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IMPROVED RELIABILITY DATA CURVE FITTING METHOD BY CONSIDERING SAMPLES DISTINCTION

UDOSKONALONA METODA DOPASOWYWANIA KRZYWYCH DO DANYCH NIEZAWODNOŚCIOWYCH UWZGLĘDNIAJĄCA RÓŻNICE MIĘDZY PRÓBKAMI

In engineering practice, we face a problem of using some collected data to evaluate a kind of machine or equipment. Curve fitting is a common method to solve this problem. Least square method is wildly applied in this procedure. If the source data of curve fitting can be grouped in samples and the distinction of samples obviously express some character in source data collecting which cannot be ignored. Conventional curve fitting method cannot handle these source data. To deal with this disadvantage, we introduce an improved curve fitting method. Through source data analysis, we can find out the relationship between sample location and weight factor in curve fitting, and use these weight factors for curve fitting. To approach the true curve, we introduce an iterative procedure to modify the weight factors. An engineering example is given to illustrate this proposed method.

Keywords: *curve fitting, sample distinction, weigh assignment, iterative process.*

W praktyce inżynieryjnej stykamy się z problemem wykorzystania zgromadzonych danych do oceny maszyn lub sprzętu. Dopasowywanie krzywych to metoda powszechnie używana do rozwiązywania tego typu problemów. W procedurze tej szeroko stosuje się metodę najmniejszych kwadratów. Jeżeli dane wejściowe dopasowywane krzywą można pogrupować tak by tworzyły oddzielne próbki, a różnice między próbkami w sposób oczywisty odzwierciedlają pewną właściwość dotyczącą gromadzenia danych, której nie można pominąć, to konwencjonalna metoda dopasowywania krzywych nie pozwala na analizę takich danych wejściowych. Aby przezwyciężyć to ograniczenie, przedstawiamy udoskonaloną metodę dopasowywania krzywych. Poprzez analizę danych wejściowych, możemy określić związek pomiędzy położeniem próbki a czynnikiem ważonym w dopasowaniu krzywej oraz wykorzystać czynniki ważone przy dopasowywaniu krzywej. Aby osiągnąć jak najdokładniejsze przybliżenie do krzywej rzeczywistej wprowadziliśmu procedurę iteratywną modyfikującą czynniki ważone. Zastosowanie zaproponowanej metody zilustrowano na przykładzie danych z badań niezawodnościowych.

Słowa kluczowe: *dopasowywanie krzywych, różnice między próbkami, ważenie danych, proces iteratywny.*

1. Introduction

In reliability engineering, data are collected through reliability experiment or real time data collection for reliability analysis. The main methods to handle these data are classic statistical analysis method and linear estimate method. The results of reliability analysis is used for conduct state evaluating, residual life estimating, maintain planning, replacement policy evaluation, warranty cost prediction, and so on.

Regression analysis and curve fitting is a method to obtain the approximate analytic expression of discrete data. In reliability engineering, linear and non-linear regression methods are widely used depending on the characters of collected data [1, 6, 12-14]. In linear regression method, the least squares method is the most used method [4].

If collected data is a suitable data serial, in other words, the collected data have been grouped in one data set, current regression and curve fitting methods can be used easily. In other situations, however, collected data could be grouped in some data sets, which are significantly different from each other. Because the difference can not be ignored, all collected data can not be regrouped and arranged in one serial. To address this problem, weight factors are introduced in curve fitting methods, such as weighted least square (WLS) method [9].

If we can get some prior curve information, curve fitting procedure could be more efficient and is expected to be more precise. If we do not have the premise condition, make the best of source sample data become the only way to solve this problem. WLS gives a valid way to dig source data information and is used for curve fitting, the idea of WLS can be referenced in our method.

In Section 2, we introduce curve fitting method with the least square method, and analyze the advantages and disadvantages of the conventional least square method. Section 3 introduces an improved least square method to solve the samples distinction problem, analyze sample data distributions, finds out relationship between sample data and true curve, uses iterative process to achieve true curve. In this method, polynomial function has been chosen as the primary function, and an engineering example is given. Section 4 gives the conclusion.

2. Curve fitting with least square method

2.1. Theory of least square method

Least square method is a common curve fitting method, and it's used in many subject domains. The primary concept of least square method is given as below [4] .

