Optimal Design of Accelerated Life Test with Multiple-Crossed Step-down Stresses Base on Monte-Carlo Simulation

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Abstract: - In order to shorten test time and realize rapid evaluation of the reliability of products, a method of optimal design on multiple-crossed step-down stress accelerated life test (hereinafter written as MCSDS-ALT) based on Monte-Carlo simulation is proposed. The optimal plan of combined stresses in the accelerated life test is designed. The analogue simulation on the step-down accelerated life test with Monte-Carlo method is carried out, the asymptotic variance estimation of the product's lifetime distribution with the stress under normal condition is regarded as the goal function, we take every test stress level and censored data under corresponding stress as variables of the design, and the related statistical analysis is also made by applying the theory of maximum likelihood estimation (MLE). The optimal model of MCSDS-ALT based on simulation is put forward. Through applying the method of cubic spline interpolation and fitting theory, the simulation scale is reduced and the test efficiency is also improved. Thus the paper can give the technical support on optimal design of accelerated test which can be applied in the life forecast of electronic equipment.

Key-Words: - Multiple-crossed step-down stress; accelerated life test; cubic spline interpolation and fitting; optimal design

1 Introduction

The accelerated life test is an effective technical way to make quantitative evaluation of products with high reliability. As the electronic products may be affected by many factors i.e., different levels of environmental stress, so the accelerated life test on them should be made if we want to get rapidly quantitative evaluation on the reliability levels of the electronic products in their actual working environments. Now, there are a large number of literatures published are concern on this topic. For example, Chen Wenhua and other coauthors [1-3] have researched the theories and methods of combined stress accelerated life test and its optimal design.

Zhang Chunhua and Wang Yashun have made the research of the accelerated life experiment and its optimization under single-crossed step-down stress conditions[4-6].

Mao Shisong, etc [7-12] have made an overview analysis on the MCSDS-ALT. The MCSDS-ALT, is an effective test method which is very close to the actual working environment of products. It is a research hotspot in this field around the world. As a newly proposed reliability test method, the test shall be also optimized, but there are only a few researches concern on the optimization of MCSDS-ALT, and the test optimization of electronic products under multiple-crossed stresses have not been proposed with a complete theoretical method yet, which cannot meet demands of actual engineering applying. Therefore, we adopt the simulation method of Monte-Carlo to simulate the MCSDS-ALT in the paper, statistical analysis on the MCSDS-ALT data produced in simulation also is made, and we put forward the optimal design of MCSDS-ALT based on Monte-Carlo simulation, and the minimize target function value is regarded as the optimal plan.

2 Method of MCSDS-ALT

If we make the assumption that there are two groups of stress levels which can be expressed as S^1 and S^2, in each stress group includes a series of stress levels. In order to make the subsequent analysis, we assume the stress level number and stress group number of the two groups both are k, and thus the types (1)and (2) are obtained.

$$S_1^{\,1} > S_2^{\,1} > ... > S_k^{\,1} > S_0^{\,1} \tag{1}$$

$$S_1^{\,2} > S_2^{\,2} > ... > S_k^{\,2} > S_0^{\,2} \tag{2}$$

The $(S_0^{\,1}, S_0^{\,2})$ represents the normal stress group which acts on products, $(S_i^1, S_j^{\,2})$ is a group with the i stress level number of the first stress group and the j stress level number of the second stress group ($i = 1,2,\cdots,k$, $j = 1,2,\cdots,k$). Under the condition that the assumption mentioned above is met, the test process can be described in details as follows.

In the test, n represents numbers of sample are tested. Firstly, they are put under the highest stress level group of $(S_1^{\,1}, S_1^{\,2})$ until r_{11} invalid ones are appeared; then, they are put under the next stress level group of $(S_2^{\,1}, S_1^{\,2})$ until r_{21} invalid ones are come forth; in this way, they are put under the next stress level group of $(S_2^{\,1}, S_2^{\,2})$ until r_{22} invalid ones are also appeared; and till they are put under the last stress level group of $(S_k^{\,1}, S_k^{\,2})$ and r_{kk} invalid ones are appeared. The application of stress process in the overall test is shown as in Fig.1.

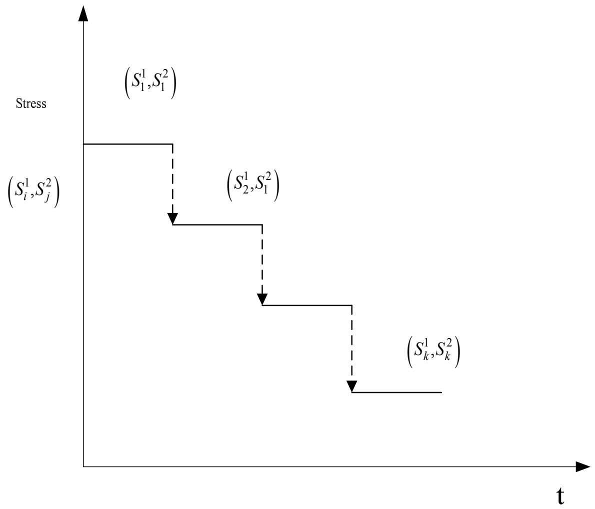

Fig.1 Stress Application Process of MCSDS-ALT

3 Model assumption

If we make the assumption that a product in use is greatly affected by the temperature and voltage. Under the combined influence of the temperature and voltage, the life of product presents Weibull distribution with two parameters, and its probability density function can be expressed as (3).

$$f(t) = \left(m/\eta^m\right) t^{m-1} \exp\left[-\left(t/\eta\right)^m\right] \quad (3)$$

Where, $\eta > 0$ is the scale parameter and $m > 0$ is the shape parameter.

