	20	22	2105	2004	96.3	1.935	1.125	102	1.133
A	11	105	2107	2005	96.4	1.940	1.120	103	1.129
B	20	21	2125	2011	96.7	1.938	1.125	106	1.135
B	22	60	2126	2011	96.7	1.932	1.115	106	1.125
B	20	28	2120	2017	97.0	1.938	1.125	102	1.133
B	29	197	2115	2018	97.0	1.933	1.120	105	1.129
A	1	25	2101	2023	97.3	1.933	1.140	100	1.148
B	22	59	2139	2024	97.3	1.941	1.135	106	1.145
B	22	63	2127	2024	97.3	1.933	1.120	102	1.128
C	44	249	2121	2025	97.3	1.932	1.120	101	1.128
B	29	192	2109	2025	97.4	1.931	1.125	102	1.133
A	1	23	2103	2026	97.4	1.927	1.130	100	1.138
B	32	225	2127	2030	97.6	1.938	1.120	101	1.128
B	22	62	2134	2031	97.7	1.938	1.135	102	1.143
B	30	199	2133	2036	97.9	1.940	1.130	107	1.140
A	9	91	2143	2039	98.0	1.945	1.130	107	1.140
B	32	228	2155	2045	98.3	1.943	1.125	104	1.134
B	20	20	2162	2045	98.3	1.940	1.135	106	1.145
B	20	29	2143	2046	98.4	1.936	1.135	95	1.141
A	6	65	2139	2048	98.5	1.943	1.135	102	1.143
C	50	299	2154	2050	98.6	1.940	1.120	102	1.128
B	31	221	2150	2052	98.7	1.933	1.120	101	1.128
B	29	185	2150	2052	98.7	1.940	1.130	105	1.139
A	8	90	2135	2056	98.9	1.942	1.135	101	1.143
A	10	102	2163	2065	99.3	1.941	1.130	95	1.136
B	22	40	2164	2065	99.3	1.936	1.130	95	1.136
A	18	174	2185	2067	99.4	1.943	1.130	105	1.139
B	29	172	2156	2070	99.5	1.937	1.120	102	1.128
B	19	17	2163	2071	99.6	1.940	1.135	95	1.141
B	22	41	2164	2072	99.6	1.941	1.120	95	1.126
B	19	15	2177	2072	99.6	1.946	1.135	102	1.143
B	19	18	2167	2074	99.7	1.941	1.135	95	1.141
B	29	195	2189	2077	99.9	1.946	1.120	108	1.130
B	31	212	2158	2078	99.9	1.935	1.120	99	1.127
B	20	24	2172	2079	100.0	1.939	1.135	95	1.141
C	48	278	2199	2081	100.0	1.940	1.120	107	1.130
C	54	316	2188	2083	100.1	1.940	1.115	106	1.125
A	18	177	2170	2084	100.2	1.941	1.135	101	1.143
C	54	319	2165	2085	100.2	1.932	1.115	106	1.125
A	9	93	2177	2085	100.2	1.944	1.135	95	1.141
C	50	298	2189	2089	100.4	1.939	1.120	102	1.128
A	6	71	2191	2092	100.6	1.947	1.135	104	1.144
A	10	97	2207	2094	100.7	1.946	1.135	103	1.144
A	6	64	2175	2095	100.7	1.942	1.135	100	1.143
B	29	196	2211	2098	100.9	1.946	1.120	108	1.130
B	32	238	2181	2100	101.0	1.932	1.120	99	1.127
B	31	219	2214	2101	101.0	1.942	1.120	104	1.129

STRING	MODULE	CELL NO.	Ah	Ah CORR	%CAP. CORR	END OF DISCHARGE OPEN CIRCUIT INTERPOLATED TEMP			
						VOLT	SGAR	TEMP	SGAC
B	27	141	2214	2101	101.0	1.953	1.130	106	1.140
B	31	223	2182	2101	101.0	1.933	1.120	99	1.127
A	1	12	2202	2102	101.0	1.946	1.130	104	1.139
B	26	135	2190	2103	101.1	1.941	1.125	95	1.131
B	32	226	2218	2105	101.2	1.942	1.125	104	1.134
B	25	130	2205	2105	101.2	1.948	1.125	102	1.133
B	31	222	2205	2105	101.2	1.942	1.125	101	1.133
A	1	2	2199	2105	101.2	1.945	1.135	101	1.143
B	26	136	2193	2105	101.2	1.943	1.135	95	1.141
B	24	84	2206	2106	101.2	1.952	1.130	102	1.138
C	49	286	2216	2109	101.4	1.944	1.120	105	1.129
C	44	250	2209	2109	101.4	1.945	1.125	101	1.133
B	19	16	2233	2113	101.6	1.952	1.135	106	1.145
C	49	294	2202	2114	101.6	1.943	1.125	99	1.132
A	10	101	2209	2115	101.7	1.946	1.135	95	1.141
C	42	233	2198	2117	101.8	1.940	1.125	99	1.132
B	32	237	2218	2118	101.8	1.941	1.120	101	1.128
B	25	132	2234	2120	101.9	1.951	1.130	106	1.140
A	8	85	2205	2123	102.1	1.949	1.140	101	1.148
A	8	78	2224	2123	102.1	1.946	1.130	106	1.140
C	42	231	2225	2123	102.1	1.944	1.120	101	1.128
A	10	99	2245	2124	102.1	1.950	1.130	107	1.140
C	43	244	2206	2125	102.2	1.945	1.125	99	1.132
B	33	241	2208	2126	102.2	1.939	1.135	99	1.142
A	8	87	2229	2128	102.3	1.951	1.120	106	1.130
B	32	224	2212	2130	102.4	1.941	1.125	99	1.132
A	6	70	2231	2130	102.4	1.949	1.130	104	1.139
B	27	143	2245	2130	102.4	1.950	1.130	106	1.140
A	1	9	2234	2133	102.5	1.954	1.135	104	1.144
B	31	217	2248	2134	102.6	1.947	1.125	104	1.134
B	24	83	2230	2135	102.6	1.906	1.135	95	1.141
B	27	145	2236	2135	102.6	1.954	1.135	102	1.143
B	27	147	2223	2135	102.6	1.945	1.135	95	1.141
A	1	13	2225	2136	102.7	1.947	1.130	101	1.138
C	43	248	2239	2137	102.7	1.951	1.120	101	1.128
B	25	131	2240	2138	102.8	1.953	1.130	102	1.138
B	19	14	2248	2139	102.9	1.949	1.135	106	1.145
C	43	247	2242	2140	102.9	1.945	1.135	101	1.143
B	26	138	2260	2144	103.1	1.953	1.125	106	1.135
B	26	140	2247	2144	103.1	1.956	1.130	102	1.138
C	51	307	2276	2147	103.2	1.942	1.115	106	1.125
B	24	106	2252	2150	103.4	1.951	1.130	102	1.138
B	27	142	2254	2152	103.4	1.955	1.135	102	1.143
B	25	129	2242	2152	103.5	1.951	1.135	95	1.141
C	42	232	2241	2158	103.7	1.940	1.130	99	1.137
B	25	133	2248	2158	103.8	1.956	1.130	95	1.136
B	24	86	2255	2159	103.8	1.951	1.130	95	1.136
C	46	266	2250	2160	103.9	1.943	1.130	100	1.138
C	44	253	2244	2161	103.9	1.943	1.125	99	1.132
C	46	263	2285	2162	104.0	1.949	1.120	106	1.130

