USE OF SAS PROCEDURES IN ESTIMATING SURVIVAL CURVES

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ABSTRACT


If a particular parametric family of distributions is assumed (as is often the case in human or animal survival studies) then maximum likelihood techniques are appropriate to estimate the parameters of the life distributions of interest. From estimates of these parameters one can estimate the average life expectancy along with other pertinent quantities of interest. This paper will present an application of SAS procedures (viz., PROC NONLIN and PROC MATRIX) towards finding such maximum likelihood estimates along with their estimated asymptotic variances. An example dealing with breast cancer will be used to illustrate the technique.

INTRODUCTION

It is often desirable to assess statistically the life characteristic of various types of individuals. These individuals may be living organisms, e.g., interest may center upon making inferences regarding the length of life after some treatment has been applied or some operation has been performed on animals or human beings; or they may be inanimate objects, e.g., light bulbs, electrical components such as fuses or vacuum tubes, and various kinds of physical equipment such as ball bearings. In either situation the lifetime of an individual generally means the time from some starting point to failure of the individual under consideration. It is assumed that the lifetime of an individual is a random variable with a certain underlying distribution, usually of the continuous type.

The specific example we shall use in this paper is one in which patients are treated for cancer of the breast and remain under observation until death or the conclusion of the study. Also, the specific underlying life distribution will be taken to be the Weibull. Interest in such a study usually centers on estimating the survival curve and subsequent estimation of average life expectancy. We wish to use the method of maximum likelihood estimation primarily because of its tractability and also because the estimators of parameters characterizing the survival curve possess desirable properties. Thus the purpose of this paper is to discuss possible uses of SAS procedures in maximizing a likelihood function (or, equivalently, minimizing the negative of the function).

POSSIBLE METHODS OF SOLUTION

Many optimization schemes exist for finding the minimum of a function. A widely used scheme is Marquardt's method which is a compromise between steepest-descent and Gauss-Newton methods. The SAS76 nonlinear regression procedure, NONLIN, estimates the parameters \( \beta \) for the function \( f(\beta, \gamma) \) such that 
\[
(y-f(\beta, \gamma))^2
\]

is minimized where \( y \) is the dependent variable and \( \gamma \) represents the independent variables. If \( y \) is defined to be zero, then NONLIN can find the values of \( \beta \) which will minimize the square of the function \( f(\gamma, \beta) \). However, these values of \( \beta \) may not minimize the function itself.

If there is only one parameter, \( \beta \), then \( f(\gamma, \beta) \) may be minimized by using NONLIN to minimize 
\[
(y-f(\gamma, \beta))^2
\]

where \( y \) is the first derivative of \( f \) with respect to \( \beta \) and \( y \) equals zero. Sometimes, it is not possible to find the minimum of a function with respect to several parameters by NONLIN. Some simplifications of the first partial derivatives of \( f \) must be possible. One possible simplification is that the \( p \) equations, resulting from setting the first partial derivatives equal to zero, in \( p \) parameters reduces to one equation in one parameter, say \( \beta^* \), and \( (p-1) \) equations which define the other \( (p-1) \) parameters in terms of \( \beta^* \). The function is minimized with NONLIN by solving for \( \beta^* \) in the first equation and

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then substituting that value in the remaining 
(p-1) equations to solve for the remaining 
parameters.

Thus, minimizing functions by the nonlinear 
regression routine may be very laborious and 
awkward. It may also be very difficult to find 
the variance-covariance matrix associated with 
the estimated parameters.

To circumvent the above problems, a SAS76 
Macro involving PROC MATRIX using Marquardt's 
method was written to find the minimum or 
maximum for a broad class of functions. The 
Macro is illustrated in the data analysis 
section and sample output is given in Appendix A.