Under the influence of different levels of temperature stress and electric stress, if the failure mechanism of product remains unchanged, its specific statistical model may be described as follows:

1.The product life is mutually independent in statistics and presents Weibull distribution with two parameters;

2.The shape parameter m of Weibull distribution function under different stress levels remains unchanged;

3.The two stresses act on the product have no interactions and the accelerator model is written as(4) .

$$\ln(\eta_i) = \gamma_0 + \gamma_1\varphi_1(S_i^1) + \gamma_2\varphi_2(S_j^2) \quad (4)$$

Based on the priori values of parameters m , γ_0 , γ_1 , and γ_2 and the expressions of $\varphi_1(S_i^1)$ and $\varphi_2(S_j^2)$, the method mentioned in paper [4] can be adopted to realize the simulation of MCSDS-ALT.

4. Description of Optimization Problem

4.1 Optimization objective

We take the local estimated values of asymptotic variance estimation of percentile under the normal stress level as the target function, which is expressed as (5).

$$U = Var\left(\xi_{p0}\right) \quad (5)$$

4.2 Design variable

Key factors of the design plan include: (1) the sample number which is expressed as n ; (2) the stress level group number k (3) the accelerated stress level group which is denoted by $(S_i^{\,1}, S_j^{\,2})$; (4) r_i is the invalid censored data of the stress level group $(S_i^{\,1}, S_j^{\,2})$. In order to reduce the test difficulties and the search dimension, the design plan may be expressed as $d_l = \left\{(S_i^{\,1}, S_j^{\,2}), r_{ij}\right\}$ (where, $i = 1, 2, \cdots, k$, $j = 1, 2, \cdots, k$).

4.3 Constraint conditions

(1) The sample number meets the condition of $0 < n \le n_{\max}$, where, $n_{\max}$ is the maximum sample number allowed in the test ;

(2) The stress level number is $k \le n$;

(3)The stress level is $S_i > S_{i+1}$ ($i = 1, 2, \cdots, k-1$) ;

(4)The invalid censored number is satisfied with the condition of $\sum r_{ij} \leq n$;

5. Optimal Design Method Based on Monte-Carlo Simulation

5.1 Theories related to interpolation and fitting optimization algorithm

The cubic spline interpolation algorithm has characteristics such as the uniform convergence, computational stability of piecewise low-order interpolation, and the overall adequate smoothness of high-order interpolation, etc, which can meet the need of multi-variable target function fitting and also have a good precision. In the paper, we adopt the cubic spline interpolation algorithm to fit the target function in order to reduce the simulation scale and the difficulty of surface fitting.

The cubic spline interpolation adopts the method of piecewise interpolation and has $n+1$ nodes within the given interval $[a,b]$, which satisfied with the condition that $a = x_0 < x_1 < x_2 \cdots x_n = b$. The results of the function with these nodes are $y_i, x_{0,} x_1, \cdots, x_n$. Cubic polynomials are constructed on every interval of $[x_i, x_{i+1}]$, shown as type (6).

$$F(x) = F_i(x) = mx^3 + nx^2 + px + q$$

$$x \in [x_i, x_{i+1}]\ i = (0,1,\cdots n-1) \quad (6)$$

The polynomial (6) is called cubic spline interpolation function. It is obviously that there needs $4n$ terms to be known in the solving this polynomial and the nodes provides $n+1$ terms; every interior point relationships are used to establish conditions and we may get another $3n-3$ conditions; then if we use the two boundary conditions , the spline function can be determined, exclusively.

The cubic spline interpolation function of $F(x)$ is a piecewise cubic polynomial and also is separately a cubic polynomial within every interval of $[x_{i-1}, x_i]$. Therefore, $F''(x)$ is a first-degree polynomial within every subinterval of $[x_{i-1}, x_i]$. If two point values of $F''(x)$ within the subinterval of $[x_{i-1}, x_i]$ have been known, which are represented as (7).

$$F''(x_{i-1}) = M_{i-1}, F''(x_i) = M_i$$

$$i = (0,1,\cdots n) \quad (7)$$

If we make the assumption that the length of every subinterval is $h_i = x_i - x_{i-1}$, according to Lagrange's interpolation polynomial, the first-degree Lagrange's interpolation polynomial of the function F"(x) within the subinterval of $[x_{i-1}, x_i]$ can be expressed as below.

$$F''(x) = M_{i-1}\frac{x_i - x}{h_i} + M_i\frac{x - x_{i-1}}{h_i}$$

$$i = (1,2,\cdots,n) \quad (8)$$

After integrating of the type $F''(x)$ with twice, the (9) will be obtained.

