Analytical methods of residual strength in injecting water pipeline

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Abstract

In this paper, common criterions about residual strength evaluation at home and abroad are generalized and seven methods are acquired, namely ASME-B31G, DM, Wes-2805-97, CVDA-84, Burdekin, Irwin and J integral methods. BP neural network are Combined with Genetic Algorithm (GA) named by modified BP-GA methods to successfully predict residual strength and critical pressure of injecting water corrosion pipelines. Examples are shown that calculation results of every kind of method have great difference and calculating values of Wes-2805-97 criterion, ASME-B31G criterion, CVDA-84 criterion and Irwin fracture mechanics model are conservative and higher than those of J integral methods while calculating values of Burdiken model and DM fracture mechanics model are dangerous and less than those of J integral methods and calculating values of modified BP-GA methods are close and moderate to those of J integral methods. Therefore modified BP-GA methods and J integral methods are considered better methods to calculate residual strength and critical pressure of injecting water corrosion pipelines.

Keywords: injecting water pipeline; corrosion defect; residual strength; BP neural network; genetic algorithm.

1. Introduction

If injecting water pipeline is corroded, residual strength and critical pressure are seriously reduced, and corrosion detection and maintenance expense will be largely increased [1]. The purposes of residual strength evaluation are whether corrosion defects may be permitted existence, and critical residual strength and critical injecting water pressure are determined in a certain corrosion defect, and critical corrosion defects in given injecting water pressure. Residual strength evaluation is one of important parts of injecting water pipeline surface engineering evaluation and the base for choosing corrosion inhibitor, bactericide and scale inhibitor [2,3]. Therefore it is very essential that residual strength evaluations in injecting water pipelines be deeply studied. In this paper, residual strength evaluation criterions at home and abroad are summarized, generalized and compared. At present, residual strength evaluation criterions mainly focus on oil and gas transporting pipelines while few criterions for injecting water pipeline. At abroad, With fracture mechanics development, residual strength evaluation criterions for safety reliabilities and economics are developed and formed, for example, CEGB-R6 for assessment of the integrity of structures containing defects (1988)[4], ASME-B31G corrosion defects criterions(1990) [5], BSI-PD6493(1991) for assessment the acceptability of flaws in fusion welding structures[6] and WES-2805-97 pressure vessel criterions in Japan[7]. FAD methods [8] basing on J integral theory are a universal tendency for calculating residual strength. In china, residual strength evaluation criterions are CVDA-84[9] and SAPV-95[10] criterions. SAPV-95 criterion bases on FAD methods[11-12].In conclusion, the criterions at home and abroad base on certain experimental environments and engineering conditions, therefore these criterions have certain application ranges, but at present, few people compare and choose these criterions. In this paper, examples are used to compare these criterions and choose a few criterions of wide application ranges and high precision.

In addition, BP neural network is combined

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with genetic algorithm(GA) into a new type neural networks having high precision and fast whole convergence. The new neural networks are successfully used to calculate residual strength and critical injecting water pressure in given corrosion defects.

2. Calculating methods of residual strength

At present, calculating methods of residual strength criterions mainly base on fracture failure mode. Usually, brittleness fracture mode bases on stress intensity factors K, elastic and plastic fracture modes base on corrosion fracture extension displacement δ. Every method has its application range, its excellence and shortcoming. Therefore, in this paper, basing on certain main method, other methods are combined into a new method.

2.1. Semi-empirical criterions (ASME-B31G) basing on whole size

According to fracture mechanism, residual strength of axial corrosion defect is calculated as below:

$$\sigma_p = (\sigma_s + 68.95)\left[\frac{1-\varphi}{1-\varphi \cdot M^{-1}}\right] / N_{safe} \tag{1}$$

where σ_p is residual strength of axial corrosion defects, MPa; M is bouffant coefficient, dimensionless; N_{safe} is safety coefficient; φ is modified coefficient ; σ_s is yield stress of material, MPa. φ is determined as below,