DESCRIPTION OF THE ALGORITHM

Let \( f(\theta) \) be a function of \( p \) parameters 
\( \theta_1, \theta_2, \ldots, \theta_p \), where \( \theta = (\theta_1, \ldots, \theta_p) \). It is 
desired to minimize \( f \) (or maximize \( -f \)) with respect to the parameters \( \theta \). Let \( g' \) be 
the vector \( (\partial f / \partial \theta_1, \ldots, \partial f / \partial \theta_p) \) and \( H \) be 
the matrix \( \{(\partial^2 f / \partial \theta_i \partial \theta_j)\} \), \( i,j=1, \ldots, p \).
Marquardt's (1963) method (cf. Smith and Shanno 
(1971)) basically employs the following 
iteration procedure. If \( \theta_0 \) is an initial 
estimate of \( \theta \), then the first order 
approximation to \( \theta \) will be denoted by \( \theta_1 \) and 
is found by

\[
\theta_1 - \theta_0 = \left( I + C \right)^{-1} g,
\]

where the square matrix \( C \) may be chosen so as to 
accelerate convergence or avoid singularities. 
We select \( C = \lambda I \) where \( \lambda \) is a non-negative 
constant sometimes referred to as a "blending 
parameter" allowing one to combine the better 
features of the method of steepest-descent and 
the Gauss-Newton iteration method. For the 
first iteration \( \lambda \) is given a value slightly 
larger than 0 (say .01, if a good initial 
estimate \( \theta_0 \) is available). If \( f(\theta_1) > f(\theta_0) \), 
we are experiencing difficulty in minimizing 
(maximizing) \( f \) and the value of \( \lambda \) needs 
to be increased until \( f(\theta_1) < f(\theta_0) \). This 
procedure is then iterated until 
convergence is attained.

Since it is well known that the properties 
of Marquardt's procedure are not scale-

invariant, we impose the usual scaling 
technique, viz., divide the \((i,j)\)-th element of \( H \) by 
\[
\left( \frac{1}{2} \frac{\partial^2 f}{\partial \theta_i \partial \theta_j} \right)^{1/2} \]

and divide the \( i \)-th element of the vector \( g \) by 
\[
\left( \frac{1}{2} \frac{\partial f}{\partial \theta_i} \right)^{1/2}
\]

The resulting incremental vector may be written 
as 
\[
\theta_1 - \theta_0 = -S \left( I + C \right)^{-1} S g,
\]

where \( S \) is a \( p \times p \) diagonal scaling matrix with 
diagonal element \( \left( \frac{1}{2} \frac{\partial^2 f}{\partial \theta_i ^2} \right)^{1/2} \). 
This scaling device places 1's on the diagonal of \( S H S \) 
and serves to improve the computation properties 
of the algorithm.

Since the parameters in our particular 
problem are limited to a certain region, large 
incremental jumps, \( \theta_1 - \theta_0 \), must be reduced 
until the new parameter value \( \theta_1 \) is confined to 
the desired region.

BREAST CANCER DATA

This study (Boag, 1949) involves 121 
patients treated for cancer of the breast by 
surgery and/or X-ray therapy in a particular 
hospital. Each of the patients entered the 
study at the time of treatment and remained 

<table>
<thead>
<tr>
<th>Table 1. Boag's Data*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Survival times (in months) of those</td>
</tr>
<tr>
<td>Who died with cancer present</td>
</tr>
<tr>
<td>---------------------------</td>
</tr>
<tr>
<td>0.3 12.2 17.5 28.2 41 78</td>
</tr>
<tr>
<td>5.0 12.3 17.9 29.1 42 80 4.0 111</td>
</tr>
<tr>
<td>5.6 13.5 19.8 30.0 44 84 7.4 112</td>
</tr>
<tr>
<td>6.2 14.4 20.4 31 46 87 15.5 132</td>
</tr>
<tr>
<td>6.3 14.4 20.9 31 48 89 23.4 162</td>
</tr>
<tr>
<td>6.6 14.8 21.0 32 48 90 48</td>
</tr>
<tr>
<td>6.8 15.7 21.0 35 51 97 46</td>
</tr>
<tr>
<td>7.5 16.2 21.1 35 51 98 51</td>
</tr>
<tr>
<td>8.4 16.3 23.0 38 52 100 65</td>
</tr>
<tr>
<td>8.4 16.5 23.6 39 54 114 60</td>
</tr>
<tr>
<td>10.3 16.8 24.0 40 56 126 83</td>
</tr>
<tr>
<td>11.0 17.2 24.0 40 60 131 88</td>
</tr>
<tr>
<td>11.8 17.3 27.9 41 78 174 96</td>
</tr>
</tbody>
</table>

*Up to 30 months the survival times are given to the nearest 
tenth of a month and after 30 months the survival and follow-up 
times are given to the nearest month.
under subsequent observation until death or the conclusion of the study. All surviving patients were in the study for at least 110.5 months. The stage of advancement of the cancer was estimated by the clinician when the patient first presented herself for treatment and cases in which the spread of the disease had become so extensive as to prohibit any cure by treatment were excluded from the study. The data appears in Table 1.

