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Application of Generic Algorithm to Inspection Planning of Fatigue Deteriorating Structure

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Abstract

Genetic Algorithm (GA) is applied to obtain optimal inspection plan for fatigue deteriorating structures. The optimization problem is defined so as to minimize inspection cost in the life-time of the structure under the constraint that the increment of failure probability in each inspection interval is maintained below a target value. Optimization parameters are the inspection timing and the inspection quality. The inspection timing is selected from the discrete intervals such as one year, two years, three years, etc. The inspection quality is selected from the followings; no inspection, normal inspection, sampling inspection or precise inspection. The applicability of the proposed GA approach is demonstrated through the numerical calculations assuming a structure consisting of four member sets. Influences of the level of target failure probability, initial defect condition and stress increase due to plate thickness reduction caused by corrosion on inspection planning are discussed.
Keywords : Inspection plan, Markov chain model(MCM), Genetic algorithm(GA), Fatigue reliability

1. Introduction

Fatigue is one of the most frequent damage in the use of structures. However, because of the complicated fatigue mechanism and the wide scattering property of fatigue life, accurate life estimation is usually difficult for real structures. Reasonable in-service inspections and succeeding maintenance are thought to be necessary for the safe operation of structures.

So far, several methods of inspection planning have been proposed. These are inspection planning controlling the failure probability below certain level[Yang, J.N.,1974][Itagaki, H., 1982][Deodatis, G., 1992] inspection planning aiming at life time cost minimization[Fujita, M.,1989][Fujimoto, Y., 1991], cost optimal inspection planning with constraint of failure probability, etc.[Fujimoto, Y., 1993]

Basically, optimization of inspection planning is a dynamic programming problem, where previous inspections influence inspection schedule in the future. Also, inspection plan during service life is so versatile that an optimal plan can not be obtained easily by direct observation. Therefore, most of the optimization methods developed in the previous studies had used sub-optimization technique where inspection options and/or period of inspection schedule were restricted considerably.

In this study, Genetic Algorithm (GA)[Goldberg, D.E., 1995][Sakawa, M., 1995] is applied to the inspection planning of fatigue deteriorating structures. GA is a search algorithm based on the mechanics of natural selection and natural genetics. Because of the simplicity of this algorithm, GA has a very wide applicability. Also, GA has especially strong merits for inspection planning problem where fatigue deterioration process is complex and mathematical treatments are implicit.

2. Optimization of Inspection Planning

The optimization problem is formulated such that "Find an inspection plan which minimizes inspection cost in the life time of structure under the following constraint; an increment of failure probability during every inspection interval must be maintained below a target value". The objective function and the constraint are expressed by the following equations[Fujimoto, Y., 1993][Fujimoto, Y., 1997].

$$\text{Objective function: Minimize} \rightarrow CT = \sum_{i=1}^{I} C_{ISI}(i) + C_{SWS}(i) \quad (1)$$

$$\text{Constraint:} \Delta P_f(i) \leq \Delta P_{f,Target} \quad \text{for every i-th inspection} \quad (2)$$

where CT is the cost in the life time. $C_{ISI}(i)$ and $C_{SWS}(i)$ are the inspection cost and the scheduled system down cost at the $i-th$ inspection, respectively. I is the number of inspections in the service life. $\Delta P_f(i)$ is the increment of failure probability between $(i-1)-th$ and $i-th$ inspection. $\Delta P_{f,Target}$ is the target value of ΔP_f.

In the above optimization, repair cost is not considered for the sake of simplicity. Also, failure risk is not included in the cost items. However, the effect of failure risk is considered in the constraint. The optimization parameters are inspection timing and the inspection quality.

3. Fatigue Reliability Analysis Using MCM

Fatigue reliability analysis was carried out employing Markov Chain Model(MCM)[Bogdanoff, J.L., 1985][Fujimoto, Y., 1997][Fujimoto, Y.,1997]. The MCM can describe the entire probabilistic feature of fatigue process in the state vector and the transition matrix. The transition matrix $\mathbf{P}$ and state vector $\mathbf{A}(t)$ are expressed as follows.

$$\mathbf{A}_{BI}(t) = \mathbf{A}(0) \times \mathbf{P}^{n_t} \quad (3)$$

$$\mathbf{A}(0) = \{a_1(0), a_2(0), \ldots, a_b(0), a_{b+1}(0), \ldots, a_{h-1}(0), 0\} \quad (4)$$

$$\mathbf{A}_{BI}(t) = \{a_1(t), a_2(t), \ldots, a_b(t), a_{b+1}(t), \ldots, a_{h-1}(t), a_h(t)\} \quad (5)$$

where $\mathbf{A}_{BI}(t)$ means the state vector before inspection at time t and $\mathbf{A}(0)$ is initial state vector describing initial damage condition. n_t means the number of transition to time t. b is the crack initiation state and h is the failure state after crack propagation. Crack condition is calculated in every unit discrete time interval which is called as duty cycle. Duty cycle of ten days is used in this paper.

$$\mathbf{P} = \begin{bmatrix} p_1 & q_1 & & & & & & & & \\ & p_2 & q_2 & & \text{crack initiation} & & & & & \\ & & \cdots & & & & & & & \\ & & & p_{b-1} & q_{b-1} & & & & & \\ & & & & p_b & q_b & & & & \\ & & & & & p_{b+1} & q_{b+1} & & & \\ & & & & & & \cdots & & & \\ & \text{crack propagation} & & & & & & p_{h-1} & q_{h-1} \\ & & & & & & & & 1 \end{bmatrix} \tag{6}$$

The transition probability from $j-th$ state to $(j+1)-th$ state is approximated by geometric distribution. The crack growth curve of a member is divided into uniform interval with crack length, and the crack states were determined [10),12)]. The transition probability q_j's are calculated by,

$$\begin{aligned} q_1 &= \frac{1}{T_1},\ q_2 = \frac{1}{T_2},\ \cdots,\ q_j = \frac{1}{T_j},\ \cdots,\ q_{h-1} = \frac{1}{T_{h-1}} \\ p_j &= 1 - q_j, \end{aligned} \tag{7}$$

where T_j is a time interval from crack state j to crack state $(j+1)$. The matrix size is determined as $b = 5$ and $h = 17$ in this study.

