BATTERY LIFETIME PREDICTION BY PATTERN RECOGNITION. APPLICATION TO LEAD–ACID BATTERY LIFE-CYCLING TEST DATA

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Summary

A novel approach to battery lifetime prediction has been evaluated by application to life-cycling data collected for 108 ESB EV-106 6-V golf cart batteries (tests conducted by TRW for NASA-Lewis) This approach utilized computerized pattern recognition methods to examine initial cycling measurements and classify each battery into one of two classes "long-lived" or "short-lived" The classifier program was based on either a linear discriminant or nearest neighbor analysis of a training set consisting of· each member of the EV battery set which had failed, the relative lifetime of each member — normalized with respect to test conditions; and a set of "features" based on measurements of the initial behavior

The raw data set included capacity trends over the first 8 or 9 cycles and records of specific gravity and water-added for each cell after initial cycling Features defined from these raw data included the individual data items as well as transformations and combinations of these data All features were represented as standardized variables. It was shown that lifetime prediction of batteries within the two categories defined could be made with about 87% accuracy. It is concluded that for a similarly-manufactured battery set, relative lifetime prediction could be based on initial measurements of the same type examined here

Introduction

Traditionally, battery lifetime prediction has involved the measurement of lifetimes for a sub-set of a "uniform" population of batteries, and then

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attributing the measured life characteristics of the sub-set to the general population Under ideal circumstances, one could then predict the average lifetime and related variance for a set of batteries, from that same population, operated under specified conditions It has not generally been possible, however, to predict the lifetime of a specific battery relative to other batteries in the population

For many reasons it would be desirable to predict lifetimes of specific batteries in such a way as to discriminate in advance between those which should be "long-lived" or "short-lived" The most obvious advantage would be to allow pre-selection of the most reliable power sources for critical missions such as space exploration or other remote operations

This concept of specific lifetime prediction was explored previously by Byers and Perone [1] for sealed Ni/Cd space cells tested at Crane Naval Weapons Support Center The basic approach involved the use of pattern recognition techniques to determine if measurements of cell initial characteristics could be used to predict the lifetime of specific cells relative to other cells with common origins operated under similar conditions The basic premise was that the ultimate fate of a cell is reflected in a multi-variate examination of its initial fabrication and/or behavioral characteristics These measurements of initial characteristics become the "features" or "descriptors" utilized in pattern recognition analysis to determine if cells which are destined to be "long-lived" can be discriminated from those destined to be "short-lived"

The results of this initial study of pattern recognition lifetime prediction [1] demonstrated that Ni/Cd cells from the same production lot, with similar fabrication and operational conditions, could be categorized from initial measurements with virtually 100% accuracy. Combinations of as few as 1 to 3 features were required to discriminate between predicted "short-lived" and "long-lived" cells These features were derived from manufacturer's pre-test data documenting behavior during initial acceptance cycle tests The most useful features involved measurements of voltage or pressure changes near the end of a charging cycle Cluster analysis of these features suggested that a quantitative value of relative lifetime might be assigned to a specific cell based on the average life of its nearest neighbors in feature space (This last observation was very tentative because of the small size of the individual clusters in the limited data set)

The results of this initial study provide several implications

(i) that for a new set of Ni/Cd cells fabricated identically to the previous set it would be possible to predict lifetimes of specific cells, relative to all other cells operated similarly, based on pattern recognition analysis of initial cycle test data,

(ii) that certain initial measurements may be more sensitive lifetime predictors, and these may be useful in identifying critical fabrication/operational factors dictating lifetime,

(iii) that quantitative lifetime prediction would be possible by applying cluster analysis to a larger data set;

(iv) that imminent failure of batteries might be predicted from monitoring of current cycle behavior

These implications need to be evaluated in a systematic future study One premise of the earlier work which will be investigated here is the general applicability of the observations with Ni/Cd cells to other battery types It is the primary goal of the study reported here to evaluate this premise by applying the same lifetime prediction techniques to a set of lead/acid batteries

The rationale for examining the TRW data base for life-cycling of 108 ESB EV-106 6-V. golf cart batteries [2] is as follows.

the study was well-designed and well-documented; the number of items with common origins and test conditions was sufficiently large for reliable pattern recognition studies (which require a large ratio of patterns to features [3]); and lead/acid batteries represent a mature technology so that positive results could be directly useful

