Pipeline corrosion analyzed by fuzzy reliability methods

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Abstract

Fuzzy reliability methods are used to study the corrosion of pipelines. Three methods are used. They consist of using fracture failure modes, failure assessment diagram (FAD) and residual strength for establishing fuzzy reliability. Calculations are made by application of JC, improved GA-JC and Mente-carlo methods. Examples for oilfield injecting water pipeline show the residual strength well agree with field data. Mente-carlo methods appear to yield results that have better agreement with field data.

Keywords: corrosion pipeline; reliability; Mente-Carlo; genetic algorithm.

1. Introduction

If a pipeline is corroded, residual strength and remain lifetime are seriously reduced. This could affect reliability and the cost of operation. Therefore, reliability analysis is very important to study the of the corrosion of pipelines [1,2]. Use is made of probability for a given condition and time as represented by certain function [3]. This enables the appropriate selection of pipeline material and running parameters for predicting the residual life [4,5].

There are three aspects of reliability analysis for pipeline corrosion with fuzzy behavior [6-8]. For example, in ASME-IWB3650 criterion [9], when K_r/S_r is higher than 1.8, brittle fracturing happens, and when K_r/S_r is less than 0.2, plastic fracturing happens, when K_r/S_r is higher than 0.2 but less than 1.8, elastic and plastic fracturing happens. When K_r/S_r is near to 0.2 or 1.8, fracturing failure mode is determined. Fracture occurs gradually with a fuzzy transition. For example, in R6 criterion, if test dot locates outside of failure evaluation curve, fracture could often occur. If test dot locates inside of failure evaluation curve, fracture often does not occur. When test dot locates near failure evaluation curve, transition is considered sudden. But in fact, transition near failure evaluation curve should be gradual and fuzzy. Therefore, fuzzy mathematical theories are combined with probability for analyzing fracture mechanics.

2. Fuzzy reliability calculating methods

2.1. Approximate calculating methods of fuzzy failure probability

Supposed $X=(x_1, x_2, \dots x_n)$, $\tilde{A}$ is supposed fuzzy aggregate about fuzzy event, $X=(x_1, x_2, \dots x_n)$ then

$$\tilde{A} = \mu_{\tilde{A}}(x_1)/x_1 + \mu_{\tilde{A}}(x_2)/x_2 + \dots \mu_{\tilde{A}}(x_n)/x_n \quad (1)$$

If the probability of event x_i happening is p_i, then the probability, $P(\tilde{A})$, of fuzzy event $\tilde{A}$ happening is shown as below.

$$P(\tilde{A}) = \sum_{i=1}^{n} \mu_{\tilde{A}}(x_i) p_i \quad (2)$$

If x is continuous, then

$$P(\tilde{A}) = \int_{-\infty}^{+\infty} \mu_{\tilde{A}}(x) p(x) dx \quad (3)$$

when fuzzy probability fracturing mechanics is applied to calculate reliability of corrosion pipe-

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line, if failure function bases on failure mode, then it becomes two levels fuzzy judge. The first fuzzy judge X_1={brittle fracture, elastic and plastic fracturing, plastic fracturing} $=\{x_{11}, x_{12}, x_{13}\}$, fuzzy aggregate $\tilde{A}_1$ for X_1 is expressed as below.

$$\tilde{A}_1 = \mu_{\tilde{A}_1}(x_{11})/x_{11} + \mu_{\tilde{A}_1}(x_{12})/x_{12} + \mu_{\tilde{A}_1}(x_{13})/x_{13} \quad (4)$$

The second judge X_2= {brittle fracturing judge, elastic and plastic fracturing judge, plastic fracturing judge}=(x_{21},x_{22},x_{23}), fuzzy aggregate $\tilde{A}_2$ for X_2 is expressed as below.

$$\tilde{A}_2 = \mu_{\tilde{A}_2}(x_{21})/x_{21} + \mu_{\tilde{A}_2}(x_{22})/x_{22} + \mu_{\tilde{A}_2}(x_{23})/x_{23} \quad (5)$$

Total fuzzy aggregate $\tilde{A}$ ={ $\tilde{A}_1$, $\tilde{A}_2$ } for X={ X_1, X_2} is expressed as below.