Inspections and repair processes are also incorporated into the model. For perfect repair model, the state vector after repair, $\mathbf{A}_{AI}(t)$, can be expressed as

$$\mathbf{A}_{AI}(t) = \{a'_1(t), a'_2(t), \ldots, a'_b(t), a'_{b+1}(t), \ldots, a'_{h-1}(t), a'_h(t)\} \tag{8}$$

$$a'_j(t) = (1 - POD_j) \times a_j(t) \tag{9}$$

where POD_j is the detection probability of crack with crack state j.

The cumulative failure probability, and detected and residual crack length distributions at respective inspection time can be calculated from resulting state vector. Failure probability (P_f) at time t is given by $a_h(t)$, and the increment of failure probability ΔP_f is calculated by

$$\Delta P_f = a_h(t+1) - a_h(t) \tag{10}$$

where $a_h(t)$ is the last term of $A_{BI}(t)$.

4. Inspection Method

Fig.1 shows the inspection capability (POD curves) for normal inspection and precise inspection, which was obtained from the questionnaire asked to naval engineers[Fujimoto, Y.,1996]. In normal inspection, cracks are observed from the distance about 2 to 5m. In precise inspection, cracks are observed from the distance about 0.5m. These POD curves are expressed by the following equations.

$$\text{Normal:}(POD)_1 = \frac{\exp\{-5.176 + 0.864\ln(2a - 100)\}}{1 + \exp\{-5.176 + 0.864\ln(2a - 100)\}} \tag{11}$$

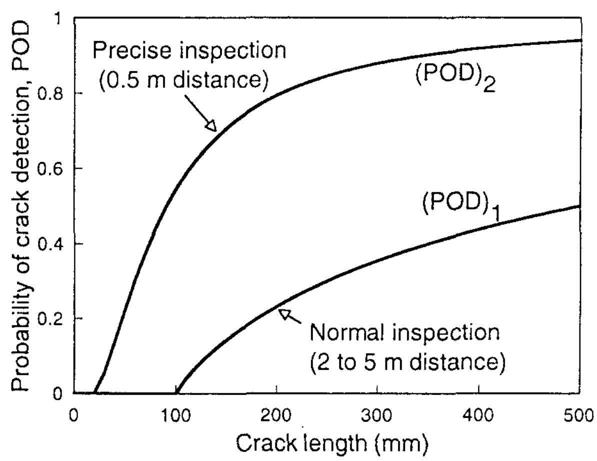

Figure 1. POD curves for normal and precise inspection

$$\text{Precise:}(POD)_2 = \frac{\exp\{-7.041 + 1.45\ln(2a - 30)\}}{1 + \exp\{-7.041 + 1.45\ln(2a - 30)\}} \tag{12}$$

where $2a$ is crack length.

On the other hand, in the sampling inspection, precise inspections are performed to limited number of sample members. If at least one crack is detected among samples, precise inspections are performed to all the rest members. Otherwise, the inspection is not performed any more. POD for sampling inspection is calculated by

$$(POD)_{Sampl} = r_s \times (POD)_2 + (1 - r_s) \times [1 - (1 - P_D)^{r_s n_M}] \times (POD)_2 \tag{13}$$

where r_s is sampling rate and n_M is the number of members in the member set. P_D is the detection ratio of a crack by the precise inspection. P_D is calculated by the following equation.

$$P_D = \int_{a_0}^{a_{cr}} (POD)_2 \times g_a(a)da \tag{14}$$

The distribution of crack length, $g_a(a)$, at each inspection time can be obtained from the state vector of MCM.

Selected inspection method influences both of the crack detection probability and the inspection cost.

5. Application of Genetic Algorithm

The optimization procedure of inspection plan is shown in Fig.2. GA is applied to generate random inspection plans and to select optimal plan among the generated ones. MCM is applied to calculate the structural reliability for the given inspection plans. In order to generate next superior generation which have better fitness, reproduction, crossover and mutation are applied to populations. Special elite selection is applied at reproduction stage.