One limitation of the use of the TRW data base, however, is the fact that detailed voltage–time data were not uniformly available Thus, this study was limited to an examination of more indirect evidence of battery characteristics These included capacity trends over the first 8 or 9 cycles, and acceptance test measurements of specific gravity and water addition required for each cell

Description of the TRW data base

The test program undertaken by TRW [2] was designed to apply a daily charge/discharge cycle program to 108 lead/acid 6-V batteries until failure The conditions controlled included characteristics of a chopper-controlled discharge (frequency, duty cycle), average/peak discharge current, and depth of discharge

Over a 2-year life-cycling period, 69 percent. of the batteries failed Experimental correlations showed that battery cycle life was inversely proportional to depth of discharge and discharge current No significant effect on lifetime was detected for different chopper discharge frequencies and duty cycles The failure distribution for items with continuous (d c) discharge current was similar to those items with chopper-controlled discharges.

The failure mode observed involved a gradual loss of capacity to the half-capacity failure point Twenty-three of the failed batteries were subjected to autopsies which showed consistent evidence of cell element aging Every battery examined exhibited short circuits caused by metallic bridging across the plates at separator edges Except for two early failures, every failed item examined exhibited buckled positive plates and oxidized positive grids This uniformity of failure mode and physical aging characteristics establishes a situation for pattern recognition analysis which is much more nearly ideal than for the earlier study with Ni/Cd cells [1].

An introduction to pattern recognition methods

There are many useful techniques for mathematical pattern recognition The reader is referred to any of several useful texts on this subject [4 - 9] for detailed discussion A brief introduction to the concepts will be provided here

Mathematical pattern recognition methods take advantage of the computer's ability to manage multi-dimensional information and perform a series of relatively simple, but numerous, statistical and geometrical computations A generalized pattern recognition procedure involves several steps The first step involves accumulation of observable data (d-dimensional pattern space) from a physical system Because the raw data space may be of large dimension, some reduction of dimensionality is desired to obtain subsequent reliable classification. This step involves the definition of r-dimensional feature space, where $r < d$. The reduction of dimensionality should include identification of those features which correlate most strongly with inter-class information The next step involves application of a decision algorithm appropriate for classifying the individual sources of information into any of Z different classes These decisions are applied in r-dimensional feature space

Classification methods

Various generally-applicable mathematical procedures for pattern classification have been developed Two of these appear to be particularly useful for the studies here One of these involves Linear Discriminant Analysis (LDA) [4, 7], and the other involves the k-Nearest Neighbor (kNN) classification criterion [7, 8].

Trainable pattern classifiers, a sub-class of learning machines [4], are used in Linear Discriminant Analysis The r pieces of information (r features) describing a pattern can be plotted as a point in r-dimensional feature space It is assumed that patterns with similar properties will occupy the same region of feature space. LDA pattern classification involves finding linear boundaries which will discriminate between these spatial regions.

A two-category pattern classifier can be defined by a discriminant function which is a scalar, single-valued function of the pattern If the patterns to be classified are linearly separable, then the discriminant function takes the form

$$s = \sum_{i=1}^{r+1} w_i x_i \qquad (1)$$

where x_i is the ith component of a pattern having r features, x_{r+1} equals one, w_i is the weight corresponding to the ith component, and s is the scalar result The category in which a given pattern is placed is determined by the sign of s

A set of representative patterns of known classes, the training set, is presented sequentially to the classifier When a pattern is incorrectly categorized, the weights of eqn (1) are adjusted in a manner to correct the error If the training set is linearly separable, this procedure will converge to a single weight vector which can correctly classify all the patterns Subsequently, unknown patterns of similar origins can be classified by the trained classifier

The k-Nearest Neighbor classification rule simply states that an unknown pattern is classified according to a majority vote of its k-nearest neighbors in r-dimensional feature space Computationally, the Euclidian distances between the single r-dimensional point representing the pattern in question and all other pattern points in r-space must be calculated to find the nearest neighbors The distance, in r-space, between two points i and j is

$$D_{ij} = \left[\sum_{k=1}^{r} (x_{ik} - x_{jk})^2 \right]^{1/2} \tag{2}$$

Because the distances are a non-linear function of the features, the kNN method can be applied to non-linear classification problems