$$\tilde{A} = \{ \mu_{\tilde{A}_1}(x_{11})/x_{11} + \mu_{\tilde{A}_1}(x_{12})/x_{12} + \mu_{\tilde{A}_1}(x_{13})/x_{13}, \; \mu_{\tilde{A}_2}(x_{21})/x_{21} + \mu_{\tilde{A}_2}(x_{22})/x_{22} + \mu_{\tilde{A}_2}(x_{23})/x_{23}\} \quad (6)$$

Then calculating formula of reliability in corrosion pipeline is shown as below.

$$R(t) = 1 - F(t) = 1 - P(\tilde{A}) = 1 - \sum_{i=1}^{3}[\mu_{\tilde{A}1}(x_{1i})\sum_{j=1}^{3}\mu_{\tilde{A}2}(x_{2j})p_{2j}] \quad (7)$$

where $\mu_{\tilde{A}_1}(x_{11})$, $\mu_{\tilde{A}_1}(x_{12})$ and $\mu_{\tilde{A}_1}(x_{13})$ respectively indicate subject degrees for brittle fracturing, elastic - plastic fracturing and plastic fracturing in certain failure mode. $\mu_{\tilde{A}_2}(x_{21})$, $\mu_{\tilde{A}_2}(x_{22})$ and $\mu_{\tilde{A}_2}(x_{23})$ respectively indicate subject degrees for brittle fracturing judge, elastic- plastic fracturing judge and plastic fracturing judge in certain fracturing failure mode p_{21}, p_{22} and p_{23} respectively indicate the probability which brittle fracturing, elastic-plastic fracturing and plastic fracturing happen.

In this paper, basing on approximate calculating Methods of fuzzy failure probability, three effective methods are put forward.

2.2. Three methods determining fuzzy fracturing failure probability

Fracture failure modes. Three failure modes are considered: brittle fracture, elastic - plastic fracture and plastic fracture. There prevails two levels of fuzziness such that the corresponding probability can be expressed as

$$P(\tilde{A}) = \sum_{i=1}^{3}[\mu_{\tilde{A}1}(x_{1i})\sum_{j=1}^{3}\mu_{\tilde{A}2}(x_{2j})p_{2j}] \quad (8)$$

where six subject function $\mu_{\tilde{A}_1}(x_{11})$, $\mu_{\tilde{A}_1}(x_{12})$, $\mu_{\tilde{A}_1}(x_{13})$ $\mu_{\tilde{A}2}(x_{21})$ $\mu_{\tilde{A}2}(x_{22})$ $\mu_{\tilde{A}2}(x_{23})$ and three fracturing failure probability p_{21}, p_{22}, p_{23} need calculating.

The probability of brittle fracturing failure happening, p_{21}, is expressed as below.

$$p_{21} = P(Z_1 = g_1(a, c, P, \sigma_s, K_{IC}, C_{paris}) < 0) = P(K_{IC}/N_{safe} - K_I < 0) \quad (9)$$

The probability of elastic-plastic fracturing failure happening, p_{22}, is expressed as below.

$$p_{22} = P(Z_2 = g_2(a, c, P, \sigma_s, \delta_c, C_{paris}) < 0) = P(\delta_c / N_{safe} - \delta < 0) \quad (10)$$

$$p_{22} = P(Z_2 = g_2(a, c, P, \sigma_s, J_{IC}, C_{paris}) < 0) = P(J_{IC}/N_{safe} - J < 0) \quad (11)$$

The probability of plastic fracturing failure happening, p_{23}, is expressed as below.

$$p_{23} = P(Z_3 = g_3(a, c, P, \sigma_s, \sigma_F, C_{paris}) < 0) = P(\sigma_F / N_{safe} - \sigma < 0) \quad (12)$$

Failure assessment diagram (FAD). When FAD is used to judge failure, it does not bases on fracturing failure mode, but consider that if test dot locate inside FAC curves then it does not fracture, if test dot locate outside FAC curves then it fractures, therefore it is one level fracturing.