For example, we get sample:

$$\{x_1, x_2, \cdots, x_n\}, \{y_1, y_2, \cdots, y_n\},$$

And we know the curve function form is

$$y = \varphi(x) = c_1\varphi_1(x) + c_2\varphi_2(x) + \cdots + c_m\varphi_m(x) \; (m<n)$$

The curve fitting problem is translated to find the vector *C* and the constraint is shown as:

$$\min R = \sum_{i=1}^{n}(\varphi(x_i - y_i)^2 = \sum_{i=1}^{n}(c_1\varphi_1(x) + c_2\varphi_2(x) + \cdots + c_m\varphi_m(x) - y_i)^2 \quad (1)$$

Primary function selection is a key point in the least square method. The primary function is formed according to the basic sample characters. More specifically, the primary function's selection is based on the basic sample data distributions. Exponential distribution functions, two-parameter Weibull distribution functions, three-parameter Weibull distribution functions, and polynomial distribution functions are commonly used as primary functions, especially under situation of no other data information. In this paper, we use the polynomial as the primary function.

Current research can be concluded in two categories. Some researchers focused on the function selection, trying to get more data information, such as the object property, sample data collection method, data distribution, and trying to get more reasonable and valid function from the prior information [5, 16, 17]. Other researchers focus on the parameter identification [2, 3, 11, 15, 18].

2.2. Disadvantages of the least square method

Given the conventional least square method for curve fitting, if we can get enough samples, and all samples have been formulated in the same type, the fitting result is rational. However, if the source sample data have been group in some sample sequences, the conventional least square method can not handle this sample form. This brought the weight least square method. We can give different weight factors to different sample items according to the importance. The conventional least square method can be rewritten as follow, which is called the weighted least square method [7, 19].

$$\min R = \sum_{i=1}^{n} r_i(\varphi(x_i) - y_i)^2 = \sum_{i=1}^{n} r_i(c_1\varphi_1(x) + c_2\varphi_2(x) + \cdots + c_m\varphi_m(x) - y_i)^2 \quad (2)$$

Because we want to minimize *R*, $\bar{r} = \{r_1, r_2, \cdots, r_n\}$, which can be called as penalty factor. If sample item $\{x_i, y_i\}$ is located close to the mean of distribution than other sample items, r_i should be bigger than any other factor to prevent the fitting result departing from the true situation.

This produces another critical problem on the definition of the factor vector $\bar{r}$. The general method is to assign according to some prior information, such as the source data collection method evaluation, experts' experience, etc. If the equipment is brand new, we can not get enough prior information for factor assignment, sample analysis becomes the only way to factor assignment.

In the next section, we assume the collected data follow some kind of distribution. The closer the sample departs from the true curve, the higher is the distribution density. We can deduce the weight factor with the sample distribution density, and modify the weight factors in iterative procedure. This idea partly comes from the research work of Jiang and Jing [8, 10].

In the improved curve fitting method based on the least square method, the weight factors are used to form the fitting source point sequences, but not the penalty function.

3. Improved curve fitting method base on least square method

3.1. Samples analysis

The first key point of this improved curve fitting method is how to get the initial weight factors and how to modify them in the iterative procedure. To get the weight factor of each sample item, we should analyze the sample first. Fig.1 shows the sample distribution and the true curve. In Fig.1, the black curve is the true curve, collected samples distribute around the curve. Points compose four sample items. We know each sample provides information for curve fitting more or less. If a sample is closer to the true curve, it should include more information than other samples and should play more important role in the curve

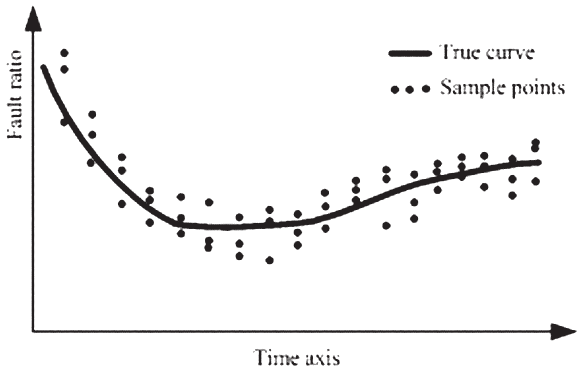

Fig. 1. True curve and sample distribution

fitting. That is to say this sample should have more weight than others.

3.2. Initial weight factor identification and initial curve generation

Through sample analysis, we know the sample that is the closest to the true curve should have the biggest weight factor in curve fitting. The new problem has been brought. Since we do not know the true curve, we do not know the exact distance between the true curve and each sample, and we can not get weight factors easily.

Though small sample means the existence of randomness in sample collection, these samples must match certain distribution. If through well pretreatment, source samples are unbiased and noises has been well suppressed. This source samples distribution has an obvious character that the more the samples gather, the more it is close to the true curve. That is to say, the higher the sample points gather density, the closer it is to the true value.

According to this character, we can deduce the weight factor from the distance between the sample and the true curve. Furthermore, we can use the distance between one sample and all other samples to represent the distance between the sample and the true curve.