Supposed $x=a/t$, if, $x\leq 4$ then b=4. If x>4, then

$$b=\left[\left(\frac{x}{1.1x-0.15}\right)^2-1\right]^{0.5}$$

(1) If $b \leq 4$, then shape of corrosion defect zones is parabola, equivalent length methods are used, namely ,

$$\varphi = \frac{2a}{3t}.$$

(2) If b>4, the shape of corrosion defect zones is rectangle, total length methods are used,

$$\varphi = \frac{a}{t}.$$

(3) Effective area methods are adopted,

$$\varphi = \frac{0.85\,a}{t}.$$

where a is corrosion defect height, mm. t is wall thickness, mm.
M is determined as below

$$M=\begin{cases}\left[1+0.6275\dfrac{L^2}{D\cdot t}-0.003375\dfrac{L^4}{D^2\cdot t^2}\right]^{0.5} & \dfrac{L^2}{D\cdot t}\leq 50\\ 0.032\times\dfrac{L^2}{D\cdot t}+3.3 & \dfrac{L^2}{D\cdot t}>50\end{cases} \tag{2}$$

where D is inlet diameter, mm. L is corrosion defect length, mm.

2.2. Basing on fracture mechanism

2.2.1. DM fracture mechanics model

(1) For brittle fracture, Neaman fracture mechanism is adopted:

$$\sigma_p = \left(\frac{K_{IC}E}{F_I\left(\frac{a}{c},\frac{a}{t},\frac{R_i}{t},\theta\right)\sqrt{\pi a}N_{safe}}\right) \tag{3}$$

where K_{IC} is fracture toughness, N/mm1.5. E is elastic module, MPa. R_i is inlet diameter, mm. θ is angle on the fracture top, radium. c is the half of defect length for embedding fracture, mm.

(2) For elastic plastic fracture fail, DM fracture mechanics theories are used as below.

$$\sigma_p = \frac{2\sigma_s}{\pi M \times N_{safe}}\arccos\left[\exp\left(\frac{-\pi E\delta_c}{8\sigma_s \bar{a}}\right)\right] \tag{4}$$

where δ_c is fracture allowance extension displacement, mm.

(3) For plastic fracture, yield strength σ_s will be changed into rheology stress σ_f.

$$\sigma_p = \frac{2\sigma_f}{\pi M \times N_{safe}} \arccos\left[\exp\left(\frac{-\pi E\delta_c}{8\sigma_f \bar{a}}\right)\right] \quad (5)$$

where σ_f is rheology stress, MPa; $\bar{a}$ is equivalent corrosion defect height.

2.2.2. Wes-2805 criterions in 1997

(1) For brittle fracture, σ_p is calculated as below.

$$\sigma_p = \sqrt{\frac{16E\delta\sigma_s}{\pi\bar{a}}} \quad (6)$$

(2) For elastic plastic fracture fail, WES-2805 criterions are adopted.

$$\sigma_p = [(\frac{8E\delta_c}{\pi\sigma_s\bar{a}}) + 5]\frac{\sigma_s}{9N_{safe}} \quad (7)$$

(3) For elastic plastic fracture fail, yield strength σ_s will be changed into rheology stress σ_f.

$$\sigma_p = \frac{\sigma_f}{M \times N_{safe}} \quad (8)$$

2.2.3. Basing on CVDA-84 criterions

(1) For brittle fracture

For surface corrosion defect

$$\sigma_p = \frac{K_{IC}\phi}{N_{safe}F\sqrt{\pi a}} \quad (9)$$

where ϕ is the second type ellipse integral. F is the correct coefficient of equivalent fracture size.

$$F = 1.1 + 5.2 \times 0.5^{\frac{5a}{c}} \times (\frac{a}{t})^{1.8+\frac{a}{c}} \quad (10)$$

$$\phi = \left[1.0 + 1.464(\frac{a}{c})^{1.65}\right]^{0.5} \quad (11)$$

For embedding fracture

$$\sigma_p = \frac{K_{IC}\phi}{\Omega \times N_{safe}\sqrt{\pi a}} \quad (12)$$

where Ω is the correct coefficient of embedding fracture. Ω is calculated as below.