Fuzzy aggregate $\tilde{A} = \mu_{\tilde{A}}(x_1)/x_1$ for X_1, fracturing failure probability $P(\tilde{A})$ is expressed as below.

$$P(\widetilde{A}) = \mu_{\widetilde{A}}(x_1)p_1 \tag{13}$$

where

$$\begin{aligned} p_1 &= P(Z_1 = g_1(a,c,P,\sigma_s,S_{IC},C_{paris}) < 0) \\ &= P(K_{r0}/N_{safe} - K_r < 0) \end{aligned} \tag{14}$$

K_{r0} is vertical coordinate value which abscissa S_r is put into R6 FAC Eq.

$$K_{r0} = (1-0.14S_r^{\,2})[0.3+0.7\exp(-0.65S_r^{\,6})] \tag{15}$$

Residual strength. This method is based on usual three failure modes: brittle fracture, elastic - plastic fracture and plastic fracture. This includes two levels fuzziness. The second level indicates that when stress σ is less than σ_p, it does not fracture. When stress σ is bigger than σ_p, fracture is assumed to occur.

Fracturing failure probability $P(\widetilde{A})$ is expressed as below.

$$P(\widetilde{A}) = \sum_{i=1}^{3}[\mu_{\widetilde{A}1}(x_{1i})\mu_{\widetilde{A}2}(x_2)p_2] \tag{16}$$

where

$$\begin{aligned} p_2 &= P(Z_2 = g_2(a,c,P,\sigma_s,S_{IC},C_{paris}) < 0) \\ &= P(\sigma_p - \sigma < 0) \end{aligned} \tag{17}$$

In this paper, where p_{21}, p_{22} and p_{23} or p_1, p_2 are called determining reliabilities, while $P(\widetilde{A})$ is named fuzzy reliability. $P(\widetilde{A})$ is final purpose for corrosion pipeline, but first determining reliabilities are acquired. It is very important for quantificational calculating determining reliabilities. In this paper, three methods are brought forward as below.

2.3. Quantification reliabilities

So far, methods quantificational calculating determining reliabilities almost base on reliability safety parameter β, include standard one rank-two matrix methods, improved one rank-two matrix methods and Mente-Carlo numerical methods. Standard one rank-two matrix methods rely on special fail function and require basic random variables meeting normal distribution. Therefore its application range is narrow and precision is very low. Improved one rank-two matrix methods do not rely on fail function style and think that reliability is the shortest distance from origin to limitation curve face, but this method requires basic random variables meeting normal distribution. Mente-Carlo numerical methods [10] produce random numbers by computer and simulate again and again, finally acquire large volume random simulating numbers standing for original random variables distribution. But this method has big error when fracturing failure probability is low. In this paper, three effective methods are put forward to calculate determining reliability basing on three methods above.

2.3.1. Rank-two matrix with J-C methods

Firstly, J-C methods are used to transform non-normal distribution variables into normal distribution variables, secondly improved one rank-two matrix methods are adopted to calculate reliability safety parameter β, finally $F(t)=\Phi(-\beta)$ is used to calculate fracturing failure probabilities.

Steps of using J-C methods to transform non-normal distribution variables into normal distribution variables are shown as below.

(1) Supposed x_i' is non-normal distribution variables, $F(x_i')$ is its distribution function, $f(x_i')$ is probability density function, x_i is equivalence normal distribution variables, $\phi(x_i)$ is distribution function, $\varphi(x_i)$ is probability density function.

$$F(x_i') = \phi\left(\frac{x_i' - \mu_{x_i}}{\sigma_{x_i}}\right), \quad f(x_i') = \frac{\varphi\left(\frac{x_i' - \mu_{x_i}}{\sigma_{x_i}}\right)}{\sigma_{x_i}} \tag{17}$$

(2) Let $F(x_i') = f(x_i')$, average value μ_{x_i} and standard deviation σ_{x_i} are acquired as below.

$$\mu_{x_i} = x_i' - \sigma_{x_i}\phi^{-1}[F(x_i')] \quad (18)$$

$$\sigma_{x_i} = \varphi\{\phi^{-1}[F(x_i')]\} / f(x_i') \quad (19)$$

In this paper, above methods are named improved J-C methods.

2.3.2. Genetic algorithm with improved J-C methods.

It is well known that calculating fracturing failure probability $F(t)=\Phi(-\beta)$ correspond to solve minimum problem under restriction condition. As far, there are many methods such as Powell method, SUMT mixture methods and Golden Section method and so on. But these methods almost calculate the derivative objective function and plunge into local convergence and lead to big error. Genetic Algorithm (GA)[11-13] is a distinguished whole convergence optimization method. Therefore, in this paper, in order to improve the shortcomings of conventional algorithm, Genetic Algorithm (GA) is utilized to optimize reliability index β.