We can assume curve fitting with n samples, each sample has m sample points, which are described as $\overline{S} = \{s_1, s_2, \cdots, s_n\}$, $s_n = \{p_{n,1}, p_{n,2}, \cdots, p_{n,m}\}$.

Thus, we can calculate the distances as follow:

$$L_{i,j} = \sqrt{\sum_{\substack{k=1 \\ k \neq i}}^{n} (p_{i,j} - p_{k,j})^2} \quad (3)$$

As the analysis before, the more the distance between one sample item and all other sample items, the less importance it take in curve fitting procedure. So we can assign initial weight factor as follows:

$$w_{i,j,0} = \frac{\frac{1}{L_{i,j}}}{\sum_{k=1}^{n} \frac{1}{L_{i,j}}} \quad (4)$$

The subscript 0 means this weight factor is the initial weight factor. The weight factor assignment considers the relationships among all sample items only. The precision of this assignment method is not considered. The fitting result precision is based on the iterative procedure, but not on the initial weight factor assignment.

Using the weight factor, we can get the first curve fitting source points as follows:

$$p_{j,0} = \sum_{i=1}^{n} w_{i,j,0} p_{i,j} \quad (5)$$

Using the first curve fitting source points, we can get the initial curve with the least square method.

3.3. Primary function determination

The primary function selection makes great influence to the fitting precise and computing efficiency, and become a key point in curve fitting.

Many researchers prefer to determine the primary function according to the source data. In mechanical and electronic engineering practice, standard 2-parameter, 3-parameter Weibull distribution and exponential distribution are the conventional choices, which should be chosen according to the underlying failure time.

Some researchers get progress in primary function determination or primary distribution identification, and provide or deduce some effective primary function and fitting method. These primary functions or distribution identification methods are mostly based on some prior information or familiar information of the collected data.

These primary functions have been proved in some basic theoretical research or engineering practices. They have one similar characteristic that the source data distributions have been known, and only the parameters need to be identified, or source data distribution can be estimated from similar system, similar product or from experience.

If these preconditions cannot be satisfied, primary distributions or primary functions selection method are not suitable. In this situation, general primary function should be used for curve fitting procedure. Polynomial is a common general primary function.

$$y = f(x) = a_0 + a_1 x^1 + \cdots + a_n x^n$$

Parameter n should be determined in fitting procedure.

3.4. Iterative process

With the initial weight factors $W_0 = \{w_{i,j,0} \mid i = 1, 2, \cdots, n, j = 1, 2, \cdots, m\}$, we can get the curve fitting result $C_0 = f_0(x)$. The subscript "0" means it is the first curve fitting result. Consequently, we can define the initial weight factors as $W_1 = \{w_{11}, w_{12}, \cdots, w_{1n}\}$.

The next step is an iterative procedure, in which we take the last step fitting result $C_0 = f_0(x)$ as the true curve to calculate weight factors. The weight factor of each sample can be changed in each step. The weight factor is assigned according to the dis-

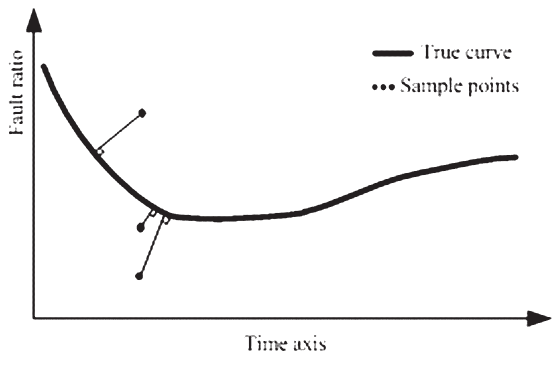

Fig. 2. Distance from sample points to fitted curve.

tance, since we get $C_0 = f_0(x)$ as fitting result. We use the distance between sample and curve, but not among samples.

Because the weight factor assignment is according to the distance, we calculate the distance firstly. The distance is between sample points and fitting curve, which means the shortest distance from the point to the curve. In other word, it means the vertical distance.

Fig.2 shows the vertical distance with three sample points at the same time point. The distance calculation method is an optimization search method.

$$L_{i,j,k} = \min\{\sqrt{(x_{i,j} - x)^2 + [y_{i,j} - f(x)]^2} \mid x \in (0, x_n)\} \tag{6}$$

The sample points in one sample can be treated as a discrete time series. As points are not independent among each other, the value of each point is related to the points before and has impact on the points subsequently. Weight factor assignment should not be considered as single point's distribution, but a sample series. So in the iterative procedure, we assign points in the same sample the same weight factor. Weight factor can be obtained according to the sample average distance $L_{i,k}$.

