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Evaluation of Flow Stress by Neural Networks and Simulated Annealing Methods

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ABSTRACT

An inverse method is presented to obtain material's flow properties by using small punch test. The flow properties were obtained by minimizing the least square error between the measured load-displacement response and calculated one. The objective function was optimized by simulated annealing method. During the optimization, neural network was used to predict load-displacement curve. The flow properties of material were well identified irrespective of initial values for numerically simulated test data as well as for experimental data.

1. INTRODUCTION

Deformation behavior is one of the most critical inputs for the remaining life evaluation of components operated under severe environments such as high pressure, high temperature, and irradiation etc. Uniaxial tensile test is widely used to measure the deformation behavior but can not be applied to in-service components due to the volume requirement of the standard testing specimens. In this respect, several innovative techniques are developed to evaluate the stress-strain relationship of small specimen sampled from the components. An example is small punch (SP) test method. During the SP testing, bending deformation is applied to thin plate specimen with ball. Finite element analysis has been introduced to acquire tensile stress-strain data since deformation during the SP test is concentrated on the confined area of the specimen. The measured load-displacement curve was repeatedly compared with trial curves[1,2]. In previous investigations, either trial-and-error method or optimal searching within a suitable database of curves is utilized for the matching scheme. These approaches are limited in the sense that prior information on material strength is required, and that the configured database can not be generally applied to new material, respectively.

In this paper, flow properties are obtained by an inverse method for the non-uniform deformation problem. This procedure employs, as the objective function of inverse analysis, the balance of measured load-displacement response and calculated one during deformation. Simulated annealing method is adopted to optimize the objective function due to its high non-linearity. In addition, artificial neural network is used to predict the load-displacement response under given material parameters which is the most time consuming and limits applications of global optimization methods to these kinds of problems. Material is assumed to follow power law hardening. The validity of the proposed inverse algorithm is demonstrated by using numerically simulated data. The effect of noise in data on the accuracy of the solution is examined. Finally, the present method is applied to evaluate the flow properties from experimental load-displacement curve.

2. ANALYSIS METHODS

2.1 Simulated Annealing

With conventional optimization algorithms, any convex function can be optimized with any initial configuration. For non-convex function, however, either a local minimum or the global minimum is found by moving towards the lower values depending on the initial configuration. For handling such global optimization problems, we used simulated annealing method which is based on the principles of statistical thermodynamics[3].

In simulated annealing method the optimization variables $\mathbf{X}$ act like particles in the solid and objective function $\Phi(\mathbf{X})$ represents the total energy bound to the solid. The standard implementation of the simulated annealing is summarized as follows;

By perturbing initial state i, get a candidate for the next state in the neighborhood. The behavior of a system subject to such a neighborhood move is determined from an observation of the objective function. If the objective function $\Phi(\mathbf{X}_j)$ after perturbation is less than the objective function $\Phi(\mathbf{X}_i)$ before perturbation, the perturbed system is accepted as the new candidate. If the state j is higher than the state i, the probability of accepting the perturbed system follows the Metropolis criterion, which is defined as $\exp(-\Delta\Phi / k_B T)$, where k_B is Boltzmann constant. As the temperature decreases, the probability of adopting a detrimental configuration lessens. The system is allowed to reach equilibrium at each temperature; temperature is then lowered, and the annealing process continues until the system reaches a temperature corresponding to a certain freezing temperature. If the system is annealed sufficiently and slowly, the global minimum is attained. The annealing schedule depending on the variation of k_B and T determines the characteristics of convergence.

2.2 Neural Network

A multilayer neural network is composed of input layer, hidden layer(s), and output layer. Each layer consists of many processing units. The unit has multiple input slots and a single output one. The input signal is processed in the neural network and the error during the training is backpropagated. The connection weight and bias are modified using a gradient descent method so that the output signal may approach the target one. In this paper, Levenberg-Marquardt method is implemented among the gradient based algorithms due to its fast convergence, although the method requires lots of memory since the algorithm must store the approximate Hessian matrix[4]. The trained knowledge is memorized into the weight between units.