APPENDIX B (cont.)

STRING	MODULE	CELL NO.	Ah	Ah CORR	%CAP. CORR	VOLT	END OF DISCHARGE OPEN CIRCUIT INTERPOLATED TEMP SGAR	TEMP	SGAC
C	42	234	2268	2165	104.1	1.944	1.130	101	1.138
B	33	242	2249	2165	104.1	1.948	1.130	99	1.137
B	26	137	2282	2166	104.1	1.957	1.140	106	1.150
B	26	139	2269	2166	104.1	1.956	1.145	102	1.153
B	25	128	2283	2167	104.2	1.962	1.135	106	1.145
C	42	235	2284	2168	104.2	1.947	1.120	104	1.129
B	27	146	2263	2173	104.5	1.953	1.130	95	1.136
C	46	267	2266	2176	104.6	1.946	1.130	100	1.138
C	43	236	2262	2178	104.7	1.944	1.135	99	1.142
C	44	251	2299	2181	104.9	1.953	1.125	104	1.134
B	33	243	2288	2184	105.0	1.953	1.120	101	1.128
C	44	254	2271	2187	105.2	1.942	1.130	99	1.137
C	43	245	2314	2196	105.6	1.956	1.125	104	1.134
C	42	230	2318	2199	105.7	1.951	1.130	104	1.139
B	33	265	2318	2199	105.7	1.955	1.125	104	1.134
C	46	262	2313	2202	105.8	1.954	1.125	102	1.133
C	44	252	2321	2202	105.9	1.955	1.135	104	1.144
B	33	239	2324	2205	106.0	1.946	1.135	104	1.144
C	47	276	2331	2218	106.7	1.956	1.130	102	1.138
C	47	273	2321	2222	106.8	1.946	1.130	100	1.138
C	43	246	2360	2240	107.7	1.959	1.135	104	1.144
C	50	297	2379	2258	108.5	1.962	1.135	106	1.145
C	51	303	2423	2306	110.8	1.962	1.135	102	1.143

MEASUREMENTS AFTER CUTOFF VOLTAGE IS REACHED

STRING	MODULE	CELL NO.	TIME CORR	VOLT	TIME (RAW)	(ADJ)	VOLTS	TIME (RAW)	(ADJ)
A	11	109	1.3	1.710	13:36	13:37	1.635	13:51	13:52
B	20	22	1.9	1.715	13:36	13:37	1.654	13:51	13:52
A	11	105	1.4	1.716	13:36	13:37	1.655	13:51	13:52
B	20	21	2.1	1.719	13:36	13:38	1.666	13:51	13:53
B	22	60	2.5	1.720	13:36	13:38	1.665	13:51	13:53
B	20	28	2.1	1.716	13:36	13:38	1.664	13:51	13:53
B	29	197	3.9	1.714	13:35	13:38	1.657	13:51	13:54
A	1	25	0.0	1.718	13:36	13:36	1.653	13:51	13:51
B	22	59	2.4	1.722	13:36	13:38	1.676	13:51	13:53
B	22	63	2.5	1.720	13:36	13:38	1.666	13:51	13:53
C	44	249	1.4	1.723	13:35	13:36	1.669	13:51	13:52
B	29	192	3.6	1.713	13:35	13:38	1.649	13:51	13:54
A	1	23	0.3	1.719	13:36	13:36	1.655	13:51	13:51
B	32	225	2.8	1.721	13:35	13:37	1.670	13:51	13:53
B	22	62	2.3	1.724	13:36	13:38	1.669	13:51	13:53
B	30	199	3.6	1.720	13:35	13:38	1.670	13:51	13:54
A	9	91	0.9	1.729	13:36	13:36	1.684	13:51	13:51
B	32	228	2.9	1.731	13:35	13:37	1.683	13:51	13:53
B	20	20	2.0	1.732	13:36	13:38	1.685	13:51	13:53
B	20	29	2.2	1.728	13:36	13:38	1.674	13:51	13:53
A	6	65	0.5	1.729	13:36	13:36	1.682	13:51	13:51
C	50	299	0.3	1.735	13:35	13:35	1.689	13:51	13:51
B	31	221	3.2	1.728	13:35	13:38	1.676	13:51	13:54
B	29	185	3.7	1.726	13:35	13:38	1.678	13:51	13:54
A	8	90	0.6	1.729	13:36	13:36	1.679	13:51	13:51
A	10	102	1.2	1.735	13:36	13:37	1.689	13:51	13:52
B	22	40	2.6	1.737	13:36	13:38	1.684	13:51	13:53
A	18	174	1.5	1.740	13:36	13:37	1.698	13:51	13:52
B	29	172	4.0	1.727	13:35	13:39	1.676	13:51	13:55
B	19	17	1.8	1.738	13:36	13:37	1.688	13:51	13:52
B	22	41	2.3	1.735	13:36	13:38	1.685	13:51	13:53
B	19	15	1.6	1.738	13:36	13:37	1.695	13:51	13:52
B	19	18	1.5	1.738	13:36	13:37	1.690	13:51	13:52
B	29	195	3.9	1.738	13:35	13:38	1.694	13:51	13:54
B	31	212	3.2	1.731	13:35	13:38	1.680	13:51	13:54
B	20	24	1.9	1.742	13:36	13:37	1.692	13:51	13:52
C	48	278	0.6	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	54	316	0.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	18	177	1.4	1.742	13:36	13:37	1.691	13:51	13:52
C	54	319	0.0	1.740	13:35	13:35	1.693	13:51	13:51
A	9	93	1.0	1.742	13:36	13:36	1.698	13:51	13:51
C	50	298	0.4	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	6	71	0.6	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	10	97	1.2	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	6	64	0.4	1.743	13:36	13:36	1.697	13:51	13:51
B	29	196	3.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	32	238	3.1	1.740	13:35	13:38	1.690	13:51	13:54
B	31	219	3.3	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX B (cont.)