(1) Code mode of the population

Real number codes are adopted for the population.

(2) Selection of fitness function

As GA is maximal fitness function to evolution, but we want to get minimum value of reliability index β. So it must be modified as fitness function of GA. In this paper, three methods are put forward to modify error objective function, namely the reciprocal methods, making negative methods and improved making negative methods.

If the reciprocal methods are used, then

$$f = 1.0 / g(x_1, x_2, \ldots x_n) \quad (20)$$

where f is fitness function, E is minimal error objective function of BP neural network, t_k is ideal output values (test measuring values), o_k is calculating values.

If making negative methods are used.

$$f = -g(x_1, x_2, \ldots x_n) \quad (21)$$

If improved making negative methods are used, then

$$f = \begin{cases} C_{max} - g(x_1, x_2, \ldots x_n), g(x_1, x_2, \ldots x_n) < C_{max} \\ 0, else \end{cases} \quad (22)$$

where C_{max} is given bigger positive number, generally C_{max} =100 ~1000.

(3) Crossover methods

In this paper, arithmetic crossover and geometry crossover methods are adopted.

Arithmetic crossover methods:

$$v_1' = \lambda v_1 + (1-\lambda)v_2, v_2' = \lambda v_2 + (1-\lambda)v_1 \quad (23)$$

where v_1 and v_2 are last generations chromosome, v_1' and v_2 are present generations chromosome, λ is random number from 0 to 1.0.

Geometry crossover methods:

$$v_1' = \lambda(v_1 - v_2) + v_1, v_2' = \lambda(v_2 - v_1) + v_2 \quad (24)$$

(4) Mutation methods

Dynamic mutation methods are adopted.

$$v_k' = v_k + (v_k^U - v_k)\lambda(1 - t/T)^b \quad (25)$$

or

$$v_k' = v_k - (v_k - v_k^L)\lambda(1 - t/T)^b \quad (26)$$

where v_k^U and v_k^L are respective upper limit and lower limit of v_k, t, and T are respective present generations and maximal generations, b is adoptive degrees parameters, b=2~5.

In this paper, methods Combining Genetic Algorithm with improved J-C methods are called improved GA-JC methods.

2.3.3. Improved Mente-Carlo simulation methods

Steps of standard Mente-Carlo method:

1) Uniform distribution simulation numbers from 0 to 1,ζ_j (j =1,2,... M), are created. These numbers must be verified for parameter, uniformity and independence.

2) Random simulation numbers of specified random variables distribution, r_j (j =1,2,... M), are acquired.

3) the jth random simulation numbers, r_{ij} (i=1,2,...n, n is basic random simulation numbers of failure function) are replaced by random simulation variables x_i, then failure function $g(x_1,x_2,...x_n)$ is acquired.

Examples by fracturing failure judge are illuminated how to calculate fracturing failure probabilities using Mente –Carlo simulation methods. Subjective functions $\mu_{\tilde{A}_2}(x_{2j})$ are determined as below.

For brittle fracturing, if $K_{IC}*b_{21}/N_{safe}$-K_I<0, then test dots completely produce failure or fracturing, $\mu_{\tilde{A}_2}(x_{21})=1$.

If $K_{IC}*b_{21}/N_{safe}$-K_I>0, then test dots don't completely produce failure or fracturing, $\mu_{\tilde{A}_2}(x_{21})=0$.

. If $K_{IC}\times a_{21}/N_{safe}\le K_I\le K_{IC}\times b_{21}/N_{safe}$, then test dots locate fuzzy zones, and K_I value is put into subjective function $\mu_{\tilde{A}_2}(x_{21})$,and $\mu_{\tilde{A}_2}(x_{21})$ value is calculated.

For elastic-plastic and plastic fracturing, calculation methods of subjective functions $\mu_{\tilde{A}_2}(x_{22})$ and $\mu_{\tilde{A}_2}(x_{23})$ are similar as brittle fracturing.