Feature selection techniques

Feature selection involves reducing the dimensionality of a problem by eliminating pattern descriptors unnecessary for classification and retaining a sub-set of pattern descriptors (features) which are required for classification Statistical feature selection methods of the principal components type work well for data sets with well-defined distribution functions

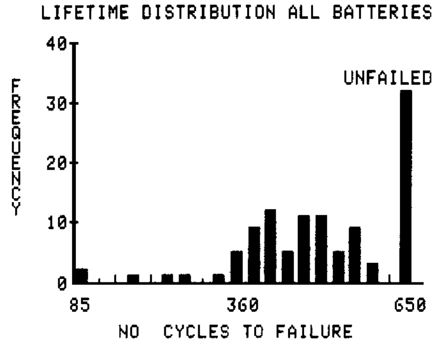
For non-parametric classification problems, various transform methods have been used [10 - 13], as well as a host of other basically empirical approaches However, most workers agree that only an empirical trial-and-error, all-possible-combinations approach guarantees finding the optimum feature set. Thus, in our work a systematic trial-and-error feature elimination procedure was used [13], guided by visual examination of feature plots All-possible-combinations of small feature sets were also used.

Results and discussion

Definition of features and sets for lifetime prediction

Lifetime distributions

Figure 1 shows the overall lifetime distribution for all 108 batteries in the TRW study. (The large block at the upper end of the distribution represents 32 batteries unfailed at the end of the test period of 589 cycles) One of the most crucial steps in the examination of the life-cycling data is the assignment of battery lifetime into various categories such as "short", "long", "average", or other The approach used in the previous study [1] involved the use of naturally-occurring break(s) in the failure distribution(s) to define "long-lived" and "short-lived" classes The same approach was adopted here



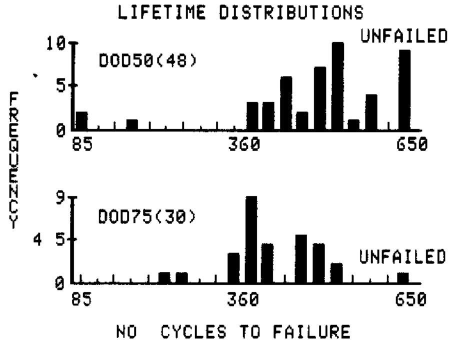


Fig 1 Lifetime distribution for all 108 batteries Large block at upper end represents 32 unfailed batteries after 589 cycles

Fig 2 Lifetime distributions for the DOD = 50 sub-set of 48 items and the DOD = 75 sub-set of 30 items Blocks at upper ends represent unfailed batteries after 589 cycles

The validity of the failure distribution for lifetime categorization depends on the uniqueness of the data sub-set selected The set presented in Fig 1 includes all items regardless of variations in test conditions, and as such is not very useful In this study, for example, it has been observed that lifetime is dependent on depth of discharge (DOD) and on average discharge current (IAV) Figure 2 illustrates the differences in lifetime distributions for DOD = 50 and DOD = 75 (Again, the upper block in each case represents items unfailed after 589 cycles.) Each of these distributions could be further sub-divided into sub-sets with constant IAV Unfortunately, these sub-set limits would be too restrictive for analysis of the TRW data base, because no more than 15 items could be included in a single sub-set Three different nominal depths of discharge were applied — 25, 50, and 75%, and 7 different values of IAV were employed, varying from 20 to 260 A

Because the reliability of pattern recognition assignments decreases significantly when the ratio of patterns to features drops below about 5 [3], it is desirable to utilize a larger pattern set to allow pattern recognition in a higher dimension feature space The basic approach taken here to define larger sub-sets of the test data for lifetime prediction involved, firstly, normalizing the cycle-life characteristic with respect to influential parameters Secondly, the items were grouped according to DOD in examining the failure distributions This allowed the identification of 3 sub-sets, corresponding to the 3 DOD values, 25, 50, and 75 Because only 27% of those in the first sub-set had failed (8 items) by the end of the test program, that sub-set was not useful here The other two sub-sets had 81% and 97% failures (39 and 29 items, respectively), and were useful sub-sets for pattern recognition