3. LOAD-DISPLACEMENT CURVE

3.1 Small Punch Testing

The dimension of the SP specimens is $10\times10\times0.5$ mm^3, and they are polished to 600 grit. The SP jig consists of a puncher 2.4 mm in diameter, a ball, upper die, and lower die with a hole 4mm in diameter. The specimen is placed on the lower die and clamped between the upper and lower dies by four clamping screws. As load is applied to the SP specimen by the ball through the punch, the specimen is displaced into the lower die. An Instron 4204 was used for SP tests. The tests were conducted at a crosshead speed of 0.5 mm/min with a load cell of 5 kN capacity. The displacement was measured by using the extensometer attached between the upper die and the lower die.

3.2 Simulation of Load-displacement Curve

The ABAQUS commercial FEM code[5] is used for the computational simulation of the load-displacement curve. The SP jig shows an axi-symmetry; therefore only a plane perpendicular to circumferential direction is modeled. The finite element grids for the SP specimen is shown in figure 1. The SP specimen is modeled with the linear quadrilaterial elements. The ball and the dies are considered to be rigid. It is assumed that material has isotropic work-hardening behavior and flows isotropically according to von Mises yield criterion. A finite sliding element is used to account for the contact between the ball and the SP specimen. The values of Poisson's ratio, Young's modules, and friction factor are 0.3, 200 GPa, and 0.25, respectively.

As drawn in figure 2, the calculated load-displacement by FEM is in close agreement with measured one as a whole. However more gaps between two values are seen when deformation approaches 0.5 mm. The difference in the low deformation regime might be mainly attributed to experimental error.

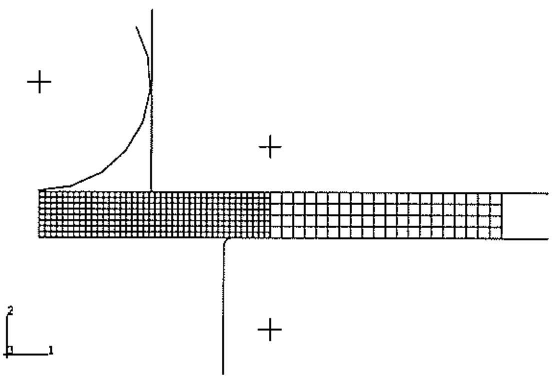


Fig. 1 Finite element model for small punch test.

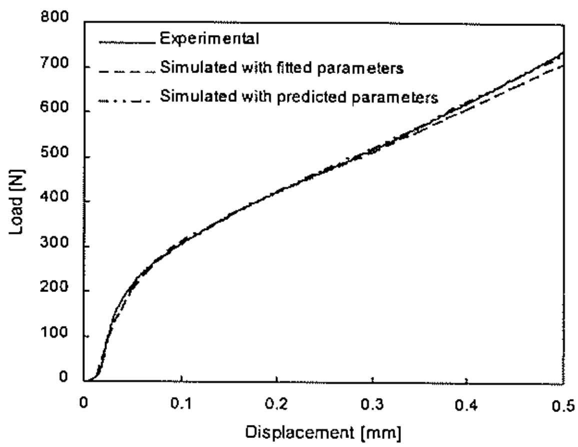


Fig. 2 Small punch load-displacement curves for SA 508 Cl. 3 steel.

3.3 Prediction of Load-displacement Curve by Neural Network

In DEC Alpha 2100 4/275 workstation, the ABAQUS code took a few minutes CPU time to simulate a load-displacement curve for a certain material condition. Generally the application of simulated annealing to a optimum problem requires more than hundreds of iterations. Thus the calculating time to get global minimum may take over one week. In order to obtain material properties in real time, we predict the load-displacement response for a given stress-strain data by using the backpropagation neural network.

Generation of Training Sets : For metals, a flow curve can be described by the following equation:

$$\varepsilon = \varepsilon_e + \varepsilon_p = \frac{\sigma}{E} + \left(\frac{\sigma}{D}\right)^n \tag{1}$$

where ε_e is the elastic strain, ε_p is the plastic strain, n is the strength exponent, and D is the strength coefficient. To train neural network, n is chosen in the range of 3.33 to 20, and D is in the range of 300 MPa to 1800 MPa. Material conditions in which strength is less than 150 MPa at 0.2 % plastic strain are excluded in training. The number of total training material conditions is 217. The sampled range is thought to include most of the metals used in heavy industries.

