Journal of Power Sources, 21 (1987) 333 - 337

STATISTICALLY DETERMINED NICKEL-CADMIUM PERFORMANCE RELATIONSHIPS

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Summary

Statistical analyses of performance and design parameters are shown to be extremely useful in improving product consistency for aerospace cells by highlighting significant differences between lots.

Considerable amounts of data are customarily taken on aerospace nickel–cadmium cells to control manufacture, to verify that the cells will be acceptable, and to select well-matched cells for assembly into batteries. These data provide an opportunity for statistical analysis on data distribution and the interrelationships between parameters. This information can be helpful in understanding behavior, for use in quality control, and in identifying possible problems with individual cells or with lots of cells and even for manufacturing process control (Table 1). This is also a logical approach for analysis of a common data pool for Ni/Cd cells. Since the data required

TABLE 1

Advantages of statistical data analysis

Technology
- Investigate interrelationships between parameters
- Help understand behavior

Manufacturing processing control
- Identify long-term changes in processes
- Identify batch-to-batch differences
- Common data pool for Ni/Cd cells

Quality control
- Identify problems with individual cells
- Identify problems with cell lots
- Help select matched cells for batteries

Cost
- Data are already available
- Computerized data-handling will save money
- Analysis can help screen out unnecessary tests

Elsevier Sequoia/Printed in The Netherlands

TABLE 2

Basis for analysis

- 30 A h sealed Ni–Cd cells
- Used manufacturing data and cell matching data
- 213 data parameters were investigated; *e.g.*,
    - Plate thickness
    - Amount of electrolyte
    - Weight of active material
    - Positive and negative capacity
    - Charge–discharge behavior
    - Many others
- Multiple manufacturing lots

TABLE 3

Statistical analysis

- Maximum and minimum values
- Arithmetic mean
- Variance
- Standard deviation
- Skewness
- Kurtosis
- Data histograms
- Correlations between test events

for analysis are already available during manufacture, there is little additional cost involved for data acquisition. In fact, computerized data handling will save money in data processing. Furthermore, data analysis should be able to help screen out unnecessary tests, for additional cost saving.

A statistical analysis was performed on sealed nickel–cadmium cell manufacturing data and cell matching data. The cells subjected to the analysis were 30 A h sealed Ni/Cd cells made by General Electric Co. A total of 213 data parameters was investigated, including such information as plate thickness, amount of electrolyte added, weight of active material, positive and negative capacity, and charge–discharge behavior (Table 2). Statistical parameters determined include the maximum and minimum values, arithmetic mean, variance, standard deviation, skewness, kurtosis, and data histograms (Table 3 and Fig. 1). Statistical analyses were made to determine possible correlations between test events; for example, if there is any connection between end of charge voltage and pressure, or between electrolyte amount and capacity.

The data show many departures from normal distribution. Some departures are inherent in the physical behavior of cells, and others are due to

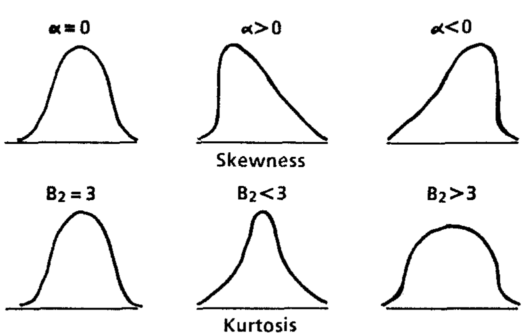

Fig. 1. Schematic representation of statistical terms used.

TABLE 4

Pressure effects

Pressure at 72 h of charge *vs.*	Correlation coefficient			
	Lot 5	Lot 6	Lot 7	Lot 8
Voltage at 72 h	0.097	0.390	0.264	0.255
Pressure at 20 h	0.663	0.589	0.447	0.792
Pressure at 120 min of discharge	0.492	0.582	0.916	0.799
Pressure at end of charge, last cycle	0.484	0.343	0.604	−0.222

TABLE 5

Open circuit voltage effects

Open circuit voltage 24 h after removing shorting wires *vs.*	Correlation coefficient			
	Lot 5	Lot 6	Lot 7	Lot 8
OCV 1.0 h after removing wires	0.306	0.319	0.942	0.972
OCV 24 h after 15 A, 1.0 min charge following 16 h shorting	−0.054	0.637	0.003	0.998

TABLE 6

Cell thickness effects

Cell center thickness *vs.*	Correlation coefficient
	Lot 8
OCV 24 h after 15 A, 1.0 min charge following 16 h shorting	0.996
Final cell weight	0.997

manufacturing bias. For example, in one lot of cells, the data fall in two distinct groups, which were identified as caused by manufacturing variations from batch processing. Skewing of pressure data sometimes occurred very strongly and appeared to be related to removal and rework of the high pressure cells.