**MAXIMIZATION OF LIKELIHOOD FUNCTION**

The Weibull probability density function is of the general form

\[ p(y) = \frac{\gamma c}{\beta} y^{c-1} \exp\left(-\frac{y^c}{\beta}\right) \quad y>0, \beta>0, \gamma>0, \]

where \( y \) is the time to failure and \( \beta \) and \( \gamma \) are parameters of the distribution.

The negative of the logarithm of the appropriate function to maximize is (cf. Moeschberger and David, 1971).

\[ -\log L = m \log \beta - \log \gamma - (\gamma-1) \sum_{i=1}^{m} \log y_i \]

\[ + \sum_{i=1}^{m} \left[ y_i^{\gamma} - \beta^{\gamma} \right] \]

where, \( m \) denotes the number of failures from the cause of interest,

\( r \) denotes the number of censored observations (i.e., those who did not die from the cause of interest),

\( y_i \) denotes the failure times of those who died from the cause of interest,

and \( B_j \) denotes the censoring times of those who did not die of cause of interest.

See Appendix A for an application of this likelihood function with respect to Cause 1, Cause 2, and general death (Cause 1 and Cause 2 combined).

**ANALYSIS**

Table 2 presents the parametric estimates of the survival curves discussed in the previous section, along with their estimated asymptotic standard deviations. Also, the estimated expected lifetimes and median lifetimes are given for the three cases previously discussed.

<table>
<thead>
<tr>
<th>Cause 1</th>
<th>Cause 2</th>
<th>Lifetime</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>40.97</td>
<td>581.00</td>
</tr>
<tr>
<td>est. s.d.</td>
<td>.8356</td>
<td>1.0578</td>
</tr>
<tr>
<td>est. s.d.</td>
<td>18.22</td>
<td>552.15</td>
</tr>
<tr>
<td>est. s.d.</td>
<td>.0793</td>
<td>.2005</td>
</tr>
<tr>
<td>(est. mean) yrs.</td>
<td>9.65</td>
<td>33.45</td>
</tr>
<tr>
<td>(est. median) yrs.</td>
<td>5.65</td>
<td>24.19</td>
</tr>
</tbody>
</table>

Other quantities of interest in competing risk theory may be obtained, namely, estimates of crude probabilities, net probabilities, and partial crude probabilities of death within specified intervals (cf. David and Moeschberger, 1978).

**FURTHER APPLICATIONS**

The method of maximizing or minimizing a function has wide application. Any type of survival analysis which involves finding maximum likelihood estimates will employ this procedure.

Recently, many experiments have been carried out in which mice are administered some compound thought to be toxic and even possibly carcinogenic. The compound is administered at various dose levels and the mice are followed over time until they are sacrificed at some prechosen point in time or until death. It is usually desirable to maximize the appropriate likelihood functions in order to assess the mortality pattern and/or the probability of the incidence of a tumor in a given interval. These types of animal studies have been carried out at various laboratories (most notably, at the National Center for Toxicological Research). In the future we plan to modify the Macro to include concomitant information for the likelihood function.