$$F(x) = M_{i-1}\frac{(x_i - x)^3}{6h_i} + M_i\frac{(x - x_{i-1})^3}{6h_i} + cx + d$$

$$i = (1,2,\cdots,n) \quad (9)$$

Where c and d are determined by the interpolation condition of $F(x_i) = y_i$. Therefore, the expression of the interpolation function $F(x)$ can be written as (10).

$$F(x) = M_{i-1}\frac{(x_i - x)^3}{6h_i} + M_i\frac{(x - x_{i-1})^3}{6h_i} + \left(y_{i-1} - \frac{M_{i-1}h_i^2}{6}\right)\frac{x_i - x}{h_i} + \left(y_i - \frac{M_i h_i^2}{6}\right)\frac{x - x_{i-1}}{6}$$

$$x \in [x_{i-1}, x_i]\ i = (1,2,\cdots n-1) \quad (10)$$

In formula (10), the interpolation function $F(x)$ is expressed by using of second derivative of $M_i (i = 0,1,2,\cdots n)$, which is also called the M expression of $F(x)$.

In the type (10), the parameter M_i is actually unknown. Only when M_{i+1} is calculated, $F(x)$ can be determined. From the derivation process of (10), we know that $F(x)$ meets the interpolation condition of $F(x_i) = y_i$, which is thus continual within the whole interval of [a, b]; in addition, $F(x)$ is a cubic polynomial within every subinterval. Therefore, we may use the continuity of $F'(x)$ in nodes to get the parameter M_i, and calculate first-order derivative on both sides of (10), and then we may get (11).

$$F'(x) = -M_{i-1}\frac{(x_i - x)^2}{2h_i} + M_i\frac{(x - x_{i-1})^2}{2h_i} + \frac{y_i - y_{i-1}}{h_i} - \frac{M_i - M_{i-1}}{6}h_i$$

$$x \in [x_{i-1}, x_i]\ i = (1,2,\cdots,n-1) \qquad (11)$$

Then we may calculate the left derivative of $F(x)$ in point of x_i

$$F'(x_i^-) = M_{i-1}\frac{h_i}{6} + M_i\frac{h_i}{3} + \frac{y_i - y_{i-1}}{h_i}$$

$$i = (1,2,\cdots,n) \qquad (12)$$

The right derivation of $F(x)$ in point of x_{i-1} is (13).

$$F'(x_{i-1}^+) = -M_{i-1}\frac{h_i}{3} - M_i\frac{h_i}{6} + \frac{y_i - y_{i-1}}{h_i}$$

$$i = (1,2,\cdots n-1) \qquad (13)$$

If we replacr i in (13) with $i+1$, and then we can calculate the right derivation of $F(x)$ in the point of x_i ,expressed as (14).

$$F'(x_i^+) = -M_i\frac{h_{i+1}}{3} - M_{i+1}\frac{h_{i+1}}{6} + \frac{y_{i+1} - y_i}{h_i} \qquad (14)$$

As $F^{'}(x)$ is continual within the interval of$[a,b]$, the left derivative and right derivative in x_{i+1} is equivalent, which means $F'(x_i^-) = F'(x_i^+)$. From formula (12)and(13), the (15) can be obtained.

$$M_{i-1}\frac{h_i}{6} + M_i\frac{h_i + h_{i+1}}{3} + M_{i+1}\frac{h_{i+1}}{6} = \frac{y_{i+1} - y_i}{h_{i+1}} - \frac{y_i - y_{i-1}}{h_i} \qquad (15)$$

If the both sides of (15) is multiplied by $\frac{6}{h_i + h_{i+1}}$, the (16) will be obtained.

$$\alpha_i M_{i-1} + 2M_i + \beta_i M_{i+1} = \lambda_i$$

$$i = (1,2,\cdots n-1) \qquad (16)$$

Where,

$$\begin{cases} \alpha_i = \dfrac{h_i}{h_i + h_{i+1}} \\ \beta_i = \dfrac{h_{i+1}}{h_i + h_{i+1}} = 1 - \alpha_i \\ \lambda_i = \dfrac{6}{h_i + h_{i+1}}\left(\dfrac{y_{i+1} - y_i}{h_{i+1}} - \dfrac{y_i - y_{i-1}}{h_i}\right) \end{cases} \qquad (17)$$

$$i = (1,2,\cdots n-1)$$

Equation (16) represents the relation between $F(x)$ and the second derivative $M_i (i = 0,1,2,\cdots n)$ in the interpolation node, which is called M relation.

The (16) can be constituted a tri-diagonal equation, based on the known boundary conditions, and which can be easily solved by applying the chasing method.