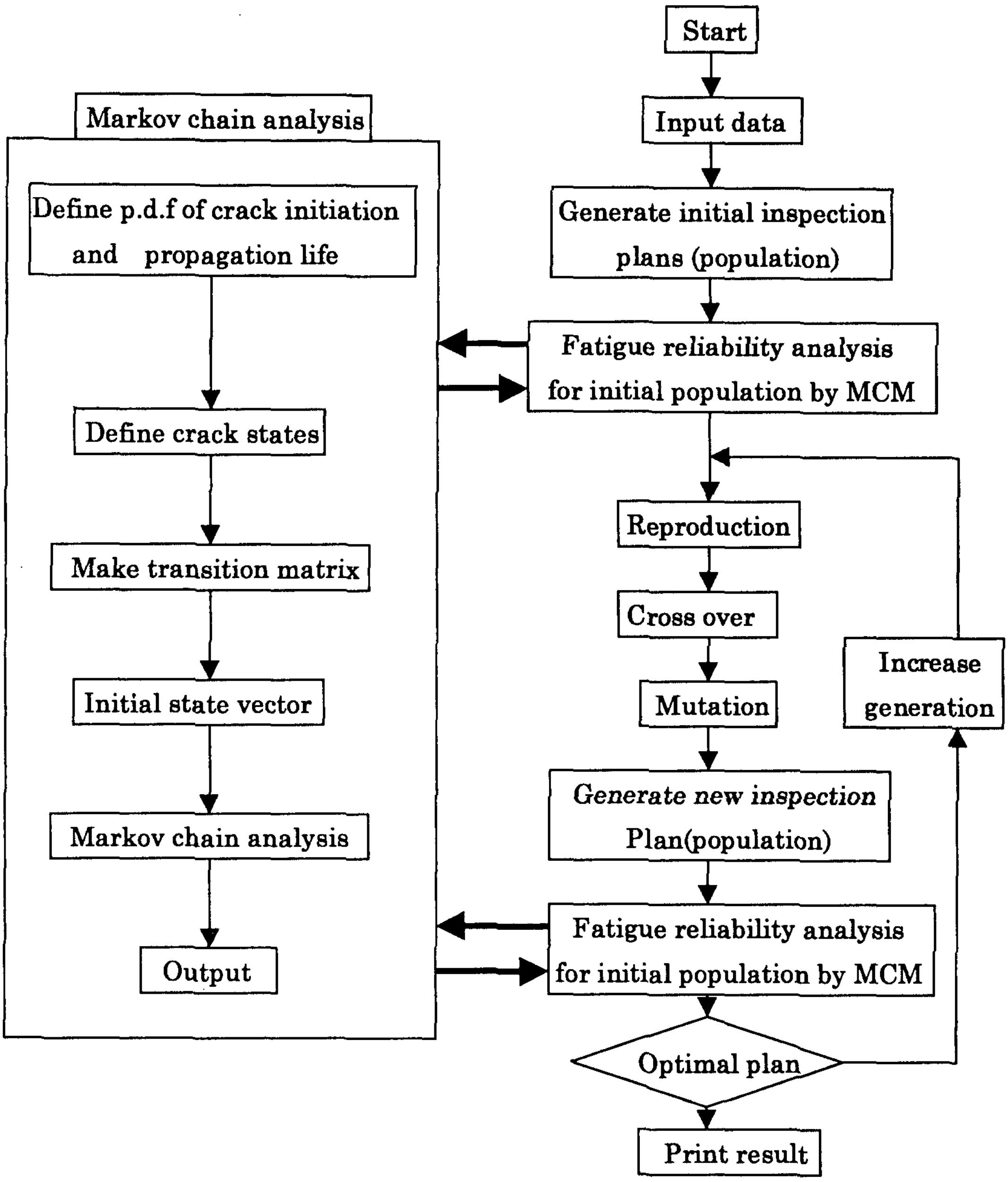

Figure 2. Optimization procedure of inspection plan by GA

Table 1. Gene corresponding to inspection timing and quality

·Example of gene for a member set

Inspection year	1	2	3	4	5	···	16	17	18	19	20
Gene	00	11	01	10	10	···	11	10	00	11	00

· Example of gene for a structure

Member set	A	B	C	D
Gene	001101···	0100010···	000011···	001101···

5.1. Gene

The genes in GA correspond to inspection plan and its format is expressed as binary alphabet "0" and "1". In this paper, gene of two bits length is prepared to describe the inspection quality. The bits "00" means no inspection, "01" means normal inspection, "10" means sampling inspection and "11" means precise inspection, respectively. An example of generated string during 20 years service is shown in Table 1. In this example, inspection interval is initially assumed as one year. The total length of the gene during usage is 40 bits. This string means that no inspection is carried out at the first inspection, precise inspection at the second inspection and normal inspection at the third inspection, etc. In the above, inspection interval is not uniform, because the bits "00" means no inspection. Namely, both inspection quality and interval are optimized by the use of the above gene.

For the analysis of a structure consisting of several member sets, the gene of inspection plan can be described as series form. Table 1 shows an example of the gene for a structure consisting of four member sets, A,B,C and D. The total length of the gene is 160 bits. The number of possible inspection plans reaches 4^{20} (about 10^{12}) even in the problem of one member set. So, it is impossible to check the qualities of all the inspection plans by Monte Carlo method.

5.2. Fitness Function

The reproduction in this paper is conducted by the probability proportional to the ratio of fitness and the sum. In this paper, fitness function is formulated on the basis of life time cost with constraint of failure probability. The life time cost consists of pure inspection cost and scheduled system down cost as shown in Eq.(1).

The fitness function of an inspection plan is the reciprocal form of total inspection cost and it is expressed by the following equation for a member set.

$$f_{m,n} = \frac{1}{\sum_{i=1}^{I} C_{ISI,m}(i)}, (n = 1, 2, 3, \cdots, N_p) \tag{15}$$

In the above, $f_{m,n}$ means the fitness of $n-th$ sample ($n-th$ inspection plan) for member set m . N_P is the population size (total number of inspection plans) and I is the number of inspections in the entire service life.

The fitness function of a structure is defined as follows, in which scheduled system down cost C_{SWS} is considered in the life time cost.

$$f_n = \frac{1}{\sum_{i=1}^{I}\{(\sum_{m=1}^{M} C_{ISI,m}(i)) + C_{SWS}(i)\}}, (n = 1, 2, 3, \cdots, N_p) \tag{16}$$

where f_n means the fitness of $n-th$ sample ($n-th$ inspection plan). M is the number of member sets included in the structure. The fitness function takes large value for an inspection plan with small cost, and takes small value for a plan with large cost.

From the constraint of Eq.(2), increment of failure probability ΔP_f must be maintained below a target value $\Delta P_{f,Target}$ at every inspection interval. If the constraint is violated at any inspection interval, ϵ is given as the fitness function instead of the cost based fitness function of Eq.(15) or (16). That is,

$$f_n = \epsilon \quad \text{if} \quad \Delta P_f(i) > \Delta P_{f,Target}. \tag{17}$$

ϵ is a very small value and $\epsilon = 10^{-8}$ is used in this study. This procedure means that if the inspection plan violates the constraint, a large penalty is added to the life time cost.