Network Architecture : Levenberg-Marquardt backpropagation method is employed to apply the multilayer network training problem. Since the Levenberg-Marquardt algorithm needs more memory than momentum method and variable learning rate method, the network is composed to predict a load-displacement point rather than the whole curve. The training of the network is carried out by using Neural Network Toolbox in Matlab 4.2C[6]. The network has one hidden layer with 20 units. For the network input vector is [D, n, δ], and output is P, where δ is displacement and P is load. The activation function is log-sigmoid function. For each material condition, 16 points are sampled on the load-displacement curve up to 0.5 mm displacement. The number of total training data is 3472. The training is terminated when the mean estimate error expressed in Eq. (2) is less than 5×10^{-6}:

$$e = \frac{1}{QS^M}\sum_{q=1}^{Q}\sum_{j=1}^{S^M}(t_{j,q} - a_{j,q})^2 \tag{2}$$

where Q is the numbers of training data, S^M is the number of units in the output layer, and $t_{j,q}$ is the j-th element of the target vector for the q-th input/target pair, and $a_{j,q}$ is the j-th element of the output vector for the q-th input/target pair, respectively. The maximum error between trained load and target one was less than 30 N, which was observed at the lowest load point.

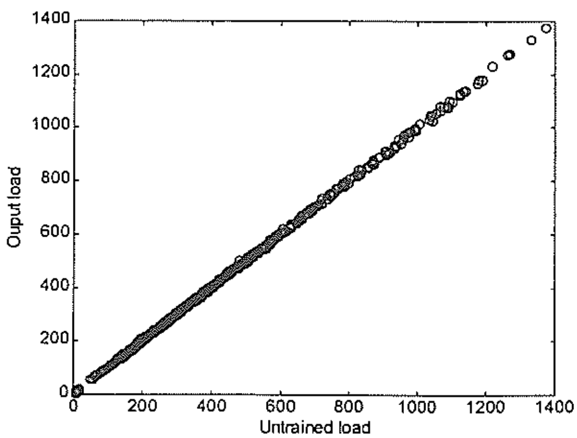


Fig. 3 Predicted results for 30 untrained load-displacement conditions

Verification of Neural Network : To test the present network, 30 stress-strain combinations are randomly selected in the ranges previously defined. Table I shows the 30 conditions. The predicted load is compared with the one calculated with the ABAQUS code as shown in figure 3. The axis of abscissa is the ABAQUS result, and the axis of ordinate is the predicted load.

Table 1 Verification results of inverse algorithm for numerically simulated test conditions

No.	Simulated data (Desired)		Verification results (Predicted)		No.	Simulated data (Desired)		Verification results (Predicted)	
	D	n	D	n		D	n	D	n
1	547.21	16.09	565.57	14.14	16	1522.07	4.82	1542.64	4.74
2	1619.31	3.71	1617.93	3.73	17	1122.91	18.53	1122.06	18.37
3	1249.28	19.70	1245.90	20.00	18	1129.30	16.51	1121.03	17.00
4	456.08	6.89	455.87	6.87	19	1476.37	6.56	1486.60	6.46
5	1280.96	3.89	1276.97	3.90	20	1078.62	7.95	1078.64	7.92
6	868.68	4.40	870.09	4.39	21	964.89	4.84	964.00	4.83
7	1648.07	5.16	1659.23	5.10	22	906.56	3.96	910.10	3.95
8	486.29	5.76	486.27	5.83	23	1584.53	5.49	1614.42	5.34
9	1492.03	4.78	1517.02	4.68	24	1796.98	6.61	1791.44	6.61
10	880.37	4.60	880.82	4.59	25	777.14	8.65	772.05	8.78
11	1691.70	3.38	1679.87	3.40	26	813.03	9.18	807.42	9.33
12	1736.64	7.87	1733.03	7.91	27	901.35	4.16	905.21	4.15
13	1731.38	5.16	1734.44	5.12	28	697.00	9.52	688.71	9.93
14	1437.69	6.48	1445.75	6.42	29	1642.42	6.03	1643.32	6.03
15	714.84	5.48	710.37	5.53	30	1343.43	4.88	1358.43	4.81

4. RESULTS AND DISCUSSION

The estimated values of the parameters describing the flow property are obtained by adjusting the parameters until the predicted load-displacement curve matches the measured one on the least square basis. The procedure attempts to minimize the following function with respect to the vector **X**=[D,n]:

$$\Phi(\mathbf{X}) = \frac{1}{2}\sum_{i=1}^{m}[r_i(\mathbf{X})]^2 = \frac{1}{2}\mathbf{r}^T\mathbf{r} \tag{3}$$

where m is the number of measurements.