Normalized lifetime distributions

Normalization of the cycle-life characteristic was accomplished according to one of two relationships The first was referred to as "REGLIFE" It was equated to the deviation of observed lifetime from the regression fit to the expression

$$FLCYNO = A + B*IAV \tag{3}$$

where FLCYNO is the number of cycles to failure, and IAV is the average discharge current The constants, A and B, are determined from a fit to all data where DOD is constant Then, for each failed battery in the DOD sub-set, the value of REGLIFE is calculated

$$REGLIFE = FLCYNO - A - B*IAV \tag{4}$$

The second normalization function was based on the calculation of a relative lifetime, referred to as "RELIF" It was equated to the ratio of the observed lifetime for a specific battery to the average lifetime for all other batteries where DOD and IAV are the same

$$RELIF = FLCYNO/AVG(FLCYNO) \tag{5}$$

The distributions of REGLIFE and RELIF were determined for all batteries in the two sub-sets corresponding to DOD = 50 and 75 (For convenience, these will be referred to as the DOD50 and DOD75 sub-sets) For the DOD50 sub-set, the maximum number of members was 48 However, 3 batteries failed prematurely at less than 173 cycles and were eliminated arbitrarily from consideration This provided a useful sub-set of 45 items Nine batteries had not failed by the end of the test period. (Six of these 9 were tested under the least strenuous conditions (IAV = 20 A)) Each of these items was assigned an arbitrary lifetime of 625 cycles, obtained from an extrapolation of a plot of lifetimes *vs* IAV The maximum measured lifetime was 589 cycles, after which the test was discontinued The median lifetime for the DOD50 sub-set of 45 items was 495 cycles.

For the DOD75 sub-set, the maximum number of members was 30 There were no premature failures. Only one battery was unfailed at the end of the test period It was assigned an extrapolated arbitrary lifetime of 600 cycles The median lifetime for the 30-item DOD75 sub-set was 403 cycles

The values of the regression constants determined from the fits to eqn. (3) for the DOD50 and DOD75 sub-sets are listed in Table 1. Figures 3 and 4 present the distributions of REGLIFE and RELIF for the DOD50 and DOD75 sub-sets of 45 and 30 items, respectively By contrast with Fig. 2, it

TABLE 1

Regression constants for fits to eqn (1)

Test sub-set	Regression constants	
	A (cycles)	B (cycles/A)
DOD50	608 9	−0 7864
DOD75	444 7	−0 2526

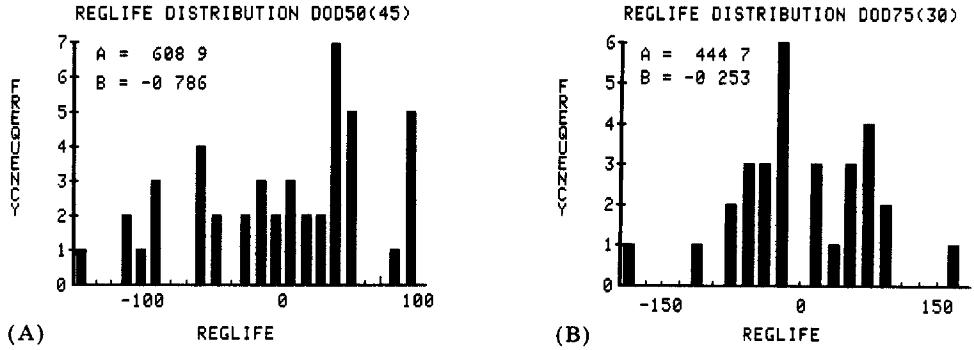


Fig 3 Lifetime distributions based on REGLIFE normalization function (REGLIFE = FLCYNO $- A - B*I$AV) (A) For DOD = 50 sub-set of 45 items, with 3 premature failures excluded (B) For DOD = 75 sub-set of 30 items

