FATIGUE LIFE PREDICTION OF STEEL STRUCTURES BASED ON DAMAGE MECHANICS

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1. INTRODUCTION

Decision concerning the maintenance of an existing bridge gives serious impact on the traffic patterns and economy of the surrounding community. Thus, it is important to extend the lifetime of bridge structures and evaluate the fatigue damage evolution accurately. It is therefore the high cycle fatigue life prediction of a steel structure, was carried out by using damage mechanics. For high cycle fatigue, even though materials do not exhibit such a macroscopic plasticity and damageable behavior. However, It is considered that plastic deformation and damage is localized at microscopic scale[1]. Thus a two-scale model is introduced to evaluate the damageable plastic-like behavior at the microscopic scale[2]. As it is difficult to identify the parameters directly at the microscale, the identification methods of material parameters are proposed to obtain the reliable material parameters and fatigue life prediction accurately.

2. ANALYTICAL METHOD

In this study, the analytical method of high cycle fatigue failure based on damage mechanics is proposed. The basic concept of damage mechanics considers the damage variable as the degree of degradation of material in the homogeneous field. Thus, the basic image of damage variable D is defined as the loss of effective area in the meso-scale that is defined by so-called 'representative volume element (RVE)' (numerically Gauss point) [1], see **Fig. 1**.

$$D=\frac{A_D}{A_0} \quad (1)$$

where A_0: the total area of considered plane, A_D: the area of all micro-defects

In general, damage is caused by the accumulated plastic strain due to stress concentration in the neighborhood of micro defects, and it is defined as

$$dp=\sqrt{(2/3)d\varepsilon_{ij}^{p}d\varepsilon_{ij}^{p}} \quad (2)$$

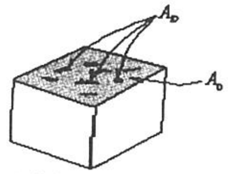

Fig. 1 Basic definition of damage variable

where dp: the accumulated plastic strain increment

It is assumed that damage occurs when the accumulated plastic strain, p exceeds a certain value $p_D(=\varepsilon_{pD}(\sigma_u-\sigma_f)/(\sigma_{eq}-\sigma_f))$, and rupture occurs at the meso-scale (macrocrack initiation), when damage variable reaches the critical value Dc(**Fig. 2**).

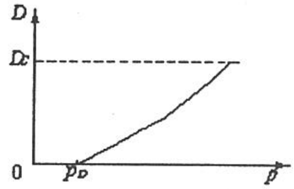

Fig. 2 Damage evolution

For high cycle fatigue, there is no plasticity occurs on the macro scale, but there is micro cracking due to irreversible plastic strain on the micro-scale μ. Thus, the damage evolution is derived from the associated flow rule with the strain energy density release rate Y and the potential of dissipation F_D at micro scale as

$$dD=\frac{\partial F_D^{\mu}}{\partial Y^{\mu}}d\lambda^{\mu}=\left(\frac{Y^{\mu}}{S}\right)^{n}dp^{\mu} \quad (3)$$

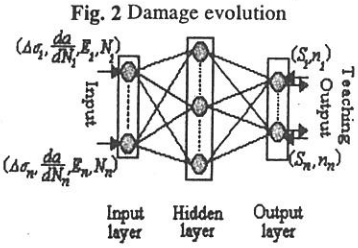

Fig. 3 neural network of parameters identification

where S: damage energy strength; n: damage exponent and Y^{μ}: the strain energy release rate is defined as

$$Y^{\mu}=\frac{1+\nu}{E}\left[\frac{\langle\sigma_{ij}^{\mu}\rangle\langle\sigma_{ij}^{\mu}\rangle}{(1-D)^2}+h\frac{\langle-\sigma_{ij}^{\mu}\rangle\langle-\sigma_{ij}^{\mu}\rangle}{(1-Dh)^2}\right]-\frac{\nu}{E}\left[\frac{\langle\sigma_{kk}^{\mu}\rangle^2}{(1-D)^2}+h\frac{\langle-\sigma_{kk}^{\mu}\rangle^2}{(1-Dh)^2}\right] \quad (4)$$

where $\langle . \rangle$: positive part, i.e., $\langle x\rangle = x$ if $x > 0$, $\langle x\rangle = 0$ if $x \le 0$; h is the crack closure.