5.3. Reproduction, crossover and mutation

After calculating the fitness for every generated plans, next superior generation is generated by genetic operators such as reproduction, crossover and mutation. Natural selection, in which populations with high fitness leave many descendants at next generation, is embodied by reproduction or selection in GA. There are several ways to reproduce the populations for superior next generation. In this study, special elite selection is applied.

Special elite selection method is like a process of entrance examination in which a small number of excellent elite on special subject is matriculated. In the special elite selection, fitness functions are calculated not only for structure but also for each member set.

At first, the fitness function, $f_{m,n}$, of a member set m is calculated for all the samples ($n = 1, 2, 3, .., N_p$) from Eq.(15). And the samples with high fitness are sorted on descending order. Then the best $r\%$ of samples are selected. Selected samples are the elite inspection plans of a member set m. These calculation and selection are also carried out for the rest member sets. After the selections are completed, parts of string of every member set which have the same ranking are connected each other, and $r\%$ of new populations are made. These genes have elite property locally for every member set but they are not global elite for the entire structure.

Secondly, the fitness function, f_n, of the entire structure is calculated for all the samples ($n = 1, 2, 3, ..., N_p$) from Eq.(16). And the samples with high fitness are sorted on descending order. The remaining $(100 - r)\%$ of new populations is selected from these samples. This reproduction can leave a certain percentage of special elite genes and the rest percentage of global elite genes.

In order to generate new population from old parents, one point crossover, which exchange parent's gene at one position, is typically used. Crossover tends to generate children only resembling parent. The generation of diverse populations can be accomplished by mutation.

6. Numerical Examples

6.1. Condition of Analysis

Table 2 shows the fatigue property and the cost content of four member sets. Numerical analysis is carried out for this hypothetical structure consisting of four member sets. The crack initiation life N_{CI} is defined by a length of $20mm$ and the failure life is defined by a crack length of $500mm$. The crack growth curve is assumed to be linear for the sake of simplicity.

Table 2. Fatigue properties and cost content of four member sets

Member	N_{CI}	N_{CP}	n_M	$\dot{r}_s$	C_1	C_2	C_3	C_4
A	4	16	100	20%	1	5	15	10
B	8	16	100	20%	1	5	15	
C	10	20	100	20%	1	2	5	
D	10	30	100	20%	1	2	5	

N_{CI} : Crack initiation life(year)　　N_{CP}: Crack propagation life(year)
n_M : Number of members　　$\dot{r}_s$: Sampling rate(%)
C_1 : Normal inspection cost　　C_2 : Sampling inspection cost
C_3 : Precise inspection cost　　C_4 : Cost due to scheduled system down

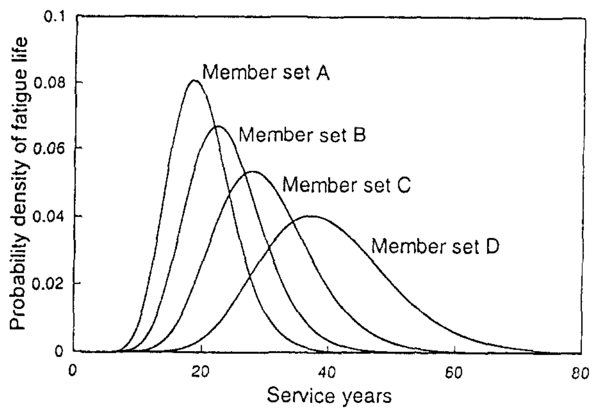

Figure 3. Probability density of fatigue life

Member 'A' has short fatigue life and member 'D' has long fatigue life. Each member set consists of 100 members. C_1, C_2 and C_3 are the inspection cost for normal, sampling and precise inspections, respectively. C_4 is the scheduled system down cost and this value is defined for the entire structure. The sampling rate r_s in the sampling inspection is assumed as 20%. Fig.3 shows the probability density functions of failure life of each member. Service life of the member sets is 20 years.

6.2. Result of Analysis

At first, sensitivity analysis is performed to find the efficient condition of GA parameters. As a result, the probability of crossover $p_c = 0.6$ and the probability of mutation $p_m = 0.01$ shows good convergence. So, these values are mainly used in this study.

Fig.4 shows an example of the optimization process of inspection planning by GA. The population size is $N_p = 200$. Special elite selection method shows better efficiency comparing with the ordinary roulette selection methods with one or two points crossover. The reason is due to the long string length of the gene. Fig.5 shows the influence of selection rate r in the special elite selection method. Better convergence of total cost is obtained when $r = 20\%$. So, the following analysis is carried out under the condition of $N_p = 200$ and $r = 20\%$.

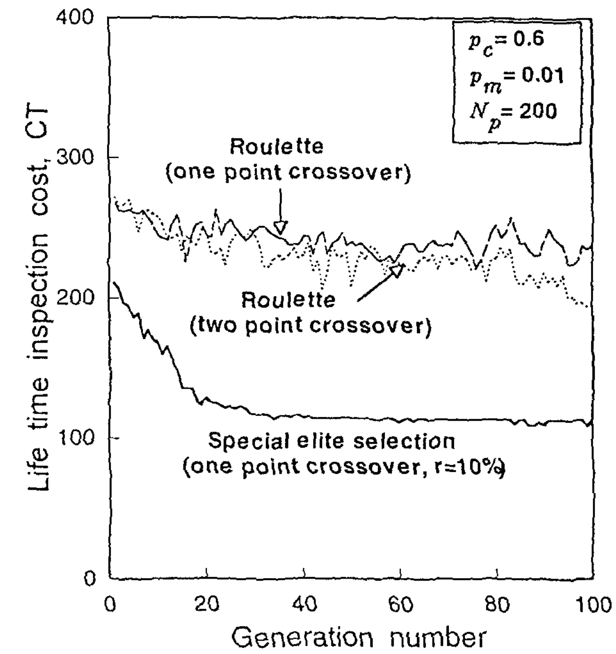

Figure 4. Optimization process of CT(Influence of selection method in GA)