MEASUREMENTS AFTER CUTOFF VOLTAGE IS REACHED

STRING	MODULE	CELL NO.	TIME CORR	VOLT	TIME (RAW)	(ADJ)	VOLTS	TIME (RAW)	(ADJ)
B	27	141	3.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	31	223	3.5	1.742	13:35	13:38	1.690	13:51	13:54
A	1	12	0.2	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	26	135	3.3	1.740	13:36	13:39	1.694	13:51	13:54
B	32	226	2.9	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	25	130	3.2	1.741	13:36	13:39	1.700	13:51	13:54
B	31	222	3.4	1.743	13:35	13:38	1.700	13:51	13:54
A	1	2	0.3	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	26	136	3.6	1.741	13:36	13:39	1.695	13:51	13:54
B	24	84	2.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	49	286	0.6	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	44	250	1.2	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	19	16	1.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	49	294	0.5	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	10	101	1.0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	42	233	2.0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	32	237	3.0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	25	132	3.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	8	85	0.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	8	78	0.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	42	231	2.0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	10	99	1.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	43	244	1.5	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	33	241	2.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	8	87	0.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	32	224	2.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	6	70	0.5	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	27	143	3.9	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	1	9	0.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	31	217	3.4	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	24	83	2.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	27	145	3.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	27	147	4.0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
A	1	13	0.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	43	248	1.6	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	25	131	3.0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	19	14	1.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	43	247	1.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	26	138	3.4	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	26	140	3.4	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	51	307	0.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	24	106	2.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	27	142	3.9	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	25	129	3.2	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	42	232	2.3	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	25	133	2.9	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	24	86	2.6	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	46	266	1.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	44	253	1.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	46	263	1.0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

					MEASUREMENTS AFTER CUTOFF VOLTAGE IS REACHED				
STRING	MODULE	CELL NO.	TIME CORR	VOLT	TIME (RAW)	(ADJ)	VOLTS	TIME (RAW)	(ADJ)
C	42	234	2.2	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	33	242	2.4	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	26	137	3.5	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	26	139	3.5	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	25	128	3.0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	42	235	2.1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	27	146	3.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	46	267	0.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	43	236	1.9	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	44	251	1.3	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	33	243	2.5	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	44	254	1.5	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	43	245	1.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	42	230	2.2	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	33	265	2.5	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	46	262	0.9	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	44	252	1.3	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
B	33	239	2.6	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	47	276	0.7	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	47	273	0.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	43	246	1.8	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	50	297	0.4	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
C	51	303	0.2	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX C

CORRECTLY CLASSIFIED CELLS,
ABERRANT CELLS, AND REPLACEMENT CELLS

Cell ID	Correctly Classified (STDEV)	Aberrant	Replacements
16	✓		✓
18	✓		✓
20	✓		
21			
22	✓		
23	✓		
25	✓		
28	✓		
29	✓		✓
59	✓		
60	✓		
62		✓	
63	✓		
65	✓		
70			✓
71			✓
83			
91		✓	
99		✓	
105	✓	eliminated	
109	✓	eliminated	
128			
131		✓	
132			
133			
135			
136	✓		
146		✓	
172	✓		
185		✓	
192	✓		
197			
199	✓		

Cell ID	Correctly Classified	(STDEV)	Aberrant	Replacements
219				
221			✓	
225				
228	✓			
230	✓			✓
235	✓			
236				
239	✓			
243	✓			
245	✓			
246	✓			
249				
251				
252	✓			
254				
262	✓			
263				
265	✓			
267				
273				
276	✓			
297				
299				
303	✓			
307	✓			
316				✓

APPENDIX D

PREDICTION RESULTS FOR PREDICTION SET CELLS
CLASSIFIERS DEVELOPED FROM STDEV AND NLM PROCEDURES

Training Set Index:	1	2	3	4	5	6	7	8	9	10	11	12	13
Criterion: STDEV Cell ID:	2	9	12	13	14	15	17	24	40	41	64	78	84
Feature Code													
F-0420101000000	3	3	2	2	3	2	3	2	2	2	2	2	3
F-0411111000000	3	2	2	2	3	3	2	2	2	2	2	2	3
F-0410121000100	3	2	2	2	3	3	3	2	2	2	2	2	3
F-0420102000000	3	3	2	2	3	2	2	2	2	2	2	2	2
F-0041012010120	3	3	3	2	3	2	3	2	2	2	2	2	3
Majority Vote:	3	3	2	2	3	2	3	2	2	2	2	2	3