$$\Omega = 1 + b\left[\frac{a}{P_1 + a}\right]^k \quad (13)$$

$$b = \left[0.42 + 2.23(\frac{a}{c})^{0.8}\right]^{-1} \quad (14)$$

$$k = 3.3 + \left[1.1 + 50.0\left(\frac{a}{c}\right)\right]^{-1} + 1.95\left(\frac{a}{c}\right)^{1.5} \quad (15)$$

where b and k are correct coefficients, P_1 is the minimum distance from embedding fracture to two freedom surface, mm.

For penetrable corrosion defect.

$$\sigma_p = \frac{K_{IC}}{M \times N_{safe}\sqrt{\pi c}} \quad (16)$$

(2) For elastic plastic fracture fail

If maximal stress in corrosion defect zones σ is less than yield stress σ_s, then

$$\sigma_p = \left(\frac{E\delta_c\sigma_s}{2\pi\bar{a}}\right)^{0.5} / N_{safe} \quad (17)$$

If maximal stress in corrosion defect zones σ is more than yield stress σ_s, then

$$\sigma_p = (\frac{E\delta_c}{\pi\bar{a}} - \sigma_s) / N_{safe} \quad (18)$$

(3) For elastic fracture, formula (8) is adopted.

2.2.4. Basing on Burdekin fracture mechanics theory

(1) For brittle fracture, Neaman fracture mechanism formula (3)is adopted.

(2) For elastic plastic fracture fail

$$\sigma_p = \frac{\sigma_s}{N_{safe}}\left(0.25 + \frac{\delta_c E}{2\pi\sigma_s \bar{a}}\right) \tag{19}$$

(3) For elastic fracture, formula (8) is adopted.

2.2.5. Irwin fracture mechanics theory

(1) For brittle fracture,

$$\sigma_p = \frac{\phi K_{IC}}{\left[M_1^2 M_2^2 \pi a + 0.212\left(\frac{K_{IC}}{\sigma_s}\right)^2\right]^{0.5} \times N_{safe}} \tag{20}$$

(2) For elastic plastic fracture fail

$$\sigma_p = \left(\frac{E\delta_c}{\pi\bar{a}} - \sigma_s\right) / N_{safe} \tag{21}$$

(3) For elastic fracture, formula (8) is adopted.

2.2.6. Basing on J integral theories

For brittle fracture and elastic fracture, above methods are adopted. But for elastic plastic fracture fail, J integral theories are used. Accurately elastic analysis for corrosion defect zone is very difficult and J integral is also calculated. Therefore approximate solution of J integral is only obtained.

According to fracture mechanics theory, J integral solutions equal to elastic solutions $J^e(a_{eff}, P)$ adding to plastic solutions $J^p(a, P, n)$.

$$J(a,P) = J^e(a_{eff},P) + J^p(a,P,n) \tag{22}$$

where a_{eff} is corrosion defect height according to Irwin plastic correct, mm.

Elastic solution $J^e(a_{eff}, P)$ is calculated as below.

$$J^e(a_{eff},P) = \frac{4\times10^3 P^2 R_o^4 \pi a_{eff}}{E[(R_i+t)^2 - R_i^2]^2} F^2(a_{eff}/t, R_i/R_o) \tag{23}$$

where P is injecting water pressure, MPa. $J^e(a_{eff}, P)$ is full elastic and plastic solution of J integral, MN/m.

a_{eff} is calculated as below,

$$a_{eff} = a + \frac{0.1768}{\pi}\left(\frac{K_I}{\sigma_s}\right)^2 \tag{24}$$

Full elastic and plastic solution $J^p(a, P, n)$ of J integral is calculated as below.

$$J^p(a,P,n) = \frac{\sigma_s^2}{E'}a\left(1-\frac{a}{t}\right)a \times H_1\left(\frac{a}{t}, n, \frac{R_i}{R_0}\right) \times \left(\frac{P}{P_0}\right)^{n+1} \tag{25}$$

where $H_1(a/t, n, R_i/R_o)$ is dimensionless function, R_o is out-radius, P_0 is plastic fail pressure of full plastic state ($n = +\infty$) ,MPa. P_0 is calculated as below.

$$P_0 = \frac{2(t-a)\sigma_s}{\sqrt{3}(R_i + a)} \tag{26}$$

$H_1(a/t, n, R_i/R_o)$ is obtained from table 1 to table 3.