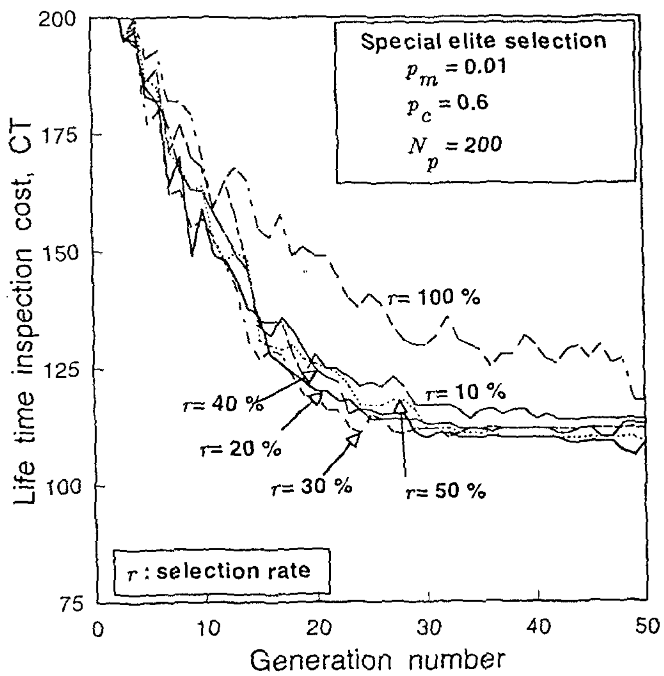

Figure 5. Optimization process of CT(Influence of selection rate)

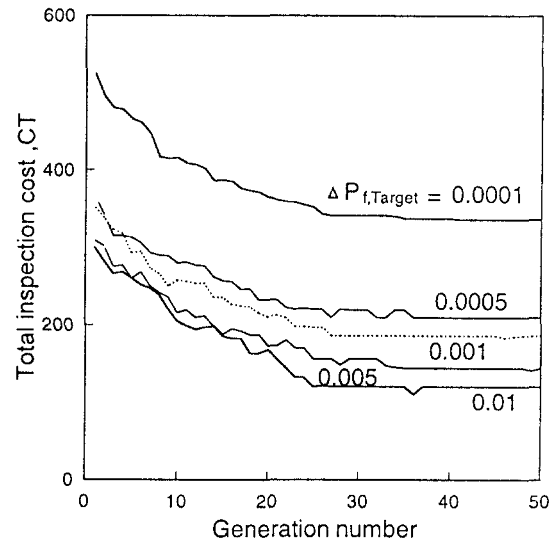

Figure 6. Optimization process of CT for respective $\Delta P_{f,Target}$

6.2.1. Influence of target failure probability on inspection planning

Optimization of inspection planning is carried out by changing the target failure probability $\Delta P_{f,T}$- $_{arget}$. Fig.6 shows the change of CT during optimization process. The lower the $\Delta P_{f,Target}$ is, the more the CT becomes.

Table 3 shows the optimized inspection plan under $\Delta P_{f,Target} = 0.01, 0.001$ and 0.0001, respectively. It is seen that number of inspections is increased with the decrease of target failure probability. It is apparent that the member set with short fatigue life needs more inspections.

Table 3. Initial defect condition for analyzed five case

$\Delta P_{f,Target}$	Memb	N_{CI} (years)	N_{cp} (years)	Inspection timing and quality (1 — 10years — 20)	$(P_f)_{20\ years}$	C_{ISI}	CT
0.01	A	4	16	00000 00N0N NNNNN 0NN00	4.78E-2	9	110
	B	8	16	00000 0000N 0NNNN 0NN00	3.86E-2	7	
	C	10	20	00000 00000 00S0N 0N000	1.41E-2	4	
	D	10	30	00000 00000 00000 00000	8.91E-3	0	
0.001	A	4	16	00000 0NSNN SNNNN NNNN0	8.96E-3	21	183
	B	8	16	00000 000NN SNSNN NNNN0	7.33E-3	19	
	C	10	20	00000 00N00 0NNNS 0NS00	5.22E-3	9	
	D	10	30	00000 00000 N0000 S00N0	1.91E-3	4	
0.0001	A	4	16	0000N NSSSS SSPNP P0NS0	9.59E-4	84	336
	B	8	16	00000 0SNSS SSSSP NPSS0	7.48E-4	77	
	C	10	20	00000 00NNS S0SNS SNNS0	6.03E-4	17	
	D	10	30	00000 00000 0NS0N SN0N0	3.71E-4	8	

N:Normal inspection S:Sampling inspection P:Precise inspection O: No inspection

Fig.7 shows the change of ΔP_f during each inspection interval for four member sets under the condition that the $\Delta P_{f,Target} = 0.001$. It is understood that ΔP_f is maintained below the target level during the entire service life.