If total simulating number is M_{Total} and there are M_I times completely fracture, then total fracturing failure probabilities are expressed as below.

$$P(\tilde{A})=\frac{M_1+\sum_{i=1}^{3}[\mu_{\tilde{A}_1}(x_{1i})\sum_{j=1}^{3}\mu_{\tilde{A}_2}(x_{2j})]}{M_{Total}} \quad (27)$$

Because standard Mente-Carlo method has big error when fracturing failure probability is low, some improvements are put forward in this paper.

1)The first improved methods reduce random simulating variables.

Only n-1 random variables are used to simulate, for examples, x_i variable does not simulate, only x_1, x_2, ...x_{i-1}, x_{i+1}, ... x_n variables simulate. Random simulating variables x_1, x_2, ...x_{i-1}, x_{i+1}, ... x_n are put into objective function Z=g(x_1, x_2, ...x_{i-1}, x_{i+1}, ... x_n) =0, improved GA-JC methods are adopted to optimize objective function and optimum values x_i^* are solved. these methods may be reduce random simulating number.

2) The second improved methods are important sample methods.

The methods sample bigger sampled dot for fracturing failure probability contributing bigger and overcome the shortcomings of uniform samples. Improved GA-JC methods are combined with the methods and reduce random simulating number.

3) The third improved methods are distributed simulating methods

The steps of distributed simulating methods are shown as below.

① the jth random simulation numbers, r_{ij} (i=1,2,...n, n is basic random simulation numbers of failure function) are replaced by random simulation variables x_i, then failure function Z=$g(x_1,x_2,...x_n)$ is acquired.

②Let Z=$g(x_1,x_2,...x_n)$ meet certain distribution., probability distribution $P'(Z)$ is acquire.

③according to $P'(Z)$, failure probability $F(t)$and reliability $R(t)$ are solved.

In this paper, reduce random simulating variables methods, important sample methods and distributed simulating methods are combined and formed into new methods. The new methods are named improved Mente-Carlo methods

3. Application analysis

Examples in certain oilfield injecting water pipeline are used to verify and choose three fuzzy reliability methods, namely methods basing on fracturing failure judge and methods basing on FAD and methods basing on residual strength and three determining reliability methods, namely improved JC methods and improved GA-JC methods and improved Mente-carlo methods. Basic parameters for corrosion pipeline are shown as below.

Determining parameters: Out diameter of pipeline Do=420m, wall thickness t=10mm.Constant m=4.13 in Paris formula. Safe factors N_{safe}=1.5, elastic module E=2.1×105MPa, Resistance pull strength σ_b=450 MPa.

Six uncertain random variables: (1)The mean values $\mu_{K_{Ic}}$ =3077N/mm1.5 of fracture roughness KI, standard difference $\sigma_{K_{Ic}}$ =80.12 N/mm1.5, variance coefficient COV(K_{IC})= 0.026, submit to logarithm normal distribution. (2)The mean values of C in Paris formula, μ_C=2.34×10-14, standard difference σ_C=2.75×10-16, variance coefficient COV(C)=0.01175, submit to normal distribution. (3)The mean values μ_a =1.02mm of initial defect height, standard difference σα=0.0459mm,. variance coefficient COV(α)=0.045, submit to three parameter Weibull distribution.(4) The mean values μL =5.05mm of initial defect length, standard difference σL=0.0839mm, variance coefficient COV (L)=0.0166, submit to logarithm normal distribution.(5) The mean values μ_{σ_s} =312MPa of yield strength, standard difference σ_{σ_s}=6.78MPa, variance coefficient COV(σ_s) = 0.0217, submit to maximal distribution.(6) The mean values μ_P =14.56 MPa of injecting pressure P, standard difference σ_p=0.89 MPa, variance coefficient COV(P)=0.0611, submit to maximal distribution.

Corrosion defect sizes for different time sequence are shown as table 1.

3.1. The comparison of three fuzzy reliability calculation methods

Three fuzzy reliability methods, namely methods basing on fracturing failure judge and methods basing on FAD and methods basing on residual strength, are adopted to calculate fuzzy reliabilities variation with time. Calculating results are shown as Fig.1.

3.2. Basing on residual strength to contrast three determining reliabilities methods

To given corrosion defect sizes, improved JC methods and improved GA-JC methods and improved Mente-carlo methods are adopted respectively to calculate the second fracturing failure probability p_2=P(σ_p-σ<0), then are put into formula (15) to calculate fuzzy reliability. Simulating number of improved Mente-carlo methods is 10000 times. Calculating results are shown as Fig.2.