Training Set Criterion: NLM													
Feature Code													
F-0201010000000	3	2	3	3	2	3	2	2	2	2	3	2	3
F-0/16/11110000000	3	2	2	2	3	3	2	2	2	2	2	2	3
F-1420110100010	3	2	2	3	3	2	2	2	2	2	2	2	3
F-1001020001000	3	3	3	3	3	3	2	2	2	2	2	2	3
F-0110010000000	3	3	2	2	2	2	3	2	2	2	2	2	3
Majority Vote:	3	2	2	3	3	3	2	2	2	2	2	2	3
Overall Majority Vote:	3	2/3	2	2	3	2/3	2	2	2	2	2	2	3

Training Set Index:	14	15	16	17	18	19	20	21	22	23	24	25	26
Criterion: STDEV Cell ID:	85	86	87	90	93	97	101	102	106	129	130	137	138
Feature Code													
F-0420101000000	3	2	2	2	1	2	3	3	1	1	1	2	2
F-0411111000000	3	2	2	2	2	2	3	3	2	3	1	2	2
F-0410121000100	3	2	2	2	1	2	3	3	1	1	1	2	2
F-0420102000000	3	2	2	3	1	2	3	3	1	3	1	3	2
F-0041012010120	3	2	2	2	3	3	3	3	3	3	1	3	2
Majority Vote:	3	2	2	2	1	2	3	3	1	3	1	2	2

Training Set Criterion: NLM													
Feature Code													
F-0201010000000	3	2	2	2	3	2	3	2	2	3	1	2	2
F-0/16/11110000000	3	2	2	2	3	2	3	2	2	3	3	2	2
F-1420110100010	3	2	2	2	2	2	3	3	3	3	3	3	2
F-1001020001000	3	2	2	2	3	2	3	2	3	1	3	3	3
F-0110010000000	3	2	3	3	2	2	3	1	3	2	1	3	2
Majority Vote:	3	2	2	2	3	2	3	2	3	3	3	3	2
Overall Majority Vote:	3	2	2	2	3	2	3	3	3	3	1	2/3	2

PREDICTION RESULTS FOR PREDICTION SET CELLS
CLASSIFIERS DEVELOPED FROM STDEV AND NLM PROCEDURES

Training Set Criterion: STDEV	Index: Cell ID:	27 139	28 140	29 141	30 142	31 143	32 145	33 147	34 174	35 177	36 195	37 196	38 212	39 217
Feature Code														
F-0420101000000		3	2	3	3	3	2	2	2	3	2	3	3	3
F-0411111000000		3	2	3	3	3	1	2	2	3	2	2	3	3
F-0410121000100		3	2	3	3	3	2	2	2	3	2	2	3	3
F-0420102000000		3	2	3	3	3	2	2	2	3	2	2	2	3
F-0041012010120		1	2	3	2	3	3	2	3	3	2	3	3	3
Majority Vote:		3	2	3	3	3	2	2	2	3	2	2	3	3

Training Set Criterion: NLM														
Feature Code														
F-0201010000000		3	2	3	3	2	3	3	2	2	1	3	2	1
F-0/16/11110000000		3	2	2	3	2	3	2	2	2	2	2	3	1
F-1420110100010		3	3	2	3	3	3	2	2	3	2	3	3	3
F-1001020001000		3	3	3	3	3	1	2	2	2	1	2	3	3
F-0110010000000		3	2	2	3	1	1	2	3	3	1	2	3	3
Majority Vote:		3	2	2	3	2/3	3	2	2	2	1	2	3	3
Overall Majority Vote:		3	2	3	3	3	3	2	2	3	2	2	3	3

Training Set Criterion: STDEV	Index: Cell ID:	40 222	41 223	42 224	43 226	44 231	45 232	46 233	47 234	48 237	49 238	50 241	51 242	52 244
Feature Code															
F-0420101000000		3	3	1	3	3	1	1	1	2	1	3	2	3
F-0411111000000		3	3	1	3	3	1	1	1	3	1	1	2	1
F-0410121000100		2	3	1	3	3	1	1	1	3	1	3	2	1
F-0420102000000		3	3	1	3	1	1	1	1	3	1	1	1	3
F-0041012010120		3	3	3	3	1	3	1	1	1	1	3	1	1
Majority Vote:		3	3	1	3	3	1	1	1	3	1	3	2	1

Training Set Criterion: NLM														
Feature Code														
F-0201010000000		1	1	1	3	1	3	1	1	3	3	1	1	1
F-0/16/11110000000		2	1	1	3	3	1	1	1	3	3	1	1	2
F-1420110100010		2	1	1	3	1	1	1	1	2	1	1	2	1
F-1001020001000		3	2	1	3	3	1	2	1	3	3	1	2	1
F-0110010000000		1	1	3	3	3	3	1	1	3	3	3	1	3
Majority Vote:		1.2	1	1	3	3	1	1	1	3	3	1	1	1
Overall Majority Vote:		3	3	1	3	3	3	1	1	3	1	1	1/2	1

PREDICTION RESULTS FOR PREDICTION SET CELLS
CLASSIFIERS DEVELOPED FROM STDEV AND NLM PROCEDURES

Training Set Criterion: STDEV	Index:	53	54	55	56	57	58	59	60	61	62
	Cell ID:	247	248	250	253	266	278	286	294	298	319
Feature Code											
F-0420101000000		3	1	1	3	1	1	1	2	1	3
F-0411111000000		3	1	2	2	1	2	1	2	1	1
F-0410121000100		3	1	2	2	1	2	1	2	1	1
F-0420102000000		3	1	1	3	1	1	1	2	1	1
F-0041012010120		1	1	2	2	1	2	1	2	1	3
Majority Vote:		3	1	2	2	1	2	1	2	1	1

Training Set Criterion: NLM											
Feature Code											
F-0201010000000		1	1	1	1	1	1	1	1	1	3
F-0/16/11110000000		1	1	1	1	1	1	1	1	1	3
F-1420110100010		1	1	1	1	1	3	1	1	1	1
F-1001020001000		2	1	3	3	3	1	1	1	2	3
F-0110010000000		1	1	1	3	1	1	1	1	1	3
Majority Vote:		1	1	1	1	1	1	1	1	1	3
Overall Majority Vote:		1	1	1	3	1	1	1	1/2	1	3