**ACKNOWLEDGMENT**

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**REFERENCES**


APPENDIX A

Macros and SAS 76.5 Survival Curve Macro

```sas
* MACRO FUNC_DATA
* Input data for PROC MATRIX;
FETCH X1 DATA=CAUSE1;
FETCH X2 DATA=CAUSE2;
FETCH X3 DATA=SURVIVOR;
X=X1; B=X2/X3; 2=Y/B;
* CAUSE1 FAILURES, SURVIVORS, BOTH;
%*

* MACRO FUNC_DER
* Function, 1st, & 2nd derivatives;
* If minimization of function is;
* Desired then use the negatives;
* Of function & its derivatives;
M=NROW(X); E1=E(1,1); E2=E(2,1);
A1=SUM(LOG(X)); A2=SUM(Z#E1);
A3=(Z#E1)'*(LOG(Z)); A4=(Z#E1)'*(LOG(Z)#2);
FUNCT = (LOG(E2)-(LOG(E1))#B - (E1#A1) + A1 + A2#E2;
FIRST = -[(A1 - A3)/E2] + A4#E2;
SECOND = (A1 - A3)/E2 + A1#E1;
// (-A3#/E2#2) + (A2#/E2#3)#2;
%

* MACRO GRID
* Starting values for estimates;
DO E1 = 0.5 TO 1.0 BY 0.1;
DO E2 = 45 TO 50 BY 1.0;
E=E1/E2;
FUNC DER
START=START//((FUNCT||E'));
* Function & estimate values;
END;
INDEX=INDEX((1,1,1));
E=INDEX((1,1,1))';
* Index of minimum function;
E=INDEX((1,1,1))';
* Minimum F estimates;
NOTE PAGE SEARCHING FOR STARTING VALUES OF ESTIMATES;
NOTE FUNCTIONS VALUE FOR POSSIBLE STARTING VALUES OF ESTIMATES;
PRINT START COLNAME=NAME7;
NOTE MINIMUM VALUE OF FUNCTION IS ROW NUMBER;
PRINT INDEX COLNAME=NAME6 ROWNAME=NAME5;
NOTE STARTING VALUES FOR ESTIMATES OF PARAMETERS;
PRINT E COLNAME=NAME1 ROWNAME=NAME4;
%

* MACRO RESTRICT
* Restrictions for estimates;
R = 0 / 0 ;
%

* MACRO NAMES
* Row & column names for output;
NAME1='VALUE';
NAME2='FUNCTION' 'C_HAT' 'O_HAT' 'MEAN Y' 'MEDIAN Y' 'LAMBDA' 'CONVERGE' 'ITERATION';
NAME3='GRID ' 'WRT O';
NAME4='EST C' 'EST O';
NAME5='FUNC_MIN';
NAME6='GRID ITR';
NAME7='FUNCTION' 'EST C' 'EST O';
NAME8='ITERATION' 'STEP ITR' 'LAMBDA';
%

* MACRO WRITE
* Print each iteration results;
PUTOUT=O;
* 0 = NO, 1 = YES;
%

* MACRO MLE
* Minimization of function;
* Using Marquardt's method;
* SAS76.5 matrix routine;
EXEC MATRIX PROW=20;
WRITE
* Print iteration results;
%`
```
NAMES ROW, COL NAMES
RESTRICT *RESTRICTIONS FOR ESTIMATES
FUNCDATA *INPUT DATA FOR PROC MATRIX
GRID *INITIAL VALUES OF ESTIMATES
FUNC_DER *FUNCTION, 1ST & 2ND DERIVATIVES
DELTA=1
LAMBDA=.01
EPS=1E-8
N=ROWS(E)
OLDFUNCT=FUNCT
DO ITR=1 TO 40 WHILE (ABS(OLDFUNCT-FUNCT)/(FUNCT+.000001) >= EPS)
SCALE=1/(SQRT(ANS(DIAG(SECOND))))
SPIRST=SCALE*FIRST
STEERPITR=0
LOOP1:
LSSECOND=SECONDS+I(N)+LAMBDA
IF DELTAR<0 & PUTOUT=-1 THEN DO;
NOTE PAGE INTERMEDIATE RESULTS;
LINK PRINTITR, "ITERATION RESULT PRINTER"
END;
INVSECD=INV(LSECD);
DELTA=INVERSE*FIRST
SPIRST=DELTA=FIRST
LAMBDA=LAMBDA100
STEERPITR=STEERPITR+1
IF STEERPITR=40 THEN GO TO STEEPBAD,
*STEEPEST DESCENT NOT WORKING;
IF PUTOUT=1 THEN DO;
*STEEPEST DESCENT ITR RESULTS;
NOTE SKIP=4 USING STEEPEST DESCENT AS DELTA F IS POSITIVE;
NOTE ITERATION, STEEPEST DESCENT ITERATION, AND NEW LAMBDA VALUE;
ITRVALUE=ITR|STEERPITR|LAMBDA;
PRINT ITRVALUE ROWNAME=NAME1 COLNAME=NAME2;
END:
GO TO LOOP1;
END;
DELTA=SCALE*DELTA
E=DELTA
IF PUTOUT=1 & STEERPITR=0 THEN DO;
PRINT NEW STEEPEST ESTIMATES;
PRINT E COLNAME=NAME1 ROWNAME=NAME2;
END;
SAP=0
DO K=1 TO N;
HALF=1 TO 50 WHILE (E(K,1)<R(K,1));
*CHECK RESTRICTIONS;
DELTA(K,1)=DELTA(K,1)/2
E(K,1)=E(K,1)-DELTA(K,1)
SAP=SAP+1
RESTRICTION COUNTER;
END;
END;
IF SAP=0 & PUTOUT=1 THEN DO;
PRINT RESTRICTION RESULTS;
NOTE SKIP=4 NEW PARAMETRIC VALUES AFTER HALVING INCREMENT;
NOTE SINE ESTIMATES DO NOT CONFORM TO RESTRICTIONS;
NOTE NEW ESTIMATES AFTER RESTRICTIONS;
PRINT E COLNAME=NAME1 ROWNAME=NAME2;
END;
OLDFUNCT=FUNCT
DO INCREASE=1 TO 9 WHILE (FUNCT>=OLDFUNCT+1E-10);
*FUNCTION IS INCREASING;
DELTA=DELTA/2
E=DELTA
FUNC DER
ITR=ITR+1
IF PUTOUT=1 THEN DO;
PRINT ITERATION RESULTS;
NOTE PAGE INTERMEDIATE RESULTS;
NOTE NEW PARAMETRIC VALUES AFTER HALVING INCREMENT;
NOTE SINCE ESTIMATES VALUE IS INCREASING;
PRINT ITRPRINT;
*ITERATION RESULT PRINTER;
END;
IF (INCREASE+1)>=9 THEN LAMBDA=LAMBDA1*1000; STEEP Descent LAMBDA;
LAMBDA=LAMBDA1/10;
END;
END OF ITR DO LOOP;
INVINFO=INV(SECOND);
*/VAR-COV MATRIX OF ESTIMATES;*/
RESULTS:
*/PRINT FINAL RESULTS;*/
NOTE PAGE;
IF ITR>40 THEN LINK BAD;
*/NO CONVERGENCE MESSAGE;*/
NOTE FINAL VALUES OF UNSCALED FIRST DERIVATIVES;
PRINT FIRST COLNAME=NAME1 ROWNAME=NAME2;
NOTE FINAL VALUES OF UNSCALED SECOND DERIVATIVES;
PRINT SECOND COLNAME=NAME3 ROWNAME=NAME3;
NOTE ESTIMATED ASYMPTOTIC VARIANCE-COVARIANCE MATRIX;
NOTE FOR PARAMETER ESTIMATES;
PRINT INVINFO COLNAME=NAME4 ROWNAME=NAME4;
RETURN;
FINAL VALUES OF UNSCALED FIRST DERIVATIVES;
PRINT FIRST COLNAME=NAME1 ROWNAME=NAME3;
NOTE SCALED FIRST DERIVATIVE VALUES;
PRINT SFIRST COLNAME=NAME1 ROWNAME=NAME3;
NOTE VALUES OF SCALED SECOND DERIVATIVES PLUS LAMBDA;
PRINT LSSECOND COLNAME=NAME3 ROWNAME=NAME3;
RETURN:

DATA CAUSE1;
*CAUSE ONE FAILURE DATA;
INPUT X1 $;
CARDS;
0.3 5 5.6 6.2 6.3 6.6 6.8 7.5 8.4 8.8 10.3 11 11.8 12 12.2 12.3 13.5 14.4 14.8 15.7 16.2 16.3 16.5 16.8 17.2 17.3 17.5 17.9 19.8 20.4 20.9 21 21.1 23 23.6 24 24 27.9 28.2 29.1 30 31 31 32 35 38 39 40 41 42 44 46 48 51 51 52 54 56 60 78 80 84 87 89 90 97 98 100 114 126 131 174
PROC PRINT DATA=CAUSE1;
TITLE1 CAUSE ONE FAILURE LIFE TIMES;
DATA CAUSE2;
*CAUSE TWO FAILURE DATA;
INPUT X2 $;
CARDS;
0.3 4 7.4 15.5 23.4 46 46 51 65 68 83 88 96 110 111 112 132 162
PROC PRINT DATA=CAUSE2;
TITLE1 CAUSE TWO FAILURE LIFE TIMES;
DATA SURVIVOR;
*SURVIVORS OF CAUSE ONE & TWO;
0.0001370
0.0001380
0.0001390
0.0001400
0.0001410
0.0001420
0.0001430
0.0001440
0.0001450
0.0001460
0.0001470
0.0001480
0.0001490
0.0001500
0.0001510
0.0001520
0.0001530
0.0001540
0.0001550
0.0001560
0.0001570
0.0001580
0.0001590
0.0001600
0.0001610
0.0001620
0.0001630
0.0001640
0.0001650
0.0001660
0.0001670
0.0001680
0.0001690
0.0001700
0.0001710
0.0001720
0.0001730
0.0001740
0.0001750
0.0001760
0.0001770
0.0001780
0.0001790
0.0001800
0.0001810
0.0001820
0.0001830
0.0001840
0.0001850
0.0001860
0.0001870
0.0001880
0.0001890
0.0001900
0.0001910
0.0001920
0.0001930
0.0001940
0.0001950
0.0001960
0.0001970
0.0001980
0.0001990
0.0002000
0.0002010
0.0002020
0.0002030
0.0002040
0.0002050
0.0002060
55
INPUT X3 ##;
CARDS;
111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143
PROC PRINT DATA=SURVIVOR;
TITLE1 SURVIVOR LIFE TIMES;