$$L_{i,k} = \frac{1}{m}\sum_{j=1}^{m} L_{i,j,k} \tag{7}$$

Sample weight factor $w_{i,k}$, namely sample points weight factor $w_{i,j,k}$, is defined as

$$w_{i,k} = w_{i,j,k} = \frac{\frac{1}{L_{i,k}}}{\sum_{i=1}^{n}\frac{1}{L_{i,k}}} \tag{8}$$

Using this weight factor, we can get the fitting points in this curve fitting step:

$$p_{j,k} = \sum_{i=1}^{n} w_{i,j,k} p_{i,j} \tag{9}$$

With this fitting source points, we can get fitting result curve $C_k = f_k(x)$. This stage is an iterative procedure. Here we get the fitting result curve with this curve, and we can calculate the distance between the sample point and the fitting curve. By reassigning weight factor according to these distances, the fitting source points with new assign weight factor can be calculated, and the new fitting curve with these source points can be obtained.

3.5. Terminal condition

The iterative procedure is an approach proceeding to the true curve. When the iterative precision is enough, we can take the fitting result as the true curve, and the iterative procedure should be stopped. When to end the iterative procedure is called the terminal condition. In the iterative procedure, the terminal condition can be defined as two forms as follow:

Form 1:

Use the curve distance to evaluate iterative effect. Define C_k as the fitting result curve of step k in the iterative procedure, minimum value $\varepsilon > 0$, and $\overline{D_{k,k-1}}$ as the distance between C_k and C_{k-1} . If $\overline{D_{k,k-1}} < \varepsilon$, the iterative procedure should be stopped.

Form 2:

Use the weight factors' changes to evaluate iterative effect. Define $W_{k,k-1}$ as the average weight factor change of step k and step $k-1$ in iterative procedure.

$$W_{k,k-1} = \sqrt{\frac{\sum_{j=1}^{m}\sum_{i=1}^{n}(w_{i,j,k} - w_{i,j,k-1})^2}{n \times m}} \tag{10}$$

Define minimum value $\varepsilon > 0$. If $W_{k,k-1} < \varepsilon$, we think the subsequent iterative procedure can not bring obvious improvement, and the iterative procedure should be stopped.

These two forms represent the progress of iterative procedure. In practice, we can choose one of them according to the practical situation. In this paper, we use Form 2 terminal condition when considering the computing complexity.

3.6. Flowchart of this improved least square method

The flowchart of this curve fitting method is shown in Fig.3.

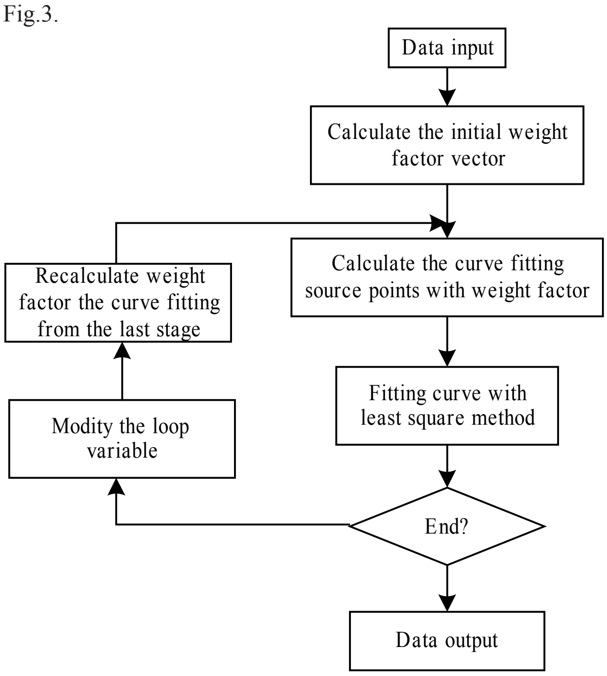

Fig. 3. Flowchart of this curve fitting method

3.6. Engineering example

In this section, we use this improved curve fitting method to handle a new type diesel engine life failure data.

For a new type diesel engine's maintenance plan and service guarantee plan, we must get the lift failure rules. Failure record is shown in Table 1. From this table, we can find that

Table 1. Failure record of some type of diesel

Unit number	Used district	Unit serial	Unit type	Failure mileage
D0303552563	Si Chuan	D0303	YC4108ZQ	110
D0303551997	Yun Nan	D0303	YC4108ZQ	398
D0303551110	Yun Nan	D0303	YC4108ZQ	1309
D0303551777	Guang Xi	D0303	YC4108ZQ	2182
…	…	…	…	…

Table 2. Four districts failure records

Mileage (10^3km)	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10
*S*1	66	100	125	82	83	58	72	57	48	43
*S*2	40	60	42	18	18	12	17	12	15	14
*S*3	16	17	28	15	22	17	9	7	15	8
*S*4	14	10	6	2	2	0	3	2	3	2
Mileage (10^3km)	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20
*S*1	46	43	27	17	14	12	10	7	3	10
*S*2	15	9	8	4	6	10	2	5	7	3
*S*3	6	3	5	3	5	3	3	1	2	3
*S*4	3	2	2	1	0	0	1	3	2	1

Table 3. Failure records in all districts

Mileage (10^3km)	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10
S	136	187	201	117	125	87	101	78	81	67
Mileage (10^3km)	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20
S	69	56	40	24	26	28	17	14	13	16

they are mainly used in four districts. We can divide collected data to form four samples, and use these four samples to curve fitting.