5.2 Optimization Algorithm

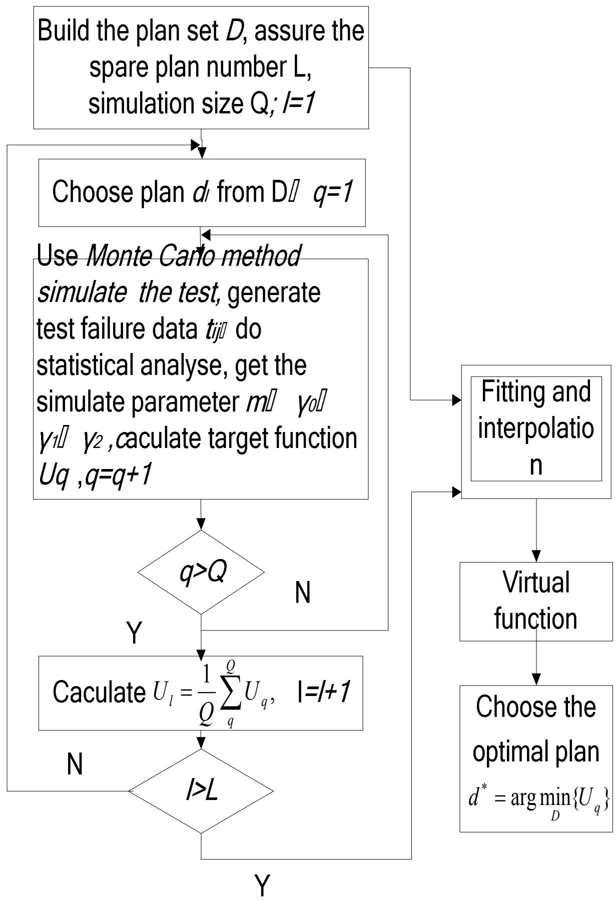

Fig.2 Optimal Design Flow Chart of MCSDS-ALT Algorithm

The basic thought of the optimization algorithm is as follows. First step is to determine the optimized objective, constraint conditions, and design variable, and second is to generate test data by using Monte-Carlo analogue simulation, and make statistical analysis by using MLE and get the target function value, last step is to select a test plan target function value of which is the minimum as the optimal test plan. The design flow chart of MCSDS-ALT based on simulation is given out in Fig.2.
The steps of Fig.2 can be described in details as follows:

Step1. Build the plan set with D.

Step2.Select a test plan of $d_l=\{(S_i^1,S_j^2),r_{ij}\}$ among the alternative plans, in which l is the number of alternative plans.

Step3. Use Monte-Carlo method to simulate MCSDS-ALT process according to the priori knowledge of (m , γ_0 , γ_1 , γ_2), and generate the test data of $\{ t_{ij}, j=1,2,\cdots,l, i=1, 2,\cdots,k\}_q$, $q=1,2,\cdots Q$, r_{ij} is the invalid censored data under the stress of S_i^1,S_j^2; simulation procedure is shown in details as follows:

(a) The priori knowledge of (m , γ_0 , γ_1 , γ_2) and the stress level group of (S_i^1,S_j^2) are substituted into Formula (4) to calculate the life characteristic quantity η_i;

(b) Sampling $t_{ij}\sim Weibull(m,\eta_i)$ with inverse transformation;

Step4. Make statistical analysis on every group of test data to get the target function U_q;

Step5. Calculate the target function:

$$U_l=1/Q(\sum_q^Q U_q) \qquad (18)$$

Step6. Return to Step2, in order to select another test plan to repeat Step2 to step 5 until the completion of L plan, then we may get the target function set of $U=\{U_l,\ 1,2,\cdots,L;\}$.

Step7.Utilizing cubic spline interpolation method to build a virtual function of the plan set D and target function set U;

Step8. Utilizing the optimization algorithm to realize target optimization on the virtual function in Step7 and then get the optimal plan set d^*.

5.3 Maximum Likelihood Estimation with Censored Test

Among common statistical methods, MLE is not affected by outer interference such as table lookup, which is commonly used in the analysis of the test data. It is applied to most theoretical models and various censored methods. According to these advantages, we can deduce the maximum likelihood function under any stress level number with Weibull distribution by using the simulation test failure data and the censored data in group tests, which is expressed as (19).

$$L(m,\gamma_0,\gamma_1,\gamma_2)=\prod_{i=1}^{k}\prod_{j=1}^{ri}\frac{m}{\eta_i}\cdot(\frac{t_{ij}(j)}{\eta_i})^{m-1}\cdot \exp(-(\frac{t_{ij}(j)}{\eta_i})^m).\prod_{r=1}^{k}\exp(-(\frac{t_{ri}(i)}{\eta_i})^m)^{(n-\sum_{i=1}^{r}ri)} \qquad (19)$$

The logarithmic function is (20):

$$\ln L(m,\gamma_0,\gamma_1,\gamma_2)=\sum_{i=1}^{k}(\sum_{j=1}^{ri}(\ln m+(m-1)\ln t_{ij}(j)-m\ln\eta_i-(\frac{t_{ij(j)}}{\eta_i})^m))-\sum_{r=1}^{k}(n-\sum_{i=1}^{r}r_i)(\frac{t_{ri}}{\eta_i})^m \qquad (20)$$