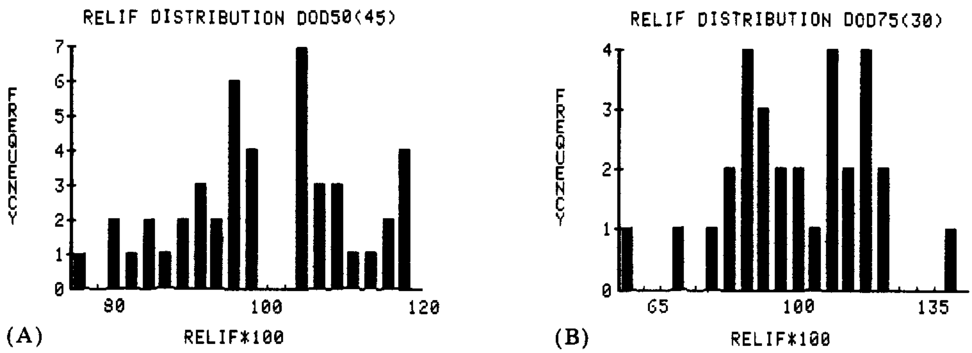


Fig 4 Lifetime distributions based on RELIF normalization function (RELIF = FLCYNO/AVG(FLCYNO)) (A) For DOD = 50 sub-set of 45 items, with 3 premature failures excluded (B) For DOD = 75 sub-set of 30 items

appears in each case that the DOD50 and DOD75 distributions might be combined into a single set However, subtle differences in the DOD50 and DOD75 distributions are observed for both REGLIFE and RELIF One of these differences is obvious in comparing the ranges of the distributions for the DOD50 and DOD75 sub-sets in Figs 3 and 4 In both cases the DOD75 range is considerably broader than for the DOD50 range Another fundamental difference becomes clear when class boundaries are defined by pattern recognition as discussed below

Categorization

Examination of Figs 3 and 4 shows that some natural breaks appear in the normalized failure distributions These can be used as a first cut assignment of lifetime classes for pattern recognition. For example, in Fig 3(A) and (B) it appears that several possible "breaks" might be considered to distinguish between "short-lived" and "long-lived" classes. The obvious breaks in Fig 3(A) occur at REGLIFE values of ~(−80, −35, and +70), those in Fig 3(B) occur at REGLIFE values of ~(−150, −80, 0, and +100) However, several other breaks appear when any regions of the histograms are expanded

The selection of any particular boundary for categorization depends on two things One of these is the purpose of the categorization. For example, several different binary categorizations could be considered, where the purposes might be to identify the very best cells, the very worst cells, or to simply distinguish between the two classes "better" and "worse". In addition, a 3-class categorization could be considered which included the best, worst, and middle classes Arbitrary boundaries can be assigned based on naturally occurring breaks once the purpose has been defined. For example, if a simple binary categorization of "better/worse" is desired, the first-cut boundaries for Fig 3(A) and (B) might be −36 and 0, respectively

The second criterion for selection of category boundaries is based on the observed performance of the selected boundary for pattern recognition classification of cells with known performance The selected boundaries can be further refined by adjusting them for optimum classification accuracy from pattern recognition examination of measurement features

Definition of features for pattern recognition

The features used for pattern recognition lifetime prediction were taken from documentation of the preliminary examination and initial acceptance tests applied to all EV-106 batteries prior to commencing life-cycle testing. These included measurements of the specific gravities, battery weights, and volume of water required to achieve uniform levels for each cell/battery as received, as well as discharge capacity values over 8 or 9 acceptance cycles

These initial acceptance data were used to generate pattern features for each battery The most useful features fell into 4 categories

(i) Initial Specific Gravity
(ii) Initial Water Volume Added
(iii) Initial Capacity Trends
(iv) Transformed/Combined Variables

A total of 10 features proved to be useful, and these are summarized in Table 2

A summary of the variances of each of the pattern features for two different sub-sets is provided in Table 3 Because of the wide disparity in values of the features, all pattern recognition studies were conducted with standardized variables, where the standardized value, $x(s)$, is defined

$$x(s) = (x(i) - x(\text{ave}))/(\text{s.d}) \qquad (6)$$

Thus, the ranges of all standardized variables were ~(+/−3)

As expected, some of the features were highly correlated However, as observed in previous studies [13 - 15], the use of statistically correlated features can be justified and useful for pattern recognition where normal distributions are not observed. This is certainly the case for our data.