All failure records in four districts are collected. The mileage ranges from 0 to 6×10^4 . We use the data mileage ranging from 1 to 2×10^4 , and divide the mileage axis to 20 intervals, and collect the failures as Table 2.

On the contrary, if we ignore the districts distinctions, the failure mileages collected in 20 intervals have been shown in Table 3.

From the failure records, we can get the failure frequency in all intervals, and list them in Table 4.

From Table 4, we can observe that the sample *S*4 looks different from the other three samples. The main reason is the sample size. Because the sample size of *S*4 is about 1/17 of *S*1, the existence of randomness makes obvious impact to the *S*4 statistical values which can be noticed in Fig.4. The cerulean points represent sample *S*4. Fig.5 is the conventional method source points scatter diagram. We ignore the districts difference, and get characteristics from all samples collected. Obviously,

Table 4. Four sample failure frequency

Mileage (10^3km)	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10
*S*1	0.0698	0.1058	0.1323	0.0868	0.0878	0.0614	0.0762	0.0603	0.0508	0.0455
*S*2	0.119	0.1786	0.125	0.0536	0.0536	0.0357	0.0506	0.0357	0.0446	0.0417
*S*3	0.0812	0.0863	0.1421	0.0761	0.1117	0.0863	0.0457	0.0355	0.0761	0.0406
*S*4	0.2188	0.1563	0.0938	0.0313	0.0313	0	0.0469	0.0313	0.0469	0.0313
Mileage (10^3km)	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20
*S*1	0.0487	0.0455	0.0286	0.018	0.0148	0.0127	0.0106	0.0074	0.0032	0.0106
*S*2	0.0446	0.0268	0.0238	0.0119	0.0179	0.0298	0.006	0.0149	0.0208	0.0089
*S*3	0.0305	0.0152	0.0254	0.0152	0.0254	0.0152	0.0152	0.0051	0.0102	0.0102
*S*4	0.0313	0.0156	0	0	0.0156	0.0469	0.0313	0.0156	0.0156	0

Table 5. Fitting result coefficients with conventional and improved method

	x^5	x^4	x^3	x^2	x^1	x^0
Equal weight fitting result	0.1735	-0.9514	2.005	-2.219	1.703	0.04554
Improved method fitting result	0.1882	-1.015	2.084	-2.244	1.7359	.0.02376