4. Results and discussion

(1) In this paper, calculating methods of fuzzy reliabilities in corrosion pipeline are deeply studied. Determining reliability and fuzzy reliability are firstly put forward and distinguished strictly. Three effective methods, methods basing on fracturing failure judge and methods basing on FAD and methods basing on residual strength, are brought forward to calculate fuzzy reliability. Three effective methods, improved JC methods and improved GA-JC methods and improved Mente-carlo methods, are put forward to calculate determining reliability.

(2) Examples in certain oilfield injecting water pipeline are used to verified and evaluated three fuzzy reliabilities and three determining reliabilities. Results of calculating show methods basing on residual strength are improved Mente-carlo methods have better agreement with field data among three determining reliability calculation methods.

Table 1. Corrosion defect sizes with time sequence.

Series	1	2	3	4
Time	99-1-1	99-2-1	99-3-1	99-4-1
height(mm)	1.02	1.067	1.109	1.138
length(mm)	5.05	5.097	5.151	5.20
Series	5	6	7	8
Time	99-5-1	99-6-1	99-7-1	99-8-1
height(mm)	1.170	1.281	1.333	1.371
length(mm)	5.25	5.296	5.345	5.401
Series	9	10	11	12
time	99-9-1	99-10-1	99-11-1	99-12-1
height(mm)	1.412	1.459	1.492	1.563
length(mm)	5.463	5.534	5.6	5.689
Series	13	14	15	16
Time	00-1-1	00-2-1	00-03-1	00-4-1
height(mm)	1.596	1.669	1.719	1.772
length(mm)	5.769	5.848	5.924	6.002
Series	17	18	19	20
time	00-5-1	00-6-1	00-7-1	00-8-01
height(mm)	1.830	1.899	2.02	2.063
length(mm)	6.09	6.19	6.311	6.439
Series	21	22	23	24
Time	00-9-1	00-10-1	00-11-1	00-12-1
height(mm)	2.156	2.3	2.368	2.54
length(mm)	6.579	6.731	6.891	6.99
Series	25	26	27	28
Time	01-1-1	01-2-1	01-3-1	01-4-1
height(mm)	2.66	2.9	3.14	3.37
length(mm)	7.18	7.41	7.675	7.998
Series	29	30		
Time	29	30		
height(mm)	01-5-1	01-6-1		
length(mm)	3.56	3.92		