TABLE 2

Classification features for each EV-106 battery based on EV-106 acceptance tests

Name	Type	Description
	Specific gravity	
AVSG		Average specific gravity 3 cells
	Water volume added	
MXH		Volume for cell requiring most water
	Initial capacity trends	
INCAP		Average capacity of acceptance cycles
MXCP		Maximum capacity from acceptance cycles
MNCP		Minimum capacity from acceptance cycles
	Transformed variables	
AVSG2		$(AVSG)^2$
MXH2		$(MXH)^2$
SGH		AVSG*MXH
DLCP		MCXP − MNCP
INDL		INCAP/DLCP

TABLE 3

Feature values for two sub-sets

Feature	DOD50 (45)		DOD75 (30)	
	Avg	S D	Avg	S D
AVSG	1 278	0 006	1 278	0 004
AVSG2	1 633	0 014	1 634	0 010
MXH (ml)	91 8	38 7	91 7	36 4
MXH2 $(ml)^2$	9888	7728	9682	7031
SGH (ml)	$11\ 7 \times 10^4$	$4\ 2 \times 10^4$	$11\ 7 \times 10^4$	$4\ 6 \times 10^4$
INCAP (A h)	106 9	1 5	107 2	1 1
MXCP (A h)	114 2	2 1	113 7	2 2
MNCP (A h)	103 8	2 1	104 3	1 1
DLCP (A h)	10 4	2 3	9 5	2 2
INDL	10 8	2 4	11 9	2 5

The selection of an optimum feature set for classification is a crucial part of any pattern recognition study, and the procedure used here is described below

Data analysis

Classification procedures

Two different techniques were used for pattern recognition lifetime prediction Linear Discriminant Analysis (LDA), and *k*-Nearest Neighbor analysis (*k*NN) (These were discussed in an earlier section) The LDA method allows accurate classification when classes can be separated by a linear boundary (line, plane, hyperplane) in feature space Once a discriminant function is found which provides accurate classification, the application of this function to pattern recognition is computationally simple However, the restriction to linearly separable classes precludes application in many cases

The kNN method allows accurate classification as long as items of similar class form clusters in feature space These need not be linearly separable for classification, as long as significantly different spatial distributions are obtained However, the kNN algorithm requires much more extensive computations at the time of classification

For simplicity, a value of $k = 1$ was used for nearest neighbor calculations A "leave-one-out" procedure was used to evaluate classification accuracy That is, each item was removed from the training set, and treated as an item of unknown class Its class is then assigned to be the same as its nearest neighbor It is then returned to the training set, and the next item is removed for classification

An iterative feature-weighting procedure was also used in the kNN method here That is, feature weights were systematically varied by multiples of 2 to obtain an optimum combination of weights for maximum accuracy.

Feature plots

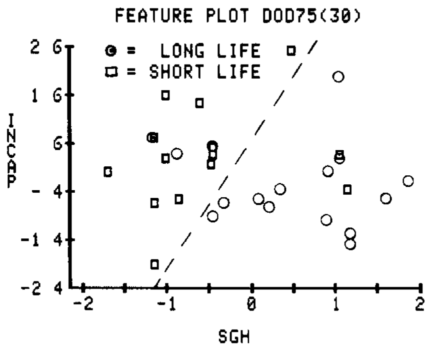
An examination of pattern distributions in feature space provides useful insight to the applicability of LDA or kNN classification techniques Figure 5 shows a feature plot of INCAP and SGH for the DOD75 sub-set, where class assignments were based on the optimum boundary for the REGLIFE distribution (discussed below) In this case the two classes are linearly separated in 2-d feature space Thus, the LDA method works very well for classification One possible linear boundary which would provide accurate classification is also illustrated in Fig 5 The kNN method does not work well for this distribution

Figure 6 shows a weighted feature plot of INDL and MXH2 for the DOD50 sub-set, where class assignments were based on the optimum boundary for the REGLIFE distribution Clearly, the long-lived and short-lived classes exhibit different distributions, but are not linearly separable in 2-space When a third feature (SGH) is added, the class distributions become separated sufficiently to allow accurate kNN classification (see Results Section)

Feature elimination procedures

Two different methods were used to obtain a minimum feature set for optimum classification One of these involved using all possible combinations of 1, 2, or 3 features from those defined in Table 2 The other involved a sequential elimination procedure [13]

The sequential elimination procedure involved first conducting classification with all features used Then one feature is removed and classification is again conducted. If classification accuracy is unchanged or improved, the feature is permanently eliminated. If not it is returned to the feature set.