From (20), we can obtain partial derivatives in different orders of the function l against m 、 γ_0 、 γ_1 、 γ_2 , and calculate partial Fisher matrix with MLE value of $\hat{m}$ 、 $\hat{\gamma}_0$、 $\hat{\gamma}_1$、 $\hat{\gamma}_2$ of the model through Newton iteration method.

$$F=\begin{bmatrix} -\frac{\partial^2 l}{\partial m^2} & -\frac{\partial^2 l}{\partial m\partial\gamma_0} & -\frac{\partial^2 l}{\partial m\partial\gamma_1} & -\frac{\partial^2 l}{\partial m\partial\gamma_2} \\ -\frac{\partial^2 l}{\partial\gamma_0\partial m} & -\frac{\partial^2 l}{\partial\gamma_0^2} & -\frac{\partial^2 l}{\partial\gamma_0\partial\gamma_1} & -\frac{\partial^2 l}{\partial\gamma_0\partial\gamma_2} \\ -\frac{\partial^2 l}{\partial\gamma_1\partial m} & -\frac{\partial^2 l}{\partial\gamma_1\partial\gamma_0} & -\frac{\partial^2 l}{\partial\gamma_1^2} & -\frac{\partial^2 l}{\partial\gamma_1\partial\gamma_2} \\ -\frac{\partial^2 l}{\partial\gamma_2\partial m} & -\frac{\partial^2 l}{\partial\gamma_2\partial\gamma_0} & -\frac{\partial^2 l}{\partial\gamma_2\partial\gamma_1} & -\frac{\partial^2 l}{\partial\gamma_2^2} \end{bmatrix} \quad (21)$$

Elements in the Fisher matrix are the second-order partial derivatives of formula (20).

5.4 Target Function and Sample Size

From the model assumed, we know that test life presents Weibull distribution, thus we can calculate the logarithmic percentile life under the normal stress level S_0 [13-15].

$$\hat{Y}_R(S_{10},S_{10})=\log(t_{R,(S_{10},S_{20})})$$

$$=\log(\hat{\eta}_0)+\log(-\log(R)).\hat{m} \quad (22)$$

If w substitute (4) into (22), the (23) can be obtained.

$$\hat{Y}_R(S_{10},S_{10})=\gamma_0+\gamma_1 S_{10}+\gamma_2 S_{20}+\log(-\log(R)).\hat{m} \quad (23)$$

From papers[16-20], we can get the basic model of the target function (24).

$$\mathrm{Var}(\ln\eta_p)=BF^{-1}B^T \quad (24)$$

Where,

$$B=[\frac{\partial\hat{Y}_R(S_{10},S_{10})}{\partial \mathrm{m}},\frac{\partial\hat{Y}_R(S_{10},S_{10})}{\partial\gamma_0},\frac{\partial\hat{Y}_R(S_{10},S_{10})}{\partial\gamma_1},\frac{\partial\hat{Y}_R(S_{10},S_{10})}{\partial\gamma_2}] \quad (25)$$

F denotes partial Fisher information matrix.

6. Analysis

In the paper, we takes direct current (DC) motor as an example in the cyclic step-down accelerated life test. As known that the life of the DC motor presents Weibull distribution and the priori-value of shape parameter is $m=2.9479$. Its normal temperature level is $T_0=55^oC$ and its normal voltage level is $V_0=10V$. From the failure mechanism of the product, we can know that the highest temperature level is $V_0=10V$ and the highest voltage level is $V_{\max}=25V$, and we can get the related data from paper [10], $T_{\min}=57^oC$ and $V_{\min}=11V$.

The researches of the test have verified that the accelerator model is Eyring model.

$$\ln(\eta_i)=\gamma_0+\gamma_1\varphi_1(S_i^1)+\gamma_2\varphi_2(S_j^2) \quad (26)$$

Where

$\varphi(T_i)=1/(T_i+273)$ and $\varphi(V_i)=\log(V_i)$, the priori values of the model are $r_0=-5.9204$, $r_1=6.0714$, and $r_2=-1.5604$.

We make the following assumptions on the test in order to simplify and optimize problems:

(1) We only analyzes MCSDS-ALT plans under the condition that the stress level k=2 and k=3, and the optimal design methods under other stress levels is nearly the same;

(2) In order to simplify the analysis, the stresses are set with equal interval, which are

$$T_i=T_{\max}-(i-1)(T_{\max}-T_{\min})/k-1$$

$$V_j=V_{\max}-(j-1)(V_{\max}-V_{\min})/k-1$$

Where $i,j=1,2,\cdots,k$.

(3) In order to guarantee the evaluation precision, we analyze at least five sample numbers under every stress level.

We assume the stress levels are separately 2 and 3, and $n=100$, the invalid sample number $n=88$ cab be obtained when $k=2$, the uniform orthogonal method is used in test in order to guarantee its generality. We assume the sample failure is $r_i=[55,20,13]$ under the corresponding stress level group, so if $k=3$, the sample failure will be $r_i=[35,25,12,8,5]$ under the corresponding stress level group, where $L=60$ and $M=100$.

Fig.3 gives out the relationship diagram between the sub-target function and the target function which are obtained from the accelerated simulation test by using of Monte-Carlo method when k=2.