Statistical relationships between data obtained during one test event and another were also obtained. The analysis used was the rank-difference method for coefficient of correlation, producing coefficients that can range from −1.0 to +1.0 for perfect negative correlation and perfect positive correlation, respectively. Completely random results would yield a correlation of 0. For example, the relationship between cell pressures for 30 A h cells at two unrelated test conditions was evaluated 20 h into the charge at 3.0 A and 75 °F *versus* 72 h into the charge at 1.5 A and 32 °F. Correlation coefficients for five lots averaged 0.62, showing that there is a definite

TABLE 7

End of charge voltage effects

End of charge voltage at cycle 31 *vs.*	Correlation coefficient			
	Lot 5	Lot 6	Lot 7	Lot 8
EOCV at cycle 1	1.000	1.000	1.000	0.999
Capacity to 1.0 V	0.999	1.000	0.871	0.990
KOH final volume	0.131	−0.061	0.186	0.976

TABLE 8

Capacity effects

Capacity to 1.0 V (*C*/10 chg. 14 h, *C*/2 disch. 75 °F) *vs.*	Correlation coefficient			
	Lot 5	Lot 6	Lot 7	Lot 8
Capacity to 1.15 V, same test (B)	0.996	0.999	0.912	0.560
Capacity to 1.0 V, test 7	0.191	−0.116	0.187	0.811
End of charge voltage, cycle 31	0.999	1.000	0.871	0.980

relationship (Table 4). Pressure at 72 h of charge also correlates with pressure after 2 h of discharge. Pressure does not correlate very well with voltage, however, and its correlation with pressure at the end of charge on the last cycle is good for only one of the four lots.

Sometimes two parameters would show a strong positive correlation for some lots but not for others. This behavior appeared to be the result of important differences between lots. In analyses of five lots, this was found to be the case for correlations of pressure *versus* voltage (ranging from 0.097 to 0.47), early life pressure *versus* pressure after cycling (ranging from −0.187 to 0.604), end of charge voltage *versus* KOH volume (ranging from 0.026 to 0.987), open circuit voltage 24 h after removing shorting wires *versus* 1.0 h afterwards (ranging from 0.306 to 0.972, Table 5), and also *versus* open circuit voltage 24 h after 15 A, 1.0 min charge following 16 h shorting (−0.054 to 0.998, Table 5).

Occasionally, there are interesting surprises, though upon reflection these are understandable. For example, the thickness of the cells, measured at the center, correlates very well with the final cell weight (Table 6), and also correlates well with the open circuit voltage 24 h after a 15 A, 1.0 min charge following 16 h shorting. Data are not available to determine whether these correlations would hold for other lots also.

The end of charge voltage after 31 cycles is found to correlate well with that same voltage at the first cycle (Table 7). It also correlates well with capacity. In only one of the four lots did the KOH final volume and the end of charge voltage appear to be related.

The capacity to 1.0 V and the capacity to 1.15 V were found to be closely related, though with some departure for one of the lots. Interestingly, the capacity to 1.0 V on one test did not correlate, for three of the four lots, with the capacity to 1.0 V for another test (Table 8). The test conditions for test 7 were $C/20$ charge for 72 h at 0 °C, and discharge at $C/2$ at 0 °C.

Product consistency from one lot to another is an important criterion for aerospace applications. It is clear from these examples that there are some significant differences between these lots. Statistical analyses are seen to be an excellent way to spot those differences.

Acknowledgement

This paper is based upon work performed under JPL Contract 953984, W.O. 342-19. The support and suggestions by Sam Bogner are gratefully acknowledged.