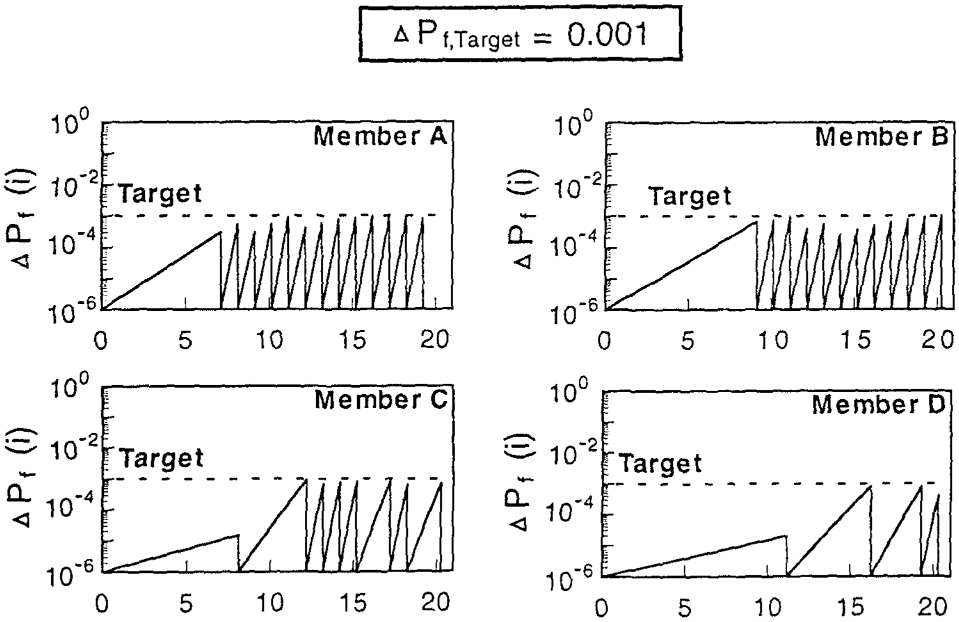

Figure 7. Change of ΔP_f in each inspection interval

Fig.8 shows the cumulative probability of failure P_f of four member sets under $\Delta P_{f,Target} = 0.001$. P_f is expressed by

$$P_f = \sum_{i=1}^{I} \Delta P_f(i) \tag{18}$$

Fig.9 compares the P_f of member set A under $\Delta P_{f,Target} = 0.001$ among the three analytical conditions; optimal plan obtained by GA, normal inspection with 1 year interval is applied throughout the service life, and precise inspection with 1 year interval is applied throughout the service life. Fig.10 shows the change of ΔP_f corresponding to the three analytical conditions. From the figure, it is seen that normal inspection with 1 year interval is not sufficient to satisfy the constraint. Precise inspection with 1 year interval is enough to satisfy the constraint. But the lifetime cost of precise inspection with 1 year interval amounts to $CT = 300$. On the other hand the cost for optimal inspection plan is only $CT = 21$.

Fig.11 shows the lifetime cost with respect to target failure probability. Total lifetime cost is composed of pure inspection cost and scheduled system down cost. The total lifetime cost increases fast with the decrease of target failure probability.

Table 4. Initial defect condition for analyzed five cases

Condition of	Length of initial crack (mm)										
initial defect	0	50	80	110	140	170	200	250	300	350	400
Case 1	1.0										
Case 2	0.9	0.1									
Case 3	0.9	0.07	0.03								
Case 4	0.9	0.05	0.03	0.02							
Case 5	0.9	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

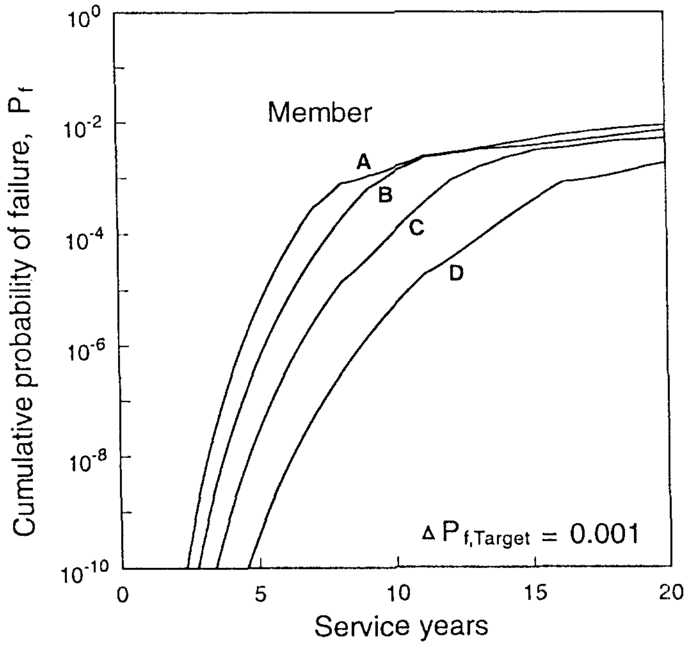

Figure 8. Cumulative failure probability for Member sets

6.2.2. Influence of initial defect condition on inspection planning

In the above, first inspection timing is mainly selected at four to ten years' after the start of service. This is due to the reason that initial defect is not considered in the state vector of the Markov Chain model. However, initial defects inevitably exist in the actual structures, especially in the welded structures. So, the effect of initial defects on inspection planning is investigated.

Table 4 shows the five cases of initial defect conditions assumed in this study. In the figure, *Case1* means the perfect member which has no defect, *Case2* means that the member has initial defect of $50mm$ length with a probability of 10%. The same initial defect condition is assumed for all the member sets. The optimization is carried out under $\Delta P_f = 0.001$.

Table 5 shows the result of optimal inspection plan for the Case 1, Case 3 and Case 5. It is seen that first inspection timing becomes early when the existence of initial defect increase. Fig.12 shows the inspection costs of each member set with the change of initial defect.

6.2.3. Influence of stress increase due to plate thickness reduction caused by corrosion

In the corrosion environment, fatigue strength is decreased by both of the plate thickness reduction due to uniform corrosion and the pits due to local corrosion. In this study, the effect of thickness reduction on inspection planning is discussed for a single member set. The reduction of plate thickness accompanies the increase of stress. In this study, it is assumed that the stress increase is linear and the rate of stress increase during 20 year's service is to be $5\%, 10\%$ and 20%. Fatigue life of the member is assumed to be shortened according to the S-N relationship $S = CN^{-0.2}$.