When we smooth Fig.3 by applying cubic spline interpolation and fitting theory, it can be improved. The results are shown as Fig.4. The result of optimum test plan is the red point shown in Fig.4.

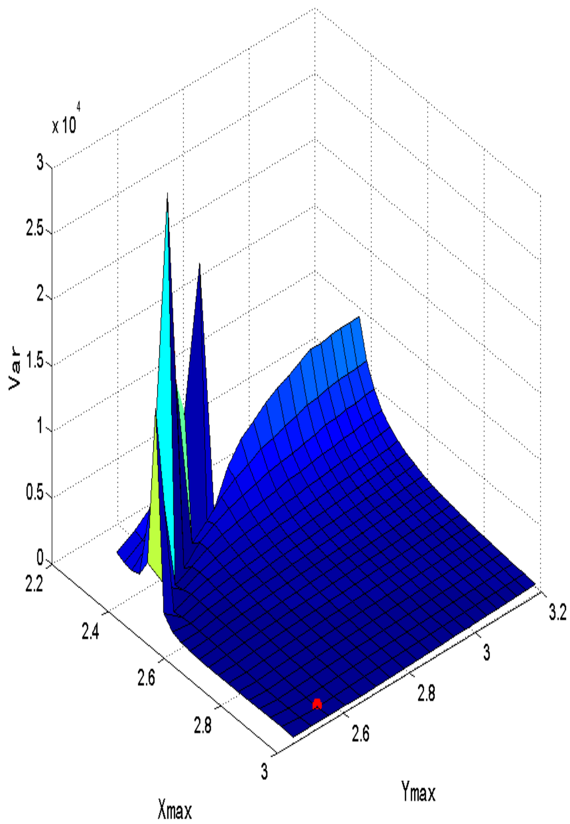

Fig.3 Simulation results of original data when k=2

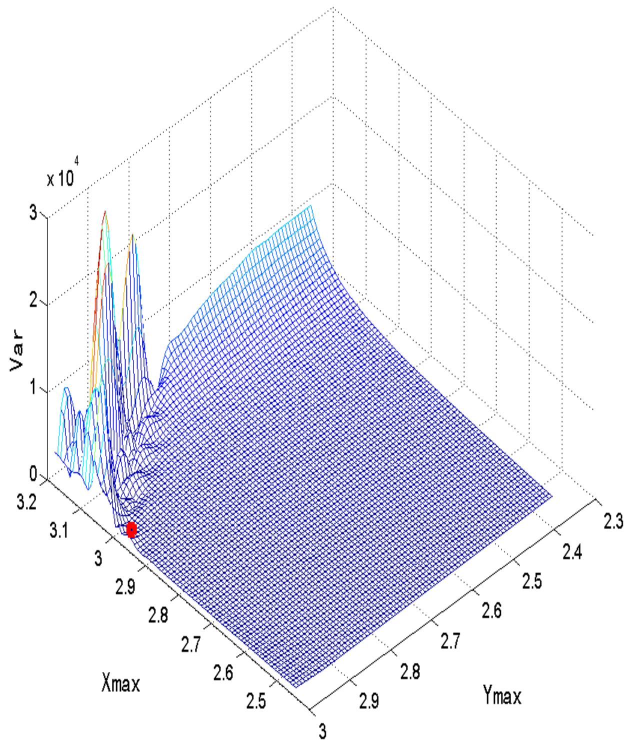

Fig.4 Cubic spline interpolation results when k=2

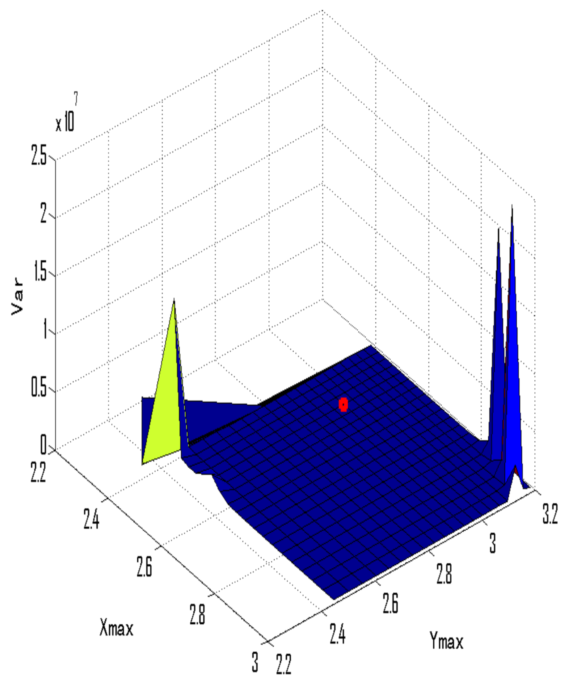

Fig.5 Simulation of original data results when k=3

Fig.5 shows the relationships between the sub-target function and the target function obtained from the accelerated simulation test by using of Monte-Carlo when k=3.

Fig.6 is the result of Fig.5 after adopting the cubic spline interpolation and fitting theory method. The result of optimum test plan is the red point as shown in Fig.6.