2.3. Combining neural network with genetic algorithm

For many factors influencing residual strength, criterions and correlation above mentioned have certain application range and have poor precision. Because BP neural networks have self - organization, self-study and nonlinear mapping function, BP neural networks may be used to determine residual strength for certain corrosion defect size.

Table 1. values when t/R_i is equal to 0.2.

a/t	$H_1(a/t,n,R_i/R_0)$			
	n=7	n=10	n=11.677	n=13.349
1/8	9.34	9.55	9.67	9.78
1/4	7.78	6.98	6.53	6.09
1/2	3.95	2.27	1.33	0.39
3/4	1.05	0.787	0.64	0.49

Table 2. values when t/R_i is equal to 0.2.

a/t	$H_1(a/t,n,R_i/R_0)$			
	n=7	n=10	n=11.677	n=13.349
1/8	8.07	7.75	7.57	7.37
1/4	7.21	6.53	6.15	5.77
1/2	4.88	2.62	1.36	0.097
3/4	1.23	0.883	0.69	0.5

Table 3. values when t/R_i is equal to 0.05.

a/t	$H_1(a/t,n,R_i/R_0)$			
	n=7	n=10	n=11.677	n=13.349
1/8	13.12	14.940	15.96	16.97
1/4	9.71	9.45	9.30	9.16
1/2	3.52	2.11	1.32	0.54
3/4	0.83	0.493	0.30	0,177

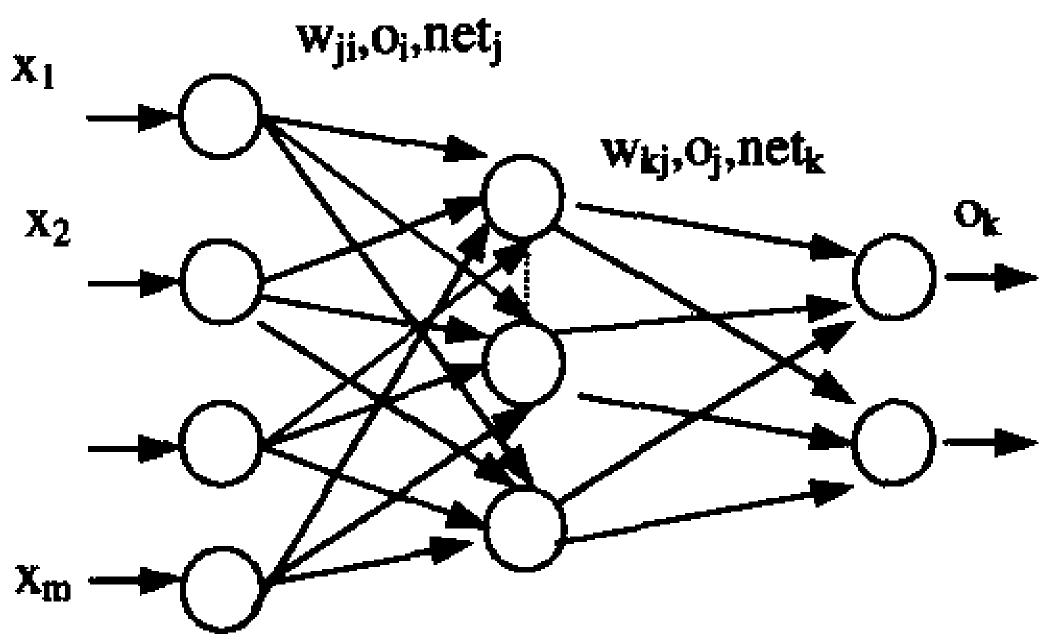

Fig.1. Three layers neural network structures.