In order to calculate the high cycle fatigue damage evolution in the RVE, the stresses at micro scale σ_{ij}^{μ} are evaluated from the macro scale stresses σ_{ij} by introducing two-scale model based on the localization of self-consistent scheme [2].

$$\sigma_{ij}^{\mu}=\sigma_{ij}-aE\varepsilon_{ij}^{\mu p} \quad (5)$$

where

$$a=(1-\beta)/(1+\nu),\quad \beta=2(4-5\nu)/15(1-\nu) \quad (6)$$

Considering the localization law, a set of constitutive equations is completed by writing the elastoplastic damageable behavior at microscale with the yield criterion takes Kinematic hardening X^{μ} into account and yield stress equal to fatigue limit.

$$f^{\mu}=\left(\frac{\sigma^{\mu D}}{1-D}-X^{\mu D}\right)_{eq}-\sigma_f \quad (7)$$

Once the equations are implemented, it is possible to compute for any loading.

Table 1. Material properties (SS400)

Elastic modulus	E	2x10^5 MPa
Poison's ratio	ν	0.3
Fatigue limit stress	σ_f	165 MPa
Yield stress	σ_Y	290 MPa
Ultimate stress	σ_u	410 MPa
Damage threshold	ε_{pD}	0.0
Critical damage	D_c	0.9
Hardening parameter	C	2000 MPa
Micro-crack closure	h	0.2

3. IDENTIFICATION OF MATERIAL PARAMETERS

To evaluate the damage evolution accurately, the two main parameters: damage energy strength S and exponent n of **Eq. (3)** need to be well identified. As it is difficult to measure the parameters directly at the microscale, two identification methods of material parameters are proposed. The first method is the simplified model that employed **Eq. (8)**, obtained from the two scale model with the assumption of $h=1, p_D=0, D_c=1$ and a proportional loading.

$$N_F = \frac{(2ES)^n C}{2(R_\nu^\mu)^n \left\{ [(\Delta\sigma + k\sigma_f)/(1+k)]^{2n+1} - \sigma_f^{2n+1} \right\}} \quad (8)$$

where $$R_\nu^\mu \approx \frac{2}{3}(1+\nu) + 3(1-2\nu)\left[\frac{(1+k)}{3(1+2k\sigma_f/\Delta\sigma)}\right]^2 \quad (9)$$

N_F: Number of cycle to failure; $\Delta\sigma$: Applied stress range; $k=3aE/2C$; C: kinematic hardening parameter.
Then the simply identification method gives material parameters (S, n), if the fatigue test data ($\Delta\sigma$,N) are substituted into **Eq. (8)**.

The second method is the inverse analysis by 3D finite element program of the high cycle fatigue phenomenon. In this method, the analytical results of fatigue behaviors ($\Delta\sigma$, N, crack growth rate da/dN, elastic modulus deterioration rate dE/dN) are applied to the neural network system as the teaching data set in order to learn the relations of material parameters and fatigue behaviors as shown in **Fig.3**. Once fatigue test data set are learned and completed neural network system, corresponding parameter set (S, n) for the arbitrary material could be obtained.

4. ANALYTICAL RESULTS

4.1. Identification

The simplified model identified the material parameters: damage energy strength S=0.5MPa, and exponent n=2.0 by the 97.7% lower probability S-N curve[3] of SS400 steel. On the other hand, the neural network evaluated the damage energy strength as S=0.556MPa, and exponent n=2.0. It is considered that this difference occurs due to the lack of information of crack growth rate and deterioration rate of elastic modulus in the simplified model. However, this difference is almost only 10%, thus the damage energy strength should be identified by the simplified model rather than neural network, if only the fatigue test data of S-N curve are available. Besides, the neural network should be used, instead.