Training Set Criterion: STDEV		% ACCURACY
Feature Code		
F-0420101000000		40%
F-0411111000000		34%
F-0410121000100		34%
F-0420102000000		35%
F-0041012010120		47%
	Average:	38%
	s:	6%

Training Set Criterion: NLM		
Feature Code		
F-0201010000000		34%
F-0/16/11110000000		29%
F-1420110100010		35%
F-1001020001000		48%
F-0110010000000		42%
	Average:	38%
	s:	8%

Combined Average: 38%
s: 6%

APPENDIX E

PREDICTION RESULTS FOR UNKNOWN SET CELLS
CLASSIFIERS DEVELOPED FROM STDEV AND NLM PROCEDURES

Training Set Index:	1	2	3	4	5	6	7	8	9	10	11	12	13
Criterion: STDEV Cell ID:	1	3	4	5	6	7	8	10	11	19	26	27	30
Feature Code													
F-0420101000000	3	3	3	3	3	3	3	3	3	3	2	3	2
F-0411111000000	3	3	3	2	2	3	2	3	2	3	2	3	2
F-0410121000100	3	3	3	2	2	3	2	2	2	3	2	3	2
F-0420102000000	3	3	3	3	3	3	3	1	3	3	2	3	2
F-0041012010120	3	3	3	3	3	3	1	3	2	2	2	3	2
Majority Vote:	3	3	3	3	3	3	2/3	3	2	3	2	3	2

Training Set Criterion: NLM Feature Code													
F-0201010000000	2	2	2	2	2	2	2	2	2	2	2	2	2
F-0/16/11110000000	2	2	2	2	2	2	2	2	2	2	2	2	2
F-1420110100010	3	3	2	2	2	3	1	3	2	2	2	2	2
F-1001020001000	2	2	2	2	2	2	2	2	2	2	2	2	2
F-0110010000000	3	3	3	2	2	3	1	3	2	2	2	2	2
Majority Vote:	2	2	2	2	2	2	2	2	2	2	2	2	2
Overall Majority Vote:	3	3	3	2	2	3	2	3	2	2	2	2/3	2

Training Set Index:	14	15	16	17	18	19	20	21	22	23	24	25	26
Criterion: STDEV Cell ID:	31	32	33	34	35	36	37	38	39	42	43	44	45
Feature Code													
F-0420101000000	2	2	2	2	2	2	2	2	2	2	3	2	2
F-0411111000000	2	2	3	2	2	2	2	2	2	2	3	2	2
F-0410121000100	2	2	2	2	2	2	2	2	2	2	3	2	2
F-0420102000000	2	2	3	2	2	2	2	2	2	2	3	2	2
F-0041012010120	2	2	2	2	2	2	2	3	2	2	2	2	3
Majority Vote:	2	2	2	2	2	2	2	2	2	2	3	2	2

Training Set Criterion: NLM Feature Code													
F-0201010000000	2	2	2	2	2	2	2	2	2	2	3	2	3
F-0/16/11110000000	2	2	2	2	2	2	2	3	2	2	2	2	2
F-1420110100010	2	2	2	2	2	2	2	2	2	2	2	2	2
F-1001020001000	2	3	2	2	2	2	2	2	2	2	2	2	2
F-0110010000000	2	2	2	2	2	2	2	2	2	2	2	2	2
Majority Vote:	2	2	2	2	2	2	2	2	2	2	2	2	2
Overall Majority Vote:	2	2	2	2	2	2	2	2	2	2	2/3	2	2

Training Set	Index:	27	28	29	30	31	32	33	34	35	36	37	38	39
Criterion: STDEV	Cell ID:	46	47	48	49	50	51	52	53	54	55	56	57	58
Feature Code														
F-0420101000000		3	2	2	3	2	2	3	2	2	2	3	2	3
F-0411111000000		3	2	2	3	2	2	3	2	2	2	3	2	3
F-0410121000100		2	2	2	2	2	2	3	2	2	2	3	2	2
F-0420102000000		3	2	2	2	2	2	3	2	2	2	3	2	3
F-0041012010120		3	2	2	3	2	2	2	2	2	2	3	2	2
Majority Vote:		3	2	2	3	2	2	3	2	2	2	3	2	3

Training Set														
Criterion: NLM														
Feature Code														
F-0201010000000		3	2	3	2	2	2	2	2	2	2	3	2	2
F-0/16/11110000000		3	2	2	2	2	2	2	2	2	2	3	2	2
F-1420110100010		2	2	2	2	2	2	2	2	2	2	2	2	2
F-1001020001000		2	2	2	2	2	2	3	2	2	2	3	2	2
F-0110010000000		2	2	3	3	2	2	3	2	2	2	2	2	3
Majority Vote:		2	2	2	2	2	2	2	2	2	2	3	2	2

| Overall Majority Vote: | | 3 | 2 | 2 | 2 | 2 | 2 | 3 | 2 | 2 | 2 | 3 | 2 | 2 |

Training Set	Index:	40	41	42	43	44	45	46	47	48	49	50	51	52
Criterion: STDEV	Cell ID:	61	66	67	68	69	72	73	74	75	76	77	79	80
Feature Code														
F-0420101000000		2	2	2	3	2	2	2	3	2	2	2	3	2
F-0411111000000		2	2	3	3	2	2	2	3	2	2	2	3	2
F-0410121000100		2	2	3	3	2	2	2	3	2	2	2	3	3
F-0420102000000		2	2	3	3	2	2	2	2	2	2	2	3	2
F-0041012010120		2	2	2	3	2	2	2	2	2	2	2	2	2
Majority Vote:		2	2	3	3	2	2	2	3	2	2	2	3	2

Training Set														
Criterion: NLM														
Feature Code														
F-0201010000000		2	2	2	2	2	2	2	2	2	2	2	2	2
F-0/16/11110000000		2	2	3	2	2	2	2	2	2	2	2	2	2
F-1420110100010		2	2	2	2	2	3	2	2	2	2	2	2	2
F-1001020001000		2	2	2	2	3	3	3	2	2	2	2	2	2
F-0110010000000		2	2	2	2	2	2	2	2	2	2	2	2	2
Majority Vote:		2	2	2	2	2	2	2	2	2	2	2	2	2

| Overall Majority Vote: | | 2 | 2 | 2 | 2/3 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |

Training Set Criterion: STDEV	Index: Cell ID:	53 81	54 82	55 88	56 89	57 92	58 94	59 95	60 96	61 98	62 100	63 103	64 104	65 107
Feature Code														
F-0420101000000		3	3	3	1	1	2	2	1	3	3	2	2	1
F-0411111000000		3	3	3	3	2	2	2	3	2	3	2	2	3
F-0410121000100		3	3	3	1	2	2	2	1	3	1	2	2	3
F-0420102000000		3	3	3	1	1	1	2	1	2	1	2	2	2
F-0041012010120		3	3	3	2	3	2	3	3	3	3	3	3	3
Majority Vote:		3	3	3	1	1/2	2	2	1	3	3	2	2	3

Training Set Criterion: NLM														
Feature Code														
F-0201010000000		3	1	2	3	2	1	2	3	2	3	2	2	2
F-0/16/11110000000		3	2	2	3	2	2	2	3	2	3	2	2	3
F-1420110100010		3	1	2	3	2	2	2	3	1	3	2	2	3
F-1001020001000		3	3	2	3	2	1	1	3	3	3	2	2	3
F-0110010000000		3	1	2	3	3	2	3	3	1	3	2	2	1
Majority Vote:		3	1	2	3	2	2	2	3	1/2	3	2	2	3

Overall Majority Vote:		3	3	2/3	3	2	2	2	3	2/3	3	2	2	3

Training Set Criterion: STDEV	Index: Cell ID:	66 108	67 110	68 111	69 112	70 113	71 114	72 115	73 116	74 117	75 118	76 119	77 120	78 121
Feature Code														
F-0420101000000		2	2	2	2	2	2	1	1	2	2	1	3	1
F-0411111000000		2	2	2	2	2	2	1	2	3	2	1	3	2
F-0410121000100		2	2	2	2	2	2	3	2	3	2	1	3	3
F-0420102000000		2	2	2	2	2	2	3	3	1	2	1	3	1
F-0041012010120		1	2	2	2	2	3	3	3	3	2	3	3	3
Majority Vote:		2	2	2	2	2	2	3	2/3	3	2	1	3	1/3

Training Set Criterion: NLM														
Feature Code														
F-0201010000000		2	2	2	2	2	1	3	1	2	1	3	1	1
F-0/16/11110000000		2	2	2	2	2	1	1	2	2	2	3	2	2
F-1420110100010		2	2	2	2	2	2	1	1	3	2	3	2	2
F-1001020001000		2	2	2	2	2	2	1	1	3	2	3	3	2
F-0110010000000		2	2	2	2	2	2	1	1	2	2	3	2	2
Majority Vote:		2	2	2	2	2	2	1	1	2	2	3	2	2

Overall Majority Vote:		2	2	2/3	2	2	2	1	1	3	2	3	3	2

Training Set	Index:	79	80	81	82	83	84	85	86	87	88	89	90	91
Criterion: STDEV	Cell ID:	122	123	124	125	126	127	134	144	148	149	150	151	152
Feature Code														
F-0420101000000		2	3	1	3	1	3	3	3	2	1	1	2	3
F-0411111000000		2	3	2	3	1	3	3	3	2	2	1	2	3
F-0410121000100		2	3	3	1	1	3	3	3	2	2	1	2	3
F-0420102000000		2	3	2	1	1	3	3	3	2	1	1	2	3
F-0041012010120		3	2	2	1	3	3	3	3	2	3	2	2	2
Majority Vote:		2	3	2	1	1	3	3	3	2	1/2	1	2	3

Training Set														
Criterion: NLM														
Feature Code														
F-0201010000000		2	3	3	3	3	3	3	3	1	2	1	2	2
F-0/16/11110000000		2	3	2	3	3	3	3	3	1	2	1	2	3
F-1420110100010		2	3	2	1	3	1	3	3	2	2	1	2	3
F-1001020001000		2	3	2	3	1	1	3	3	2	3	1	2	2
F-0110010000000		2	3	2	3	3	3	3	2	2	3	1	2	3
Majority Vote:		2	3	2	3	3	3	3	3	2	2	1	2	3
Overall Majority Vote:		2	3	2	3	1/3	3	3	3	2	2	1	2	3

Training Set	Index:	92	93	94	95	96	97	98	99	100	101	102	103	104
Criterion: STDEV	Cell ID:	153	154	155	156	157	158	159	160	161	162	163	164	165
Feature Code														
F-0420101000000		3	2	2	2	1	3	3	3	3	1	3	3	3
F-0411111000000		3	3	2	3	1	3	2	3	1	1	1	3	3
F-0410121000100		3	2	2	2	1	3	2	3	3	3	3	3	3
F-0420102000000		3	2	2	2	1	3	2	3	3	2	3	3	3
F-0041012010120		3	1	3	3	1	3	2	3	3	3	2	3	3
Majority Vote:		3	2	2	2	1	3	2	3	3	1/3	3	3	3

Training Set														
Criterion: NLM														
Feature Code														
F-0201010000000		2	1	1	2	1	3	2	1	1	1	3	3	3
F-0/16/11110000000		3	2	2	2	1	1	2	1	1	3	3	3	3
F-1420110100010		3	2	2	2	1	3	3	1	1	3	3	3	3
F-1001020001000		2	3	2	2	1	3	2	2	1	1	3	3	3
F-0110010000000		1	2	2	2	1	1	3	1	3	3	3	3	3
Majority Vote:		2/3	2	2	2	1	3	2	1	1	3	3	3	3
Overall Majority Vote:		3	2	2	2	1	3	2	3	1/3	3	3	3	3