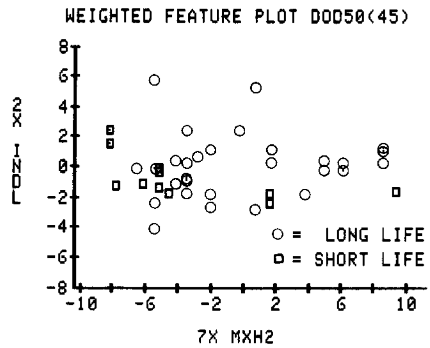


Fig 5 Feature plot for DOD = 75 sub-set of 30 items Lifetime class assignments based on optimum boundary from REGLIFE distribution (see Table 4) (REGLIFE = FLCYNO $- A - B*I$AV)

Fig 6 Weighted feature plot for DOD = 50 sub-set of 45 items Lifetime class assignments based on optimum boundary from REGLIFE distribution (see Table 5) (REGLIFE = FLCYNO $- A - B*I$AV)

This process continues until a minimal feature sub-set is obtained where no further improvement in classification accuracy is observed by elimination This method proved useful for minimal feature sets greater than 3 However, the elimination sequence is too arbitrary to guarantee identification of the optimum feature sub-set, particularly for small sets The all-possible-combinations approach was practical and effective for up to 3 features

Optimizing class boundaries from lifetime distributions

Although several different category definitions were used in this study, this report focusses on the simple binary classification issue where batteries were simply divided into longer-lived and shorter-lived classes It was expected that this would lead to some overlap in the middle, and that less than 100% accuracy would be achieved. However, identification of these two classes appeared to be a realistic goal for real applications of these methods to battery lifetime prediction When only high accuracy was the goal we were able to achieve that by discriminating only the very best or the very worst batteries from the rest

The method used to identify the optimum class boundaries from lifetime distributions involved, first, selecting arbitrarily, a naturally-occurring break in the distribution Pattern classification was applied to the defined classes as a training set, and the resultant accuracy observed The boundary was then adjusted in either direction searching for maximum classification accuracy

Classification results

Examination of Tables 4 and 5 verifies that pattern recognition provides accurate prediction of lifetime class based on battery acceptance test data Both the LDA and *k*NN methods proved useful The LDA method

TABLE 4

Summary of classification results with linear discriminant analysis (Long-lived batteries = class 1, short-lived = class 2)

DOD	Data base sub-set		Classification criterion/boundary	Features required	Classification results		
	No items	Class distribution (1)/(2)			% correct	%(2)	%(1)
50	39(a)	29/10	RELIF/(0 909)	(5) AVSG2, MXH2, SGH, INDL, INCAP	87 2	100	82 8
50	45	38/7	RELIF/(0 877)	(4) MXH2, SGH, INDL, INCAP	85 5	84 2	5 7
50	44(b)	32/12	REGLIFE/(−34 34) A = 608 9 B = −0 7864	(3) SGH, INDL, INCAP	81 8	92 0	78 0
75	30	16/14	RELIF/(0 977)	(2) SGH, INCAP	83 3	85 7	81 2
75	30	16/14	REGLIFE/(−15 04)	(2) SGH, INCAP	83 3	85 7	81 2
50/75	69(a)	57/12	RELIF/(0 878)	(4) MXH2, INDL, DLCP, INCAP	81 2	75 0	82 5

(a) Features of batteries with IAV = 20 removed from data base (All but one unfailed at end of test)
(b) One battery (s/n = 16) removed from data base because of anomalously low life for IAV = 20

TABLE 5

Summary of classification results with K-nearest neighbor analysis (Long-lived batteries = class 1, short-lived = class 2)

DOD	Data base sub-set		Classification criterion/boundary	Features required	Classification results		
	No items	Class distribution (1)/(2)			% Correct	%(2)	%(1)
50	39(a)	29/10	RELIF/(0 909)	(3) AVSG2, MXH2, DLCP	87 2	70 0	93 1
50	45	32/13	REGLIFE/(−34 34) A = 608 9 B = −0 7864	(3) MXH2, SGH, INDL	84 4	84 6	84 4
75	30	17/13	RELIF/(0 953)	(2) SGH, DLCP or MXH2, DLCP	66 7	69 2	64 7
75	30	18/12	REGLIFE/(−22 2) A = 444 7 B = −0 2526	(2) SGH, INDL or MXH2, INDL	76 7	66 7	83 3
50/75	69(a)	57/12	RELIF/(0 878)	(4) AVSG2, MXH2, SGH, INCAP	85 5	50 0	93 0