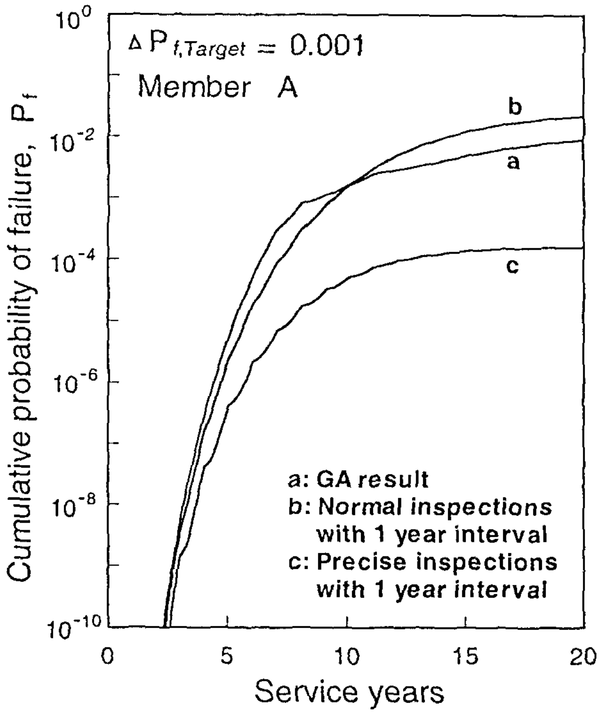

Figure 9. Cumulative failure probability of member A under predicted inspection plan

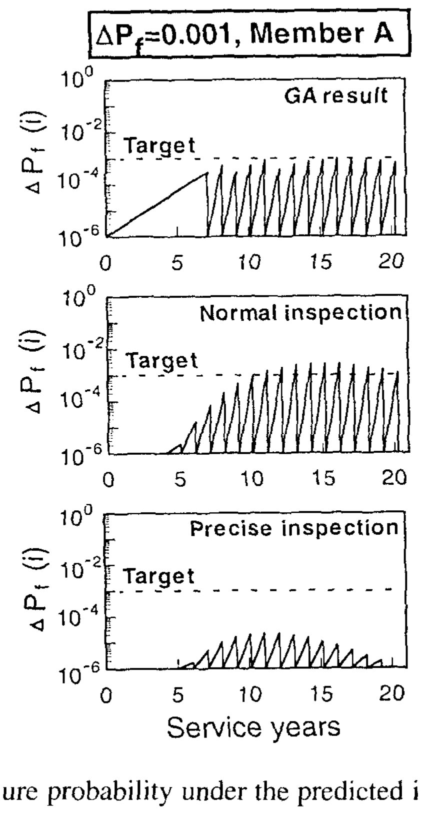

Figure 10. Change of failure probability under the predicted inspection plan

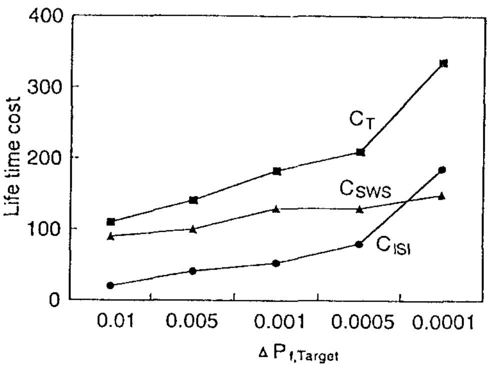

Figure 11. Lifetime inspection cost for respective $\Delta P_{f,Target}$

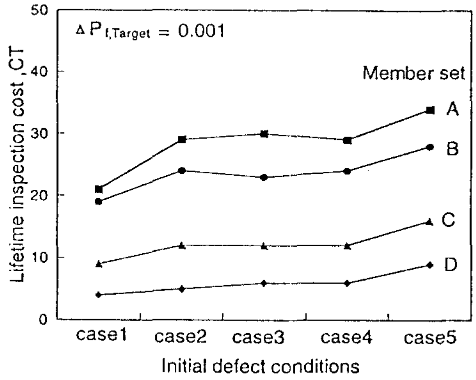

Figure 12. Lifetime inspection cost for several initial defects condition

The time dependent effect of stress increase can be modeled by adopting non-stationary Markov Chain Model, in which the transition matrix is changed at every duty cycle[Fujimoto, 1989].

Table 6 shows the optimal inspection plan of member set A under the respective conditions of stress increase. In this analysis $\Delta P_{f,Target}$ is assumed as 0.001. It is seen that sampling and precise inspections are applied often when the rate of stress increase becomes large. It is also seen that the inspection cost C_{ISI} becomes larger according to the stress increase. Fig.13 shows the change of cumulative probability of failure P_f corresponding to the inspection plans. In the figure, P_f's are gradually shifted to left side according to the stress increase. This means that failure probability is increased by the plate thickness reduction and more inspections are necessary for such condition.

Table 5. Optimal inspection plan for respective initial defect conditions

Initial defect condition	Memb	N_{CI} (years)	N_{CP} (years)	Inspection timing and quality 1 10years 20	$(P_f)_{20\ years}$	C_{ISI}	CT
Case 1	A	4	16	00000 ONSNN SNNNN NNNNO	8.96E-3	21	183
	B	8	16	00000 OOONN SNSNN NNNNO	7.33E-3	19	
	C	10	20	00000 OONOO ONNNS ONSOO	5.22E-3	9	
	D	10	30	00000 00000 NOOOO SOONO	1.91E-3	4	
Case 3	A	4	16	0000S ONNSN NSNNN SNNNO	7.33E-3	30	222
	B	8	16	0000N NNNNN SNSNN NNNNO	7.22E-3	23	
	C	10	20	00000 OSNON ONNSN NOSOO	4.87E-3	12	
	D	10	30	00000 OOOSO OSOON OSOOO	1.56E-3	7	
Case 5	A	4	16	NNSNN NNNSN SSONN NNNNO	1.07E-2	34	267
	B	8	16	NNNNN NNONS OSOSN NNNNO	9.61E-3	28	
	C	10	20	ONNNN SONNO SOOSN OSNOO	7.43E-3	16	
	D	10	30	OONNO NNOON OSOOO OSOOO	5.85E-3	9	