Training Set	Index:	105	106	107	108	109	110	111	112	113	114	115	116	117
Criterion: STDEV	Cell ID:	166	167	168	169	170	171	173	175	176	178	179	180	181
Feature Code														
F-0420101000000		1	3	3	1	2	2	3	1	3	3	3	2	2
F-0411111000000		1	1	3	2	2	2	3	1	3	3	3	2	2
F-0410121000100		1	3	3	3	2	2	3	3	3	3	3	2	3
F-0420102000000		1	3	2	1	3	2	3	1	3	2	3	2	2
F-0041012010120		1	3	2	1	3	2	2	3	2	3	3	2	2
Majority Vote:		1	3	3	1	2	2	3	1	3	3	3	2	2

Training Set														
Criterion: NLM														
Feature Code														
F-0201010000000		1	1	3	3	2	2	2	2	2	1	1	2	2
F-0/16/11110000000		1	1	3	3	2	3	2	2	2	1	2	2	2
F-1420110100010		1	1	3	1	2	2	3	1	3	2	1	2	2
F-1001020001000		1	1	3	3	2	2	3	1	2	1	2	2	2
F-0110010000000		1	1	3	1	2	2	2	1	2	2	1	2	2
Majority Vote:		1	1	3	3	2	2	2	1	2	1	1	2	2

Overall Majority Vote:		1	1	3	1	2	2	3	1	2/3	3	3	2	2

Training Set	Index:	118	119	120	121	122	123	124	125	126	127	128	129	130
Criterion: STDEV	Cell ID:	182	183	184	186	187	188	189	190	191	193	194	198	200
Feature Code														
F-0420101000000		1	1	2	3	3	2	2	3	2	2	3	2	2
F-0411111000000		1	1	2	2	2	1	2	2	2	2	3	2	2
F-0410121000100		1	1	2	2	2	2	2	2	2	2	3	2	2
F-0420102000000		1	1	2	3	2	2	2	2	2	2	3	2	2
F-0041012010120		3	2	3	2	2	3	2	2	3	2	3	2	2
Majority Vote:		1	1	2	2	2	2	2	2	2	2	3	2	2

Training Set														
Criterion: NLM														
Feature Code														
F-0201010000000		1	2	2	2	1	3	2	2	1	2	2	2	1
F-0/16/11110000000		1	1	2	3	2	3	2	2	2	2	2	1	1
F-1420110100010		1	2	2	3	2	3	2	3	2	2	3	2	2
F-1001020001000		2	2	2	3	2	1	3	3	2	2	3	2	1
F-0110010000000		2	2	2	2	2	1	2	3	2	2	3	1	2
Majority Vote:		1	2	2	3	2	3	2	3	2	2	3	2	1

Overall Majority Vote:		1	1/2	2	2/3	2	3	2	2	2	2	3	2	2

Training Set Criterion: STDEV Feature Code	Index: Cell ID:	131 201	132 202	133 203	134 204	135 205	136 206	137 207	138 208	139 209	140 210	141 211	142 213	143 214
F-0420101000000		2	3	3	3	2	2	2	2	2	3	3	3	1
F-0411111000000		2	3	3	1	1	2	2	2	2	2	3	3	3
F-0410121000100		2	3	3	2	1	2	2	2	2	3	2	3	3
F-0420102000000		2	3	3	3	1	2	2	2	1	3	3	2	3
F-0041012010120		2	3	3	3	3	3	2	2	3	2	2	3	3
Majority Vote:		2	3	3	3	1	2	2	2	2	3	3	3	3

Training Set Criterion: NLM Feature Code														
F-0201010000000		3	1	1	2	2	2	2	1	2	1	2	1	1
F-0/16/11110000000		3	1	1	1	1	2	2	2	1	1	2	2	1
F-1420110100010		2	1	1	1	2	2	2	2	2	2	3	3	1
F-1001020001000		3	1	2	2	2	2	2	2	2	3	3	2	3
F-0110010000000		2	1	1	1	2	2	2	2	2	1	3	3	1
Majority Vote:		3	1	1	1	2	2	2	2	2	1	3	2/3	1

| **Overall Majority Vote:** | | 2 | 1/3 | 3 | 1 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 1/3 |

Training Set Criterion: STDEV Feature Code	Index: Cell ID:	144 215	145 216	146 218	147 220	148 227	149 229	150 240	151 255	152 256	153 257	154 258	155 259	156 260
F-0420101000000		2	2	3	1	3	1	3	3	1	1	3	3	2
F-0411111000000		2	2	3	1	3	1	3	3	1	1	3	3	3
F-0410121000100		2	2	3	1	3	1	3	3	1	1	3	3	1
F-0420102000000		2	2	3	1	3	1	3	3	1	1	3	3	2
F-0041012010120		3	2	2	1	1	1	3	3	1	1	1	1	2
Majority Vote:		2	2	3	1	3	1	3	3	1	1	3	3	2

Training Set Criterion: NLM Feature Code														
F-0201010000000		2	2	1	3	3	3	3	2	1	1	3	3	3
F-0/16/11110000000		2	2	1	3	3	3	3	2	1	1	3	3	1
F-1420110100010		2	2	1	3	3	3	3	3	1	1	3	3	1
F-1001020001000		2	2	2	1	3	3	3	3	1	1	3	3	3
F-0110010000000		2	2	1	1	3	3	3	3	1	1	3	3	1
Majority Vote:		2	2	1	3	3	3	3	3	1	1	3	3	1

| **Overall Majority Vote:** | | 2 | 2 | 1/3 | 1 | 3 | 1/3 | 3 | 3 | 1 | 1 | 3 | 3 | 1 |

Training Set	Index:	157	158	159	160	161	162	163	164	165	166	167	168	169
Criterion: STDEV	Cell ID:	261	264	268	269	270	271	272	274	275	277	279	280	281
Feature Code														
F-0420101000000		1	1	1	3	1	3	1	2	3	1	1	1	1
F-0411111000000		1	1	1	3	1	3	1	1	1	1	1	1	1
F-0410121000100		1	1	1	3	1	1	1	1	1	1	1	1	1
F-0420102000000		1	1	1	3	1	3	1	2	3	1	1	1	1
F-0041012010120		1	1	1	3	1	1	3	2	1	3	1	1	1
Majority Vote:		1	1	1	3	1	3	1	2	1	1	1	1	1