Three layers neural network structure is in common use structure. It includes input layers, implicit layers and output layers. Three layer neural network structures are shown as Fig.1.

Input layer nodes (i=1,2,3...n, n is input node numbers) stand for residual strength influence factors such as injecting water temperature T, injecting water pressure P, corrosion defect height a, defect length $2C$, yield stress σ_s, fracture toughness S_{IC} (such as K_{IC}, δ_c, J_{IC}) and Paris formula constant C. Output layer nodes O_k (k=1,2,..p, p is output node numbers) indicate test result such as residual strength. But conventional BP neural networks have many shortcomings such as slow convergence velocity and local convergence etc.[13-16]. Therefore it is very essential to make the improvements for BP neural network. Genetic Algorithm(GA)[17-19] is a distinguished whole convergence optimization method. Therefore, in this paper, in order to improve the shortcomings of BP neural network, Genetic Algorithm(GA) is utilized to optimize connection weight values wij and threshold values θ_j between input layer nodes and implicit layer nodes, connection weight values wjk and threshold values θ_k between implicit layer nodes and output layer nodes.

At present, combination mode of GA and BP neural network mainly focuses on using GA to optimize connection values and threshold values of BP neural network. Calculating steps of the methods are shown as below.

(1) Code mode of the population

Real number codes are adopted for the population. Using matrix P to express connection weight values and threshold values which two-layer BP neural network need optimizing. Matrix P is shown as below.

$$P=\begin{bmatrix} w_{111} \cdots w_{11k} \cdots w_{1n1} \cdots w_{1nk} \mid w_{211} \cdots w_{21n} \cdots w_{2k1} \cdots w_{2kn} \mid \theta_{21} \cdots \theta_{2k}\ \theta_{31} \cdots \theta_{3n} \\ \cdot\ \cdot\ \cdot \qquad \cdot\ \cdot\ \cdot \qquad \cdot\ \cdot\ \cdot\ \cdot \\ \cdot\ \cdot\ \cdot\ \cdot \\ \cdot\ \cdot\ \cdot\ \cdot\ \cdot\ \cdot\ \cdot \\ \cdot\ \cdot\ \cdot\ \cdot\ \cdot \end{bmatrix} \quad (27)$$

where n is input node numbers(or corrosion influence factors),K is output node numbers(or corrosion velocity), w_{ik} (i=1,2,...n; j=1,2,...p) is connection weight values between input layers and output layers. θ_k (k=1,2,...p) is threshold values of output layer nodes. Matrix P stands for sizes of chromosome number. Therefore the essential of GA is the operation to matrix P such as selection, crossover, inheritance and mutation.

(2) Selection of fitness function

As GA is maximal fitness function to evolution, whereas BP neural network is minimal error as objective function to optimize, therefore error objective function of BP neural network 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.

The reciprocal methods

$$f=\frac{1}{E}=\frac{1.0}{\frac{1}{2}\sum_{k=1}^{p}(t_k-o_k)^2} \quad (28)$$

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.

Making negative methods

$$f=-E=-\frac{1}{2}\sum_{k=1}^{m}(t_k-o_k)^2 \quad (29)$$

Improved making negative methods

$$f=\begin{cases} C_{max}-\frac{1}{2}\sum_{k=1}^{m}(t_k-o_k)^2, & \frac{1}{2}\sum_{k=1}^{m}(t_k-o_k)^2<C_{max} \\ 0, & \text{else} \end{cases} \quad (30)$$

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:

$$v_1' = \lambda v_1 + (1-\lambda)v_2 ;\quad v_2' = \lambda v_2 + (1-\lambda)v_1 \tag{31}$$

where $v1$ and $v2$ are last generations chromosome, $v1$ and $v2$ are present generations chromosome, λ is random number from 0 to 1.0.