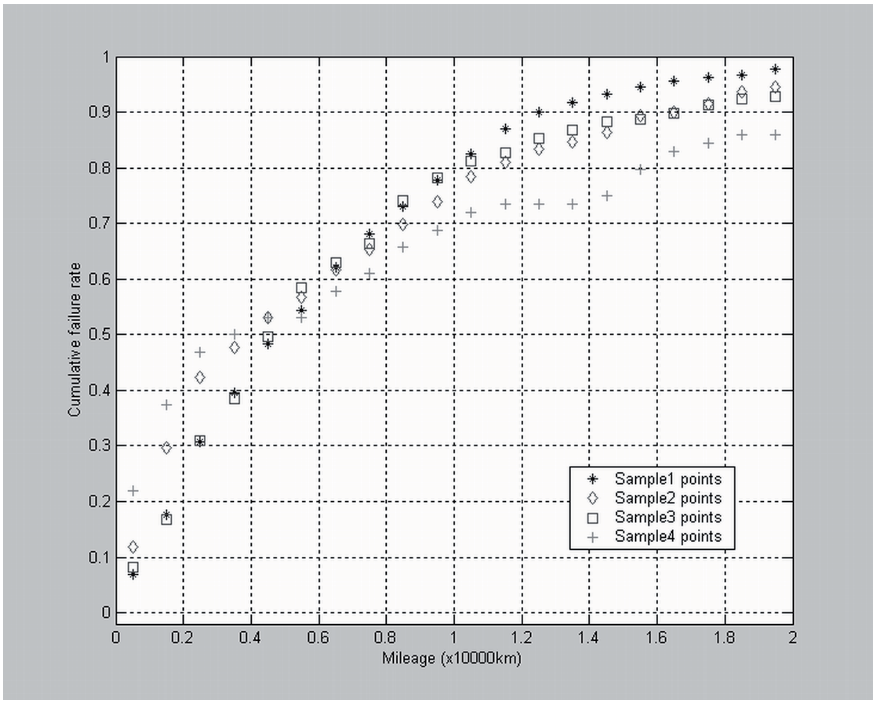

Fig. 4. Four districts sample scatter diagram

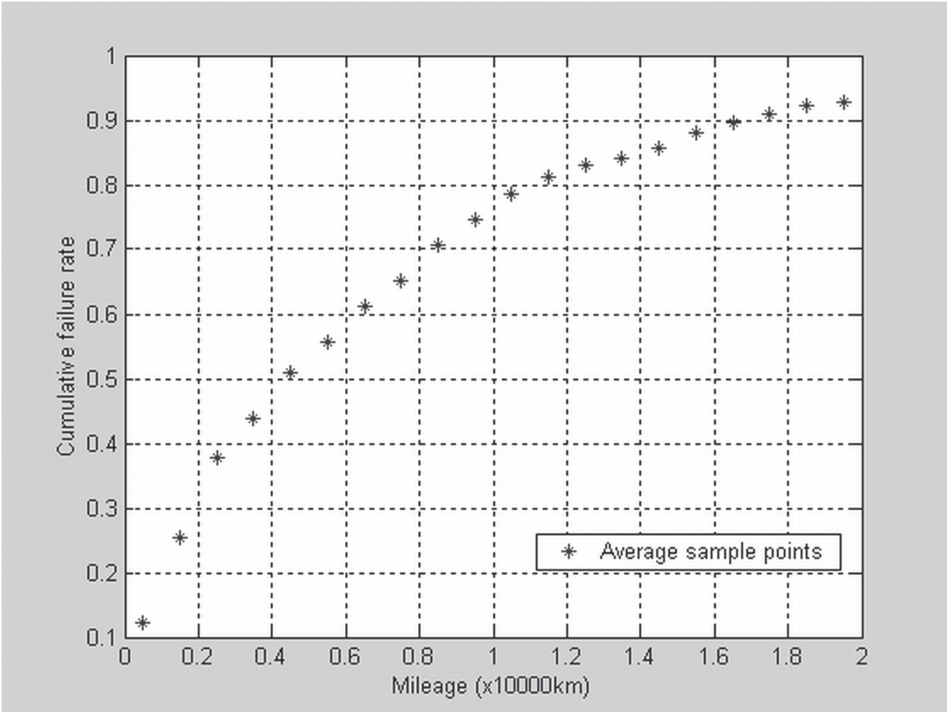

Fig. 5. All districts sample scatter diagram

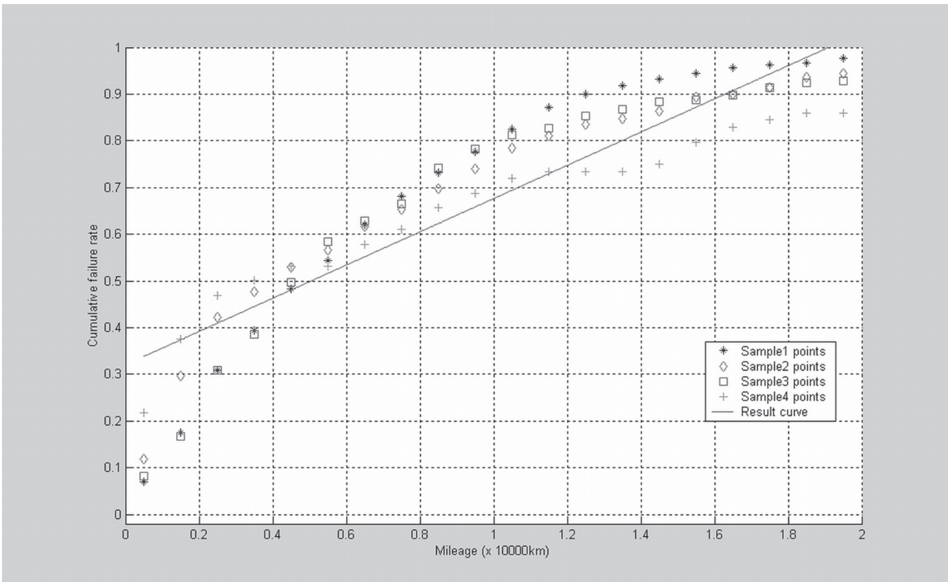

Fig. 6. Fitting with 1-order polynomial

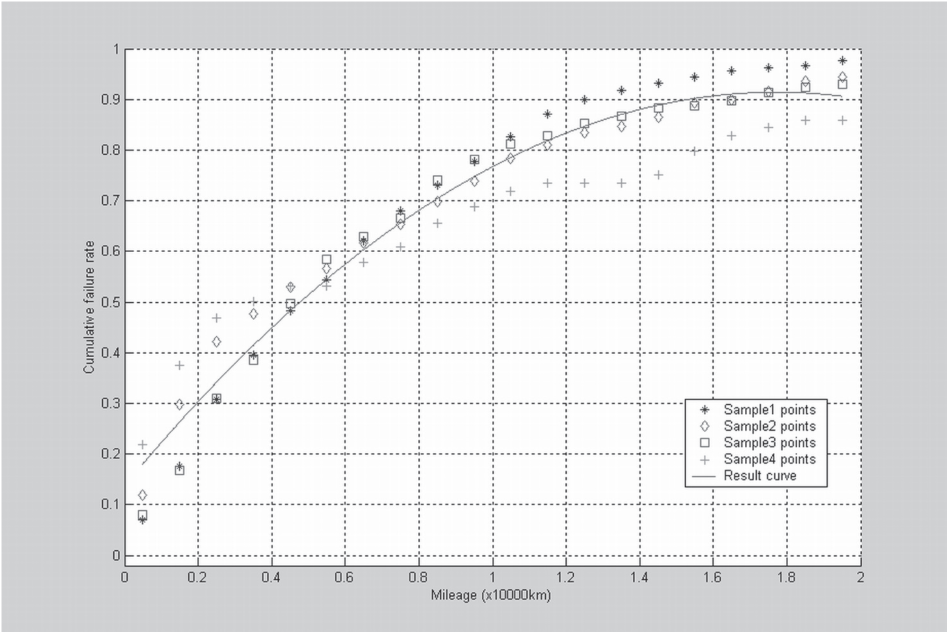

Fig. 7. Fitting with 2-order polynomial

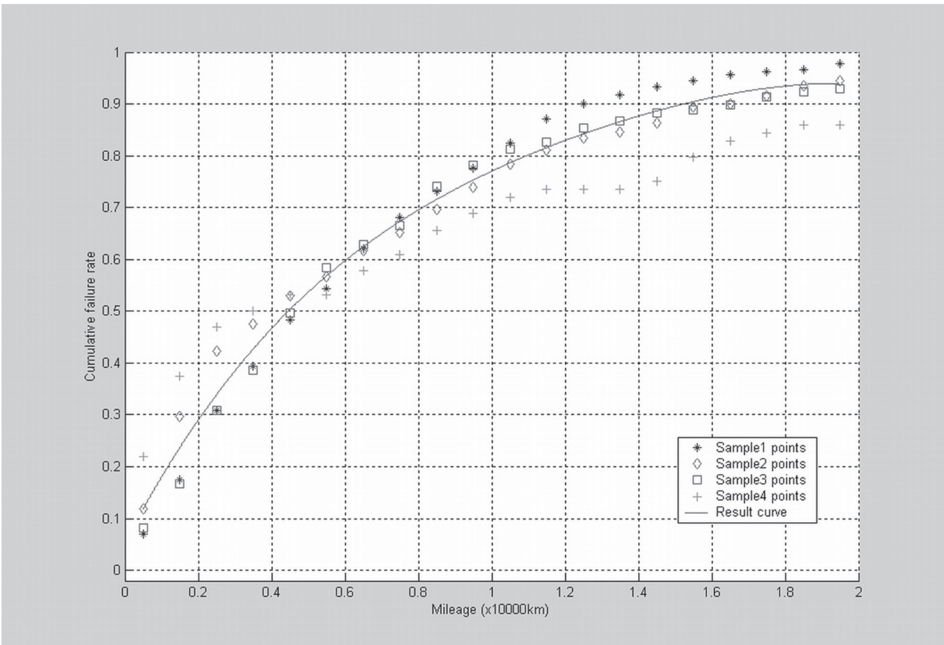

Fig. 8. Fitting with 4-order polynomial

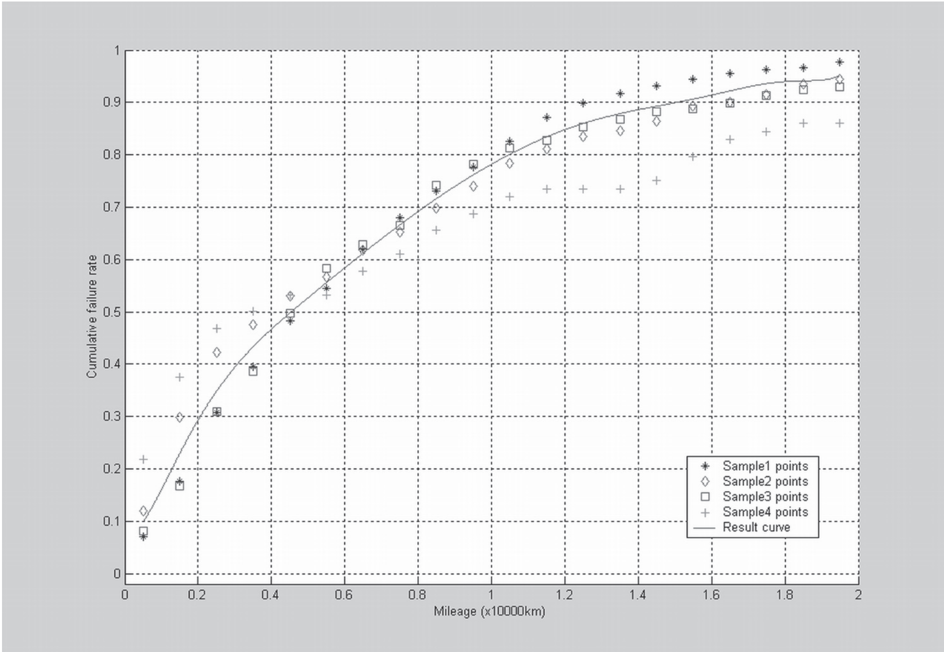

Fig. 9. Fitting with 10-order polynomial

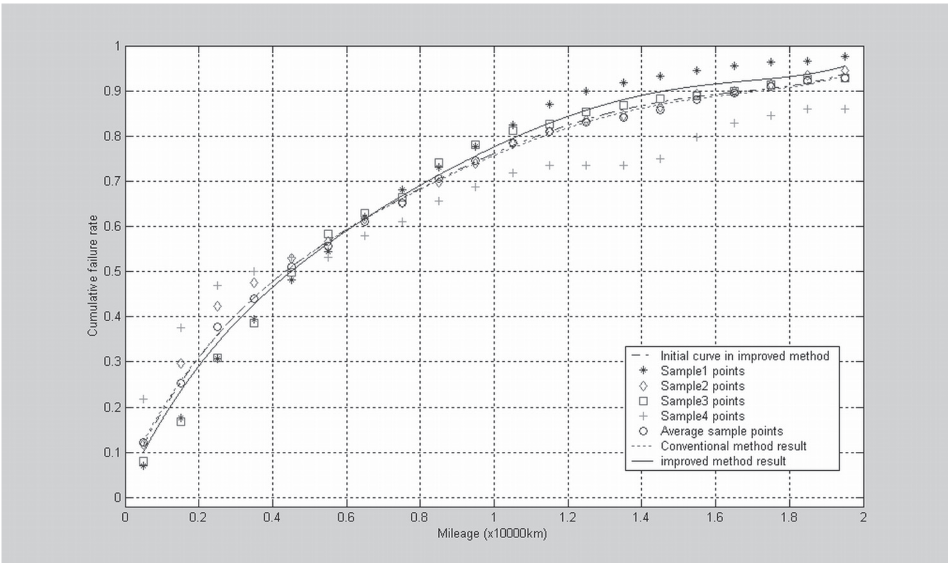

Fig. 10. Fitting result with conventional and improved method

this method loses the impact of districts to diesel. However, the samples like Table 4 can be handled in the improved method.

Polynomial fitting experiments had been done with polynomial order from 1 to 10, and the fitting result has been show as Fig.6 to Fig. 9. Higher order polynomial fitting attempts to use more computing resource