Training Set														
Criterion: NLM														
Feature Code														
F-0201010000000		1	1	1	1	1	3	3	1	1	1	3	1	1
F-0/16/11110000000		1	1	1	1	1	1	1	1	1	2	3	1	1
F-1420110100010		1	1	1	1	1	1	1	1	3	2	1	1	1
F-1001020001000		1	1	1	1	1	1	3	1	3	1	3	1	1
F-0110010000000		1	1	1	1	1	3	1	2	1	2	1	1	1
Majority Vote:		1	1	1	1	1	1	1	1	1	2	3	1	1
Overall Majority Vote:		1	1	1	1/3	1	1/3	1	1	1	1	1	1	1

Training Set	Index:	170	171	172	173	174	175	176	177	178	179	180	181	182
Criterion: STDEV	Cell ID:	282	283	284	285	287	288	289	290	291	292	293	295	296
Feature Code														
F-0420101000000		1	1	3	2	1	3	2	1	2	2	1	3	3
F-0411111000000		1	1	3	2	1	3	2	2	1	2	1	2	1
F-0410121000100		1	1	1	2	1	3	2	1	2	2	1	2	1
F-0420102000000		1	1	1	2	1	3	2	1	2	1	1	3	3
F-0041012010120		1	1	3	2	1	3	1	2	1	1	1	2	3
Majority Vote:		1	1	3	2	1	3	2	1	2	2	1	2	3

Training Set														
Criterion: NLM														
Feature Code														
F-0201010000000		3	3	1	2	2	1	1	1	2	1	1	1	1
F-0/16/11110000000		1	1	1	2	2	2	2	3	2	2	1	2	2
F-1420110100010		3	1	2	3	1	2	2	3	3	2	3	2	2
F-1001020001000		3	1	2	2	2	1	1	3	2	1	1	1	1
F-0110010000000		3	1	2	2	2	2	2	1	2	2	2	2	2
Majority Vote:		3	1	2	2	2	2	2	3	2	2	1	2	2
Overall Majority Vote:		1	1	1	2	1	3	2	1	2	2	1	2	1

Training Set Criterion: STDEV Feature Code	Index: Cell ID:	183 300	184 301	185 302	186 304	187 305	188 306	189 308	190 309	191 310	192 311	193 312	194 313	195 314
F-0420101000000		2	1	3	2	3	3	1	3	1	1	2	2	1
F-0411111000000		3	1	1	3	3	1	1	3	1	1	3	3	1
F-0410121000100		2	3	1	2	3	3	1	3	1	1	3	3	1
F-0420102000000		3	1	3	2	3	3	1	3	1	1	3	2	2
F-0041012010120		2	3	3	2	2	3	1	2	3	3	3	1	2
Majority Vote:		2	1	3	2	3	3	1	3	1	1	3	2/3	1

Training Set Criterion: NLM Feature Code														
F-0201010000000		3	3	1	3	3	3	2	3	1	1	3	1	1
F-0/16/11110000000		1	1	1	3	3	3	1	3	1	1	3	2	1
F-1420110100010		1	1	1	2	3	3	1	3	1	1	2	1	1
F-1001020001000		1	1	1	3	3	3	1	3	3	3	2	1	3
F-0110010000000		3	1	3	2	3	3	1	2	3	1	2	2	1
Majority Vote:		1	1	1	3	3	3	1	3	1	1	2	1	1
Overall Majority Vote:		3	1	1	2	3	3	1	3	1	1	3	1/2	1

Training Set Criterion: STDEV Feature Code	Index: Cell ID:	196 315	197 317	198 318	199 320	200 321	201 322	202 323	203 324	204 325	205 326	206 327	207 328	208 329
F-0420101000000		1	1	3	2	1	3	3	1	1	3	1	1	3
F-0411111000000		1	1	3	2	1	1	2	1	1	3	1	3	3
F-0410121000100		1	1	3	2	1	3	2	1	1	3	1	3	3
F-0420102000000		1	1	3	3	1	1	2	1	3	3	3	1	3
F-0041012010120		3	1	3	1	3	1	3	1	3	3	1	1	3
Majority Vote:		1	1	3	2	1	1	2	1	1	3	1	1	3

Training Set Criterion: NLM Feature Code														
F-0201010000000		3	1	1	1	1	3	2	1	2	3	1	2	3
F-0/16/11110000000		1	1	1	1	1	3	2	1	1	3	1	1	3
F-1420110100010		1	1	1	1	1	1	1	1	1	1	1	1	3
F-1001020001000		3	1	3	2	1	3	3	1	3	3	2	3	3
F-0110010000000		1	1	3	1	1	3	1	1	1	1	3	1	3
Majority Vote:		1	1	1	1	1	3	1/2	1	1	3	1	1	3
Overall Majority Vote:		1	1	3	1	1	3	2	1	1	3	1	1	3

Training Set	Index:	209	210	211	212	213	214	215	216	217	218	219
Criterion: STDEV	Cell ID:	330	331	332	333	334	335	336	337	338	339	340
Feature Code												
F-0420101000000		2	1	1	2	1	1	1	1	3	1	1
F-0411111000000		2	1	1	2	1	3	1	1	3	1	3
F-0410121000100		3	1	1	3	3	3	1	1	3	1	3
F-0420102000000		2	1	1	2	1	3	1	1	3	1	3
F-0041012010120		3	1	1	3	3	1	1	1	3	1	3
Majority Vote:		2	1	1	2	1	3	1	1	3	1	3

Training Set												
Criterion: NLM												
Feature Code												
F-0201010000000		3	1	1	3	3	3	3	3	3	1	3
F-0/16/11110000000		3	1	1	3	1	3	1	3	3	1	1
F-1420110100010		1	1	1	3	1	1	1	3	3	1	1
F-1001020001000		3	3	1	3	3	1	1	1	3	1	3
F-0110010000000		3	1	1	3	1	1	1	1	3	3	1
Majority Vote:		3	1	1	3	1	1	1	3	3	1	1
Overall Majority Vote:		3	1	1	3	1	1/3	1	1	3	1	3

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