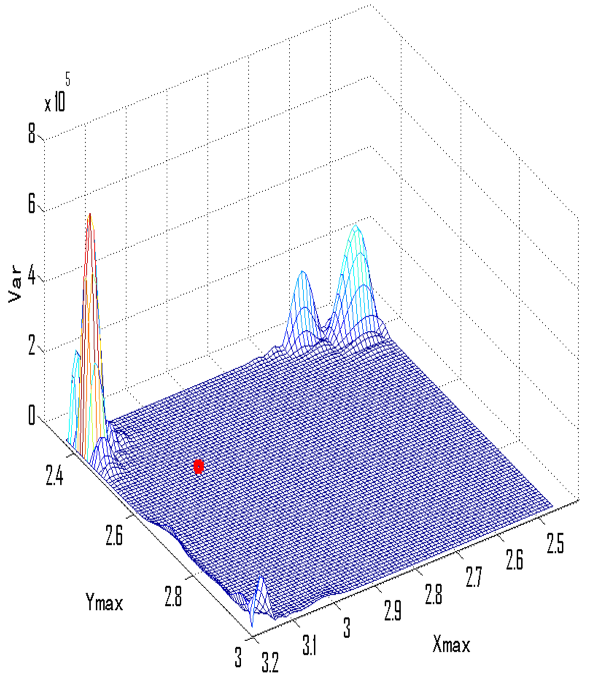

Fig.6 Results of cubic spline interpolation when k=3

In Fig.5 and Fig.6, we can find that the values of target function at the periphery are too large which make the bottom part of Fig.5 and Fig.6 too flat. It seems that values of the target function at the bottom are almost the same. But actually they are different, in order to see them clearly, the target function data at the periphery where the value is too big are removed.

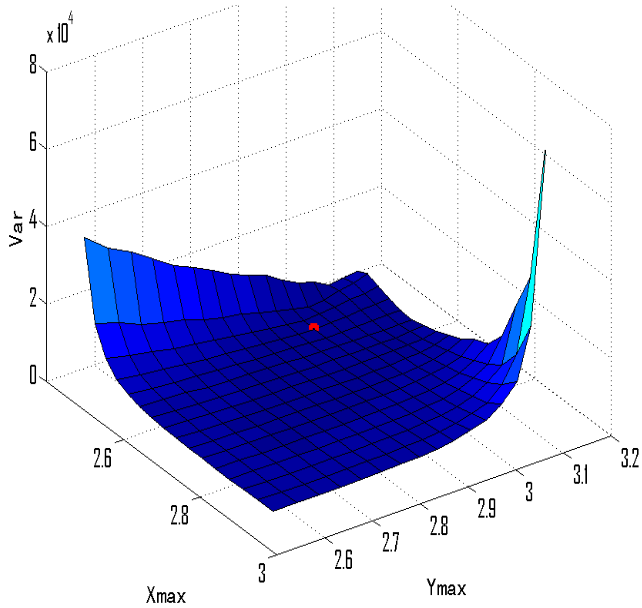

Fig.7 Simulation results of local original data when k=3

Fig.7 is the result after removing the target function data at the periphery.Fig.8 is the result after cubic spline interpolation and fitting. The optimum test plan results are shown by the red point in them.

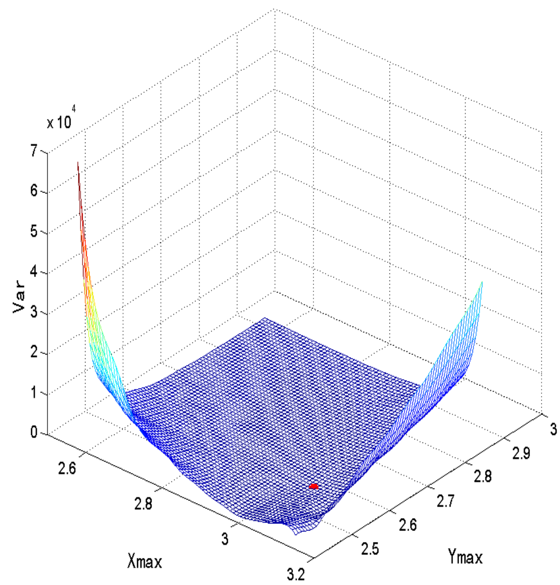

Fig.8 Local cubic spline interpolation results (*k=3*)

Tab.1 Optimum test plan results

k		2	3
Original	X_{max}	2.9880	2.5000

data	Y_{max}	2.9444	2.9789
	Var	6.3101	15.296
Interpolation and fitting data	X_{max}	2.9871	3.0358
	Y_{max}	2.9643	2.5637
	Var	5.2301	11.339

Through the optimization and analysis on the target function and its variables by using of spline interpolation method, we can get the optimal plan design when $k = 2$ and $k = 3$, which is shown in Tab.1.

Through the analysis of Tab.1 and the fitting on the target function with the cubic spline interpolation and fitting algorithm, the simulation scale can be reduced and the test efficiency is also improved. In actual engineering application, if the test expense is limited with high precision, the test plan with low stress level number shall be used. Otherwise, the test plan with good stability and high stress level number shall be adopted even if the precision is not high.