and expects to get obvious influence. From Fig. 6 to Fig. 9, we can find the fitting result does not have obvious improvement with the increase of polynomial order if the polynomial order is bigger than 2. Here we use the polynomial fitting method with an order of 5 to handle source data.

Fig.10 shows the fitting result with the conventional and the improved method introduced in this paper. In Fig.10, four different shape group points denote four samples. Dotted line curve denotes the fitting result with the conventional polynomial fitting method, the dot dash one is the initial fitting curve using the improved method, and the iterative result has been shown as the solid one. From Fig.10, we can find in the area where sample points dense gather, the fitting results of these two methods are similar with each other. However, it should be noted in the interval of $(1.0\sim1.8)\bullet10^3$, the improved method fitting result is more close to the area where sample dense gather, and this result is more convincing. In other words, in this interval, one of these four samples is apart from others. The improved method is more flexible to handle this abnormal data situation, and this ability mostly comes from the iterative procedure.

The fitting result coefficients with conventional and improved method do not have enough obvious difference. But from the curve figure, we can find the improved method has obvious advantage in this curve fitting situation.

4. Conclusion

From the engineering example and fitting result analysis, we can find when the samples dense gather, improved polynomial fitting method can get similar fitting result as the conventional method. However, if one or more samples are apart from the others, the improved polynomial fitting method can get more convincing result than the conventional method.

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