MLE
*CAUSE ONE SURVIVOR CURVE;
TITLE1 F = M*LN(O) - M*LN(C) - C*SUM(LN(X)) + SUM(LN(X)) + SUM(Z*C)/O; 00002150
TITLE3 CAUSE ONE FAILURES;

MACRO GRID
*ESTIMATES FOR CAUSE TWO;
DO E1 = 1.05 TO 1.10 BY .01;
DO E2 = 581.0 TO 582.0 BY 0.2;
E=E1/E2;
FUNC DER
START=START/(FUNCT (E')); 00002160
END;
INDEX=START(>,<,1);
E=START(INDEX,2 3)'; 00002170
NOTE PAGE SEARCHING FOR STARTING VALUES OF ESTIMATES;
NOTE FUNCTIONS VALUE FOR POSSIBLE STARTING VALUES OF ESTIMATES;
PRINT INDEX COLNAME=NAME1 ROWNAME=NAME5;
NOTE STARTING VALUES FOR ESTIMATES OF PARAMETERS;
PRINT E COLNAME=NAME1 ROWNAME=NAME4;

MLE
*CAUSE TWO SURVIVOR CURVE;
TITLE3 COMBINED CAUSE ONE AND CAUSE TWO FAILURES;00002180

MACRO FUNCDATA
*DATA FOR CAUSE TWO;
FETCH X1 DATA=CAUSE1;
FETCH X2 DATA=CAUSE2;
FETCH X3 DATA=CAUSE2;
x=X2; b=X1/X3; z=X/B; *CAUSE2 FAILURES,SURVIVORS,BOTH; 00002430

MLE
*CAUSE TWO SURVIVOR CURVE;
TITLE3 CAUSE TWO FAILURES;

MACRO GRID
*ESTIMATES FOR BOTH CAUSES;
DO E1 = 0.5 TO 1.0 BY 0.1;
DO E2 = 45 TO 50 BY 1.0;
E=E1/E2;
FUNC DER
START=START/(FUNCT (E')); 00002540
END;
INDEX=START(>,<,1);
E=START(INDEX,2 3)'; 00002550
NOTE PAGE SEARCHING FOR STARTING VALUES OF ESTIMATES;
NOTE FUNCTIONS VALUE FOR POSSIBLE STARTING VALUES OF ESTIMATES;
PRINT INDEX COLNAME=NAME6 ROWNAME=NAME5;
NOTE MINIMUM VALUE OF FUNCTION IS ROW NUMBER;
PRINT INDEX COLNAME=NAME6 ROWNAME=NAME5;
NOTE STARTING VALUES FOR ESTIMATES OF PARAMETERS;
PRINT E COLNAME=NAME1 ROWNAME=NAME4;

MLE
*SURVIVOR CURVE FOR BOTH CAUSES; 00002190
TITLE3 COMBINED CAUSE ONE AND CAUSE TWO FAILURES; 00002200