7 Conclusions

In the paper we analyze the target optimization and design variables in MCSDS-ALT based on Monte-Carlo simulation. We make constant-stress accelerated life test and step-down accelerated life by applying the related theory, and we fit the target function through using the cubic spline interpolation fitting algorithm, the result show that it cab reduces the simulation scale, improves the test efficiency. Form the research in the paper we can obtain the sample size with the optimal plan and also can draw some useful conclusions to guide the MCSDC-ALT.

The method proposed can improve the theoretical system of the accelerated test optimal design, thus it will provide a powerful theoretical support for subsequent accelerated test and performance analysis on the product. So our research work will lay a good foundation for the optimal design of MCSDS-ALT in the actual engineering application.

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References

[1] Chen Wenhua, Feng Hongyi, Qian Ping, Zhou Shengjun, and Lu Xianbiao. *Optimal Design Theory and Method of Combined Stress Accelerated Life Test Plan* . Chinese Journal of Mechanical Engineering, Vol.42 No.12, 2006, pp101-105[in Chinese].

[2] Chen Wenhua, Feng Hongyi, Qian Ping, Zhou Shengjun, and Lu Xianbiao. *Theory and Method of the Simulation and Evaluation of the Combined Stress Accelerated Life Test Plan*. Journal of Astronautics, Vol.28 No.6, 2007, pp1768-1773[in Chinese].

[3] Chen Wenhua, Liu Junjun, Pan Jun, Gao Liang, and He Qingchuan. *Theory and Method for Optimum Design of Accelerated Life Test Plan under Step-stress*. Chinese Journal of Mechanical Engineering, Vol.46 No.10, 2010, pp182-187[in Chinese].

[4] Zhang Chunhua, Chen Xun, and Wen Xisen. *Step-down-stress Accelerated Life Testing Method*. Acta Armamentarii,Vol.26,No.5 2005,pp662-665[in Chinese].

[5] Zhang Chunhua, Chenxun, and Wen Xisen. *Step-down-stress Accelerated Life Testing Statistical Analysis*. Acta Armamentarii, Vol.26,No5, 2005, pp666-669[in Chinese].

[6] Wang Yashun, Zhang Chunhua, and Chen Xun. *Step-down-stress Accelerated Life Testing (Continuance)-Optimal Design*. Acta Armamentarii, Vol.28,No6,2007, pp686-691[in Chinese].

[7] [Mao Shisong and Wang Lingling. *Accelerated Life Tes*. Beijing: Science Press, 1997[in Chinese].

[8] Wang Yuming and Cai Jinyan. *Numerical Simulation of MCSDS-ALT.* Computer Simulation, Vol 25, No(12),2008,:pp342-345[in Chinese].

[9] Gan Xusheng, Zhang Hongcai, Cheng Yongmei, and Xiong Xianzhe. *Aerodynamic Parameter Fitting Based on Robust Least Squares Support Vector Machines* . Computer Engineering and Applications, Vol 43, No.31: 2007, pp233-240 [in Chinese].

[10] Chen hua Li. *Optimal step-stress plans for accelerated life testing considering reliability/life prediction* . Boston, Massachusetts, the degree of Doctor of Philosophy in Industrial Engineering Northeaster University, 2010[in Chinese].

[11] Xu Xiaoyong, Zhong Taiyong. *Construction and Realization of Cubic Spline Interpolation Function* . Ordnance Industry Automation, vol.11,2006, pp111-119[in Chinese].

[12] Wang Yuming, Cai Jinyan, Jia Zhanqiang. *New approach based on double-crossed step-down-stress accelerated life testing.* 8th International Conference on Electronic Measurement and Instruments, vol.8, 2007,pp185-189.

[13] Erkanli A, Soyer R. *Simulation-based designs for accelerated life test*. Journal of Statistical Planning and Inference, Vol.90,2000,pp335-348.

[14] MeekerWQ, LuValleMJ. *An Accelerated Life Test Based on Reliability Kinetics. Technometrics*. Vol.37,1995,pp133-146.

[15] Kwee-poo Yeo Loon-ching Tang. *Planning Step-Stress Life-Test with a Target Acceleration-Factor.* IEEE Transactions on Reliability. Vol.48(1), 1999,pp61-67.

[16] Erkanli A Soyer R. *Simulation-based designs for accelerated life tests.* Journal of Statistical Planning and Inference. 90,2000, pp335-348.

[17] Pascual]francis. *Accelerated life test planning with independent Weibull competing risks with known shape parameter*. IEEE Trans on Reliability. Vol.56(1),2007,pp 85-93.

[18] Pascual Francis. *Accelerated life test planning with independent Weibull competing risks*. IEEE Trans on Reliability,Vol.57(3) 2008,pp435-444.

[19] Yurkowsky W, Schafter R E Finkelstein J. M. *Accelerated testing technology,* RADC-TR-67-420. Rome Air Development Center, 1967.

[20] W Nelson. Accelerated Testing: *Statistical Methods , Test Plans , and Data Analysis*. New York: John Wiley &Sons, 1990.