(a) Features of batteries with IAV = 20 removed from data base (All but one (s/n = 16) were unfailed at end of test) provided the most accurate lifetime classifications for all sub-sets For each sub-set, overall classification accuracy of ~85% was achieved Best results were obtained for the DOD50 sub-set, where classification accuracy for short-lived batteries approached 100% High accuracy in identifying potential short-lived batteries provides a significant incentive for practical applications of predictive lifetime classification

There did not appear to be any significant advantage for either of the two lifetime normalization methods, REGLIFE or RELIF Both worked well However, the RELIF distribution was the only one that could be used for the DOD50/75 sub-set because the REGLIFE distributions for DOD50 and DOD75 were so different

The size of the DOD50 sub-set was varied in these studies to examine the effects of various anomalies in the test items These are documented in Tables 4 and 5 The primary concern was how to handle the batteries which had not failed by the end of the test In one case (DOD50 sub-set with 39 items, (DOD50 (39)) all batteries where *I*AV was 20 A were excluded, as most of these had not failed by the end of the test. The classification accuracy for this sub-set was the highest of all, with short-lived batteries being identified with 100% accuracy

Another questionable test item was a battery (s/n = 16) in the DOD50 sub-set which had an exceptionally low lifetime (438 cycles) for an *I*AV of 20 A Because all other batteries tested under these conditions were unfailed at the end of the test (589 cycles), this battery might be considered anomalous. By way of confirmation, an autopsy [2(a)] of this battery revealed that the negative plates were "hard and dry", a condition not found in any of the other autopsies Thus, this item was excluded from some of the sub-sets examined Also, this battery was excluded from regression analysis of the DOD50 sub-set Thus, the REGLIFE distribution is based on the lifetimes of a 44-battery DOD50 sub-set

The boundary values of REGLIFE and RELIF required for optimum classification accuracy are listed in Tables 4 and 5 It is interesting to note that for both distributions the optimum boundary between short-lived and long-lived cells is shifted to larger values for the DOD75 sub-set compared with the DOD50 sub-set This results in a larger percentage of batteries being categorized as "short-lived" in the DOD75 sub-set This is not inconsistent with the fact that the actual depth of discharge was ~93%, as pointed out in the TRW/NASA report [2] Moreover, for large values of *I*AV, the effective depth of discharge approaches 100% Thus, it is not surprising that the fraction of batteries which cluster together as a short-lived group is larger for the DOD75 sub-set Also, the relatively poor classification accuracy obtained when the DOD50 and DOD75 sub-sets are combined is very likely explained by the significantly different distributions of the two classes for the two sub-sets

The validity of the pattern recognition results is substantiated by the low ratio of features to patterns required for accurate classification in each case The largest ratio required was for the DOD50 (39) sub-set with the

LDA method (~1:8), (Table 4) Typically, the ratio required was ~1 15 In any case, the ratios obtained were much lower than required (~1 5) for credible pattern recognition classification [3]

The most useful features for predictive lifetime classification appeared to be SGH and INCAP, based on the high frequency of their appearance in the minimum feature sets for accurate classification This observation is certainly consistent with the intuitive perception that differences in specific gravity, water added, and initial capacity trends should be meaningful predictors of battery life It is clear, however, that the relationships between all features studied and battery lifetime are non-linear and multivariate

Conclusions

This study has clearly demonstrated the feasibility of predictive lifetime classification for uniformly fabricated lead–acid batteries Moreover, the utility of acceptance tests documenting trends in specific gravity, water added, and initial capacity has been shown. The accuracy of predictive classifications is sufficiently high, particularly for the identification of short-lived batteries, for the practical application of this method to be explored

Perhaps of more importance is the fact that this type of study may provide new insight to factors which affect battery life — as reflected in the useful features for predictive lifetime classification For example, we should like to know why water-added is a sensitive indicator To examine such questions, we are currently undertaking a new study documenting added water and acid content changes (as well as other measures) during acceptance cycles in a life-cycling experiment with lead–acid batteries

The general applicability of the predictive features and the classification methods studied here for lead–acid batteries of various origins remain to be investigated In addition, it is desirable to examine the utility of more-detailed charge–discharge voltage trend data for predictive lifetime classification Moreover, it would be desirable to examine a significantly larger population of test articles to evaluate the feasibility of quantitative lifetime prediction which had been suggested in the earlier study with Ni/Cd cells [1]

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