4.2. Fatigue Analysis

The high cycle fatigue analysis of a steel plate with a circular hole was demonstrated as shown in **Fig. 4**. The 8-node solid FE-mesh of a quarter of the plate was analyzed. The material properties of the plate (SS400) were assumed as shown in **Table 1** (S=0.5MPa, n=2.0).

The high cycle fatigue damage analysis was carried out until the failure of specimen. In this simulation, the failure condition was assumed that damaged zone (which satisfy the condition D=Dc) spread to overall cross-section of the specimen (see **Fig. 5**).

Fig. 6 shows the effect of mean stress on the damage evolution. It was observed that the damage evolution becomes faster with increasing mean stress. Thus, fatigue life increase with decreasing in mean stress (**Fig. 7**). This is because the large mean stress produces high tensile stress, which must decrease the micro-crack closure effect. The fatigue life prediction of the plate with a hole was compared with the experiment data[3] in **Fig. 8**. It was found that the analytical results agree well with the experiment data. Therefore, the proposed method can give the proper fatigue life prediction.

5. CONCLUSIONS

The high cycle fatigue damage analysis and lifetime prediction of a steel specimen could be carried out by the proposed method. In order to obtain the fatigue life prediction accurately, two identification methods of the damage parameters: the simplified model and neural network were proposed. It was found that both methods could give the reliable material parameters. It is also observed that the proposed method could simulate the influence of mean stress on the fatigue life of a typical steel structural member and it could also give reasonable results for fatigue life prediction. Therefore, the reliable fatigue life prediction can be obtained by using the experimental identification method of material properties.

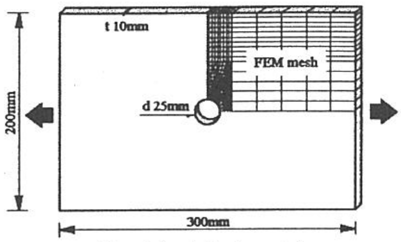

Fig. 4 Analytical model

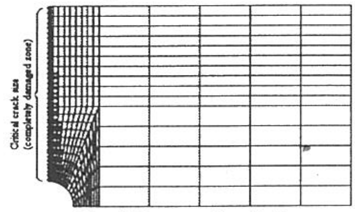

Fig. 5 Damage distribution

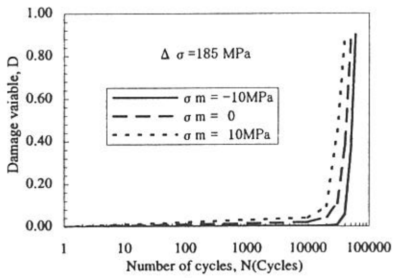

Fig. 6 Damage evolution

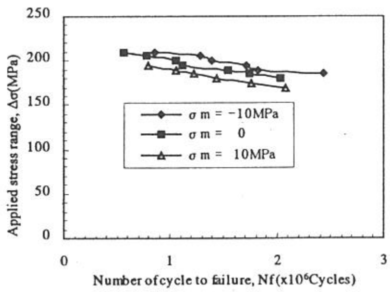

Fig. 7 Effect of mean stress on fatigue life

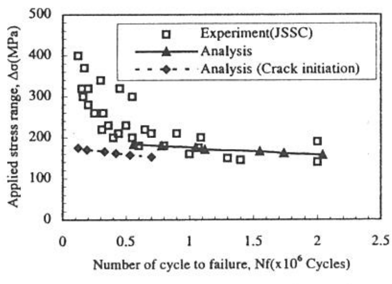

Fig. 8 fatigue life prediction and test data

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