N: Normal inspection S: Sampling inspection P: Precise inspection O: No inspection

Table 6. Optimal inspection plan for different condition

Member	Stress increase	Inspection timing and quality 1 10years 20	C_{ISI}
A	0%	0 0 0 0 0 O N S N N S N N N N N N N N O	21
	5%	0 0 0 0 0 O N S S S O N S N S P O N O O	44
	10%	0 0 0 0 0 S O S N S S N S S P N O N O O	49
	15%	0 0 0 0 0 O S S S N S P N P N O N N O O	55
	20%	0 0 0 0 N O S S S S S P N P O N N O O O	59

N: Normal inspection S: Sampling inspection
P: Precise inspection O: No inspection

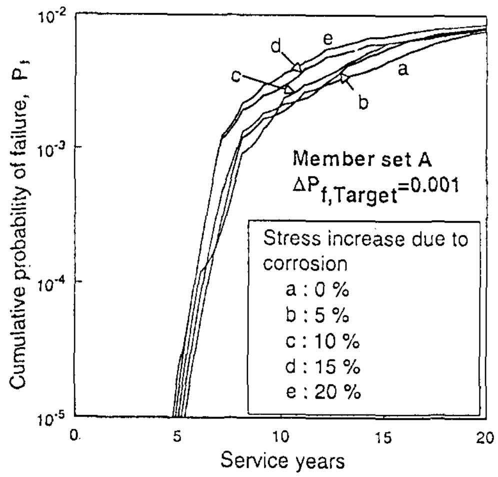

Figure 13. Cumulative failure probability for different corrosion conditions

7. Conclusions

In this paper, Genetic Algorithm(GA) is applied to optimize the inspection planning of fatigue deteriorating structure. The optimization problem is formulated to minimize inspection cost in the life time of structure under the constraint that the increment of failure probability in each inspection interval is maintained below a target value. The optimization parameters are the inspection timing and the inspection quality. Inspection timing is selected from the discrete interval such as one year, two years, three years, etc. Inspection quality is selected from normal, sampling and precise inspection. Markov Chain Model is employed to calculate the failure probability of members as well as the inspection effect. Influences of the level of target failure probability, initial defect condition and stress increase due to plate thickness reduction caused by corrosion are investigated through the numerical analysis assuming a hypothetical structure. The results throughout this paper are summarized as follows.

1) Genetic algorithm is a very useful tool at the inspection planning of fatigue deteriorating structures, where fatigue process is complex and mathematical treatments are implicit.
2) Special elite selection method is quite effective at the reproduction of inspection planning of a structure in which the string of gene is very lengthy.
3) Level of target failure probability influences much on inspection timing and inspection quality. Life time inspection cost increases fast with the decrease of target failure probability.
4) Timing of first inspection becomes early when large initial defect exists in the structure.
5) Inspection planning considering the stress increase due to plate thickness reduction caused by corrosion can be accomplished by applying a non-stationary Markov Chain Model.

References

1. Yang, J.N. and Trapp, W.J., 1974, Reliability Analysis of Aircraft Structures Under Random Loading and Periodic Inspections, AIAA Journal, Vol.12, No.12, Dec., pp.1623-1630.
2. Itagaki, H., Asada, H. and Itoh, S., 1982, Assurance of Continued Safe Operation for Aging Structure, J. of the Society of Naval Architects of Japan, Vol 151, pp.269-277. (in Japanese)
3. Deodatis, G., Fujimoto, Y., Ito, S. and Spancer, J., 1992, Non-Periodic Inspection by Bayesian Method I, Probabilistic Engineering Mechanics, Vol.7, pp.191-204.
4. Fujita, M., Schall, G. and Rackwits, R., 1989, Adaptive Reliability- Based Inspection Strategies for Structures Subject to Fatigue, Proc. of 5th ICOSSAR, ASCE Publications, Vol.2 , pp.1619-1626.
5. Fujimoto, Y., Swilem, S.A.M. and Iwata, M., 1991, Inspection Planning for Deteriorating Structures Based on Sequential Cost Minimization Method, J. of the Society of Naval Architects of Japan, vol.170, pp.755-768.
6. Fujimoto, Y., 1993, A Study on the Inspection Planning for Deteriorating Structures - Stable Inspection Planning Method Taking into Account of Inevitable Uncertainties, J. of the Society of Naval Architects of Japan, Vol 173, pp.367-375. (in Japanese)
7. Goldberg, D.E., 1989, Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Wesley.
8. Sakawa, M. and Tanaka, M. , 1995, Genetic Algorithm, Asakura Shoten.
9. Fujimoto Y. et al., 1989, Reliability Assessment of Deteriorating Structure by Markov Chain Model, J. of the Society of Naval Architects of Japan, Vol.166, pp.303-314.(in Japanese)
10. Fujimoto, Y., Kim, S.C., Shintaku, E. and Ohtaka, K., 1996, Study on Fatigue Reliability and Inspection of Ship Structures Based on Enquete Information, J. of the Society of Naval Architects of Japan, Vol 181, pp.601-609.(in Japanese)
11. Bogdanoff, J.L and Kozin, F. ,1985, Probabilistic Models of Cumulative Damage, John Wiley & Sons, Inc., New York.
12. Fujimoto, Y., Kim, S.C. and Shintaku, E., 1997, Sensitivity Analysis on Fatigue Reliability and Inspection of Ship Structural Members, J. of the Society of Naval Architects of Japan, Vol.181, pp.367-375.
13. Fujimoto, Y., Kim, S.C. and Hamada, K., 1997, Inspection Planning of Fatigue Deteriorating Structures Using Genetic Algorithm, J. of the Society of Naval Architects of Japan, Vol 182, pp.729-739.