Geometry crossover methods:

$$v_1' = \lambda(v_1 - v_2) + v_1 ;\quad v_2' = \lambda(v_2 - v_1) + v_2 \tag{32}$$

(4) Mutation methods

Dynamic mutation methods are adopted.

$$v_k' = v_k + (v_k^U - v_k)\lambda(1-t/T)^b \tag{33}$$

or $v_k' = v_k - (v_k - v_k^L)\lambda(1-t/T)^b$ (34)

where v_k and v_k 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, the new neural networks of combination GA and BP are named by GA-BP neural network (shorted for GA-BP).

3. Application example analysis

Eight methods , namely,ASME-B31G、DM method、Wes-2805-97、CVDA-84、Burdekin method、Irwin method、J integral method and GA-BP method are used to calculate residual strength of injecting water pipeline added into corrosion inhibitor in certain experimental zones.

Base data for injecting pipeline are shown as below, pipeline out -diameter DO =420mm, wall thickness t=10mm; fracture roughness KIC =3077N/mm1.5, Paris formula C=2.34×10-14, m=4.13; safe factor N_{safe}=1.5, elastic module E=2.1 × 105MPa, yield stress σ_s=312MPa, Resistance pull strength σ_b=450 MPa. Corrosion defect sizes for different time sequence are shown as Table 4.

Eight methods are used to calculate residual strengths in different time. Calculation result are shown as Fig.2

In Fig. 2, curves from up to down show Wes-2805-97, ASME-B31G,CVDA-84, Irwin method, GA-BP method, J integral method, Burdekin method and DM method in turn. After residual strength is calculated, ASME-B31G criterions are used to calculate critical injecting water pressure.

$$P = \sigma_p \times [(R_i + t)^2 / R_i^2 - 1.0]/2.0 \tag{35}$$

Critical injecting pressure variation with time is shown as Fig.3.

Table 4. 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		

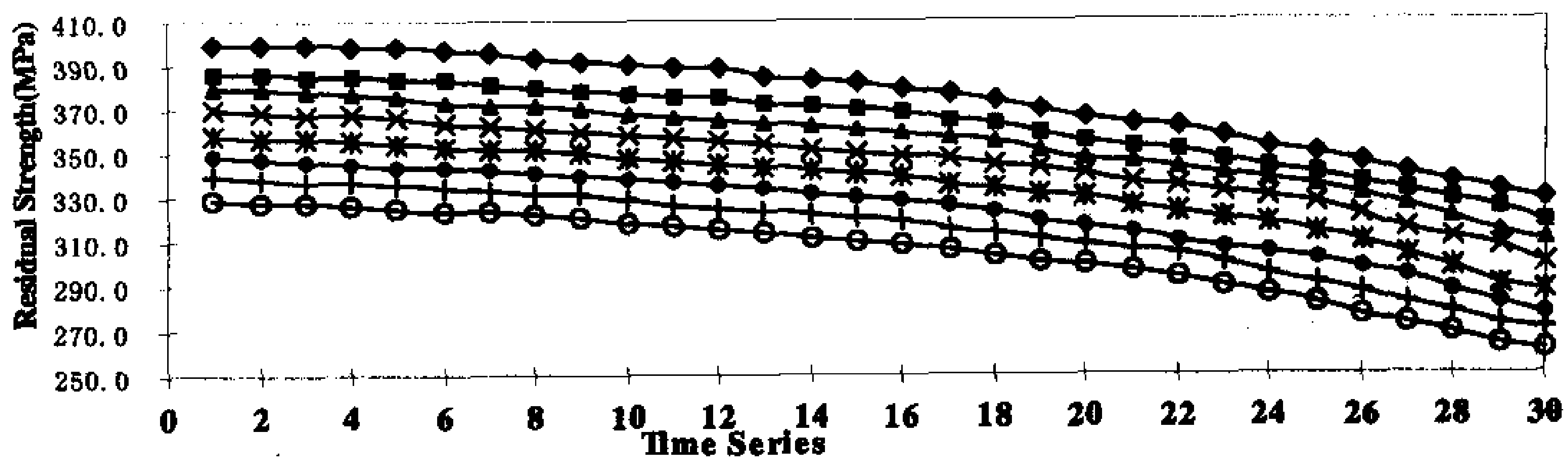

Fig. 2. Residual strength variation with time.