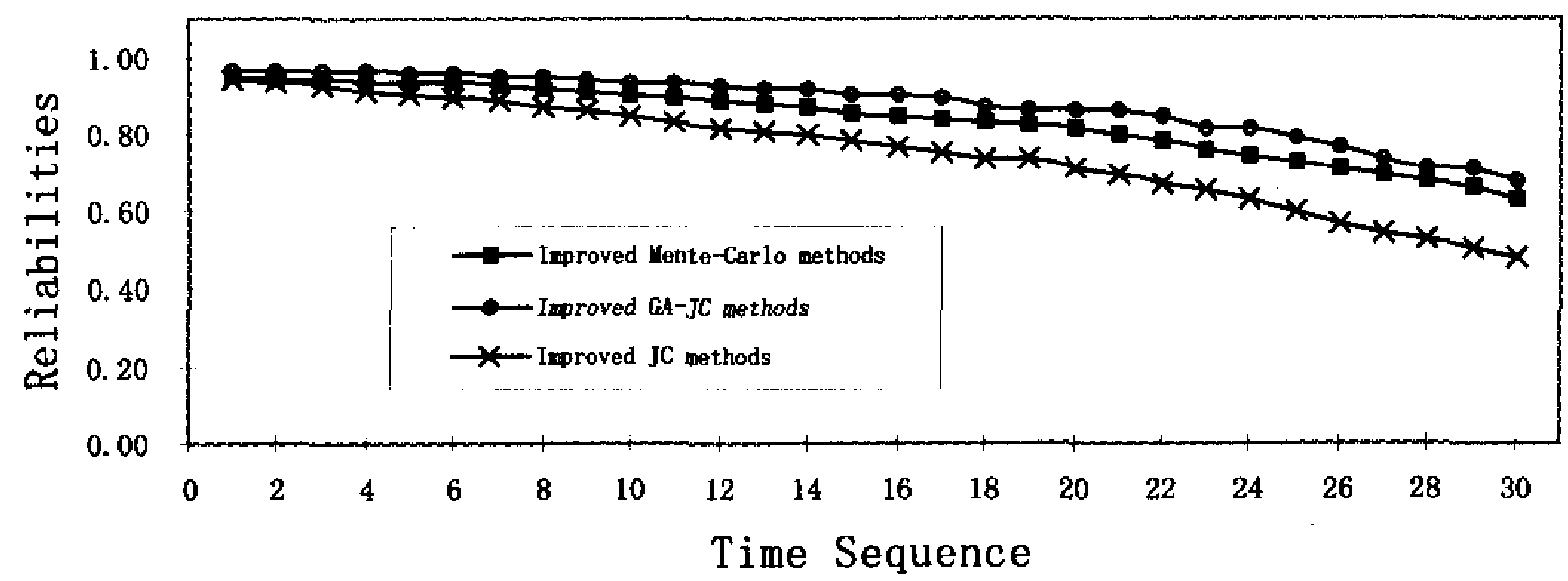

Fig. 1. Basing on three models to calculate fuzzy reliability.

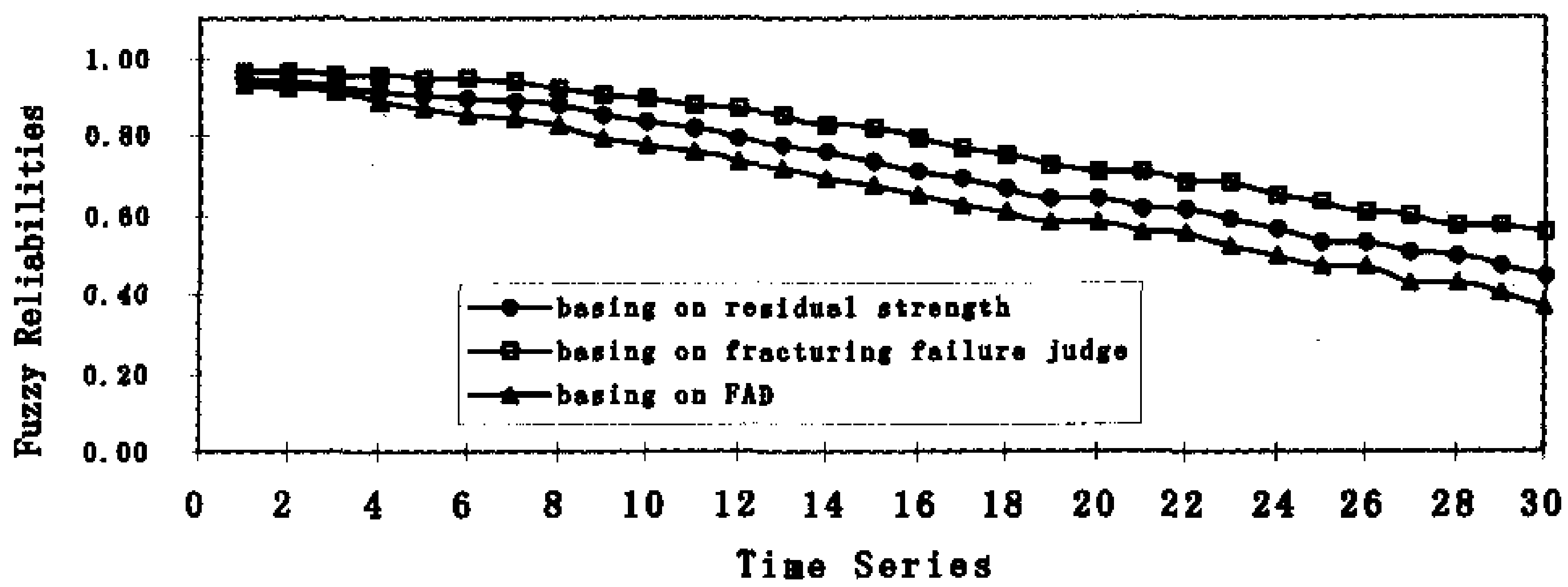

Fig. 2. Basing on residual strength to contrast three determining reliabilities methods.

Acknowledgements

The paper is finished with the help of all staff of exploitation lab in SouthWest Petroleum Institute.

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