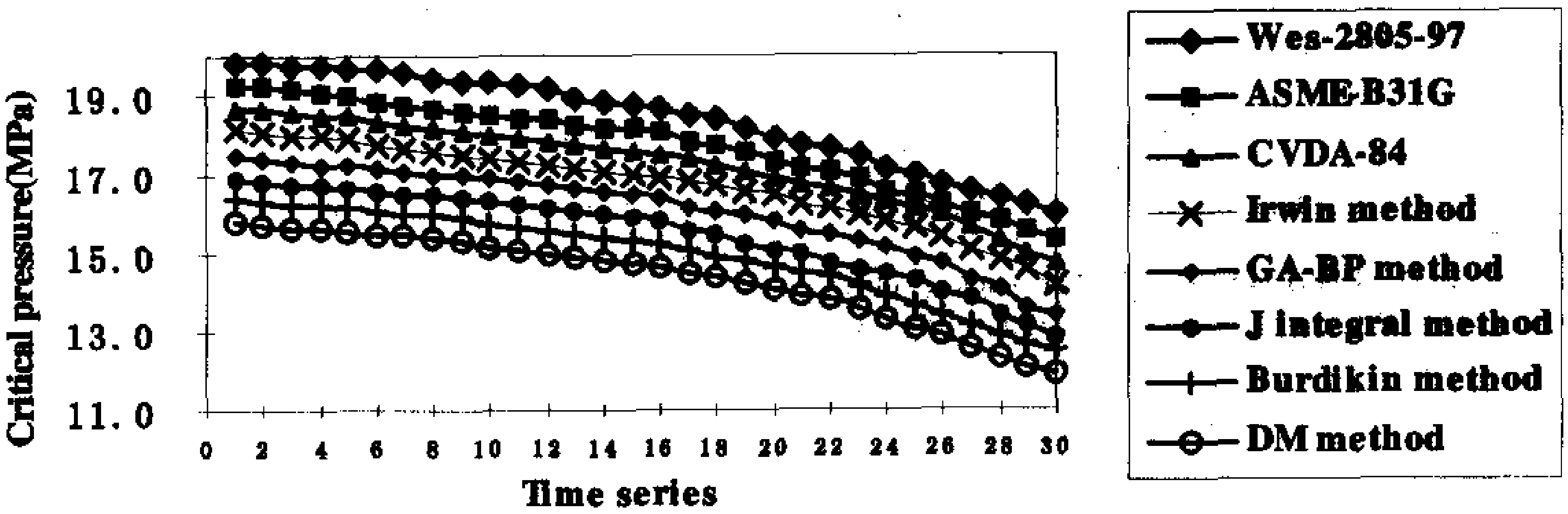

Fig.3. Critical injecting pressure variation with time.

4. Result and discusses

In this paper, BP neural network are combined with GA into a new neural network, (short for GA-BP). The new methods are successfully used to predict residual strength and critical pressure for injecting water pipeline.

Common criterions about residual strength evaluation at home and abroad are generalized and seven methods are acquired, namely, ASME-B31G, DM, Wes-2805-97, CVDA-84, Burdekin, Irwin and J integral methods. BP-GA methods and seven methods are used to predict residual strength and critical pressure of injecting corrosion pipelines for certain corrosion defect sizes. Examples are shown that calculation results of every kind of method have great difference and calculating values of Wes-2805-97 criterion, ASME-B31G criterion, CVDA-84 criterion and Irwin fracture mechanics model are conservative and higher than those of J integral methods while calculating values of Burdiken model and DM fracture mechanics model are dangerous and less than those of J integral methods and calculating values of modified BP-GA methods are close and moderate to those of J integral methods. Therefore modified BP-GA methods and J integral methods are considered better.

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