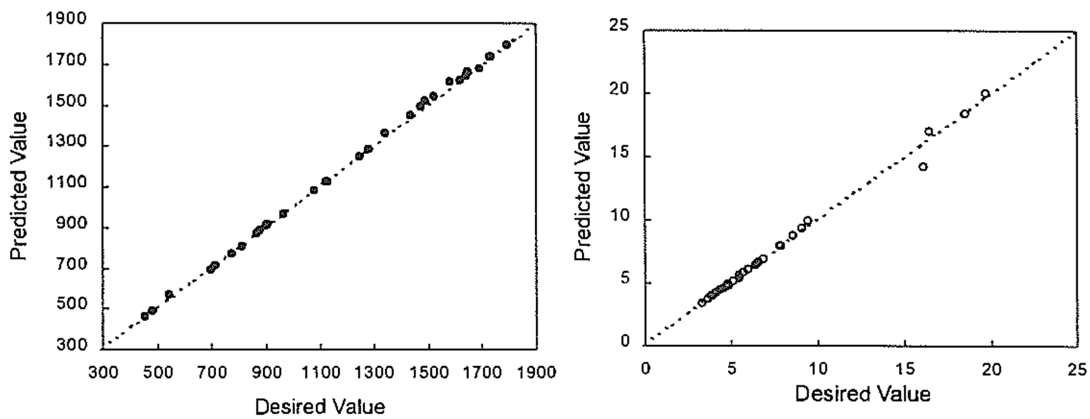
The residual vector is defined by

$$\mathbf{r} = \mathbf{P}^* - \widetilde{\mathbf{P}} \tag{4}$$

where, $\mathbf{P}^*$ is the measured load, and $\widetilde{\mathbf{P}}$ is the predicted one. The minimization of the Eq. (3) is accomplished by means of simulated annealing method.

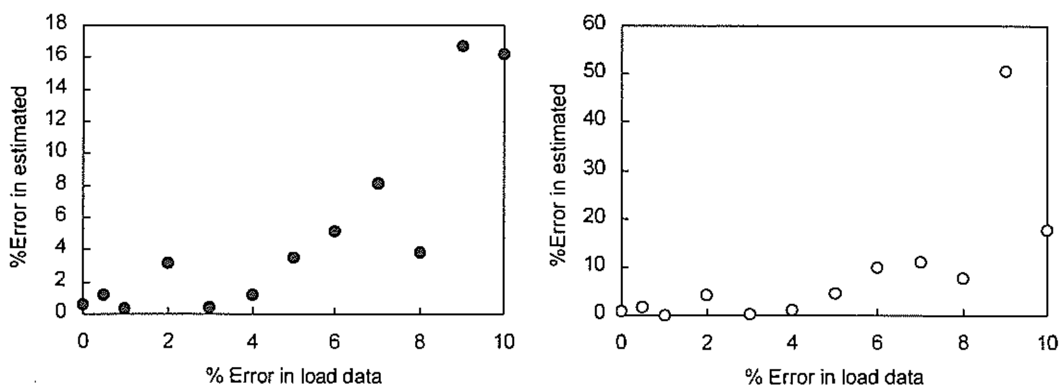
4.1 Determination of Flow Stress for Simulated Data

To check the validity of the present method, D and n are predicted for the 30 data presented in table 1. The evaluated results are shown in table 1 and figure 4. The largest errors in estimating D and n are 3.35% and 12.1%, respectively. In the same condition, the relative error in flow stress stays smaller than 2.3% with its average value, 1.24% over the strain range up to 30%.



(a) (b)

Fig. 4. Predicted results of material's parameters for the 30 numercally simulated data, (a) Result for D, and (b) Result for n.



(a) (b)

Fig. 5 Effect of noise in load data on error in estimated load, (a) Error in D, and (b) Error in n.

Because inverse problems are ill-posed, solutions are likely to be unstable to small noises in the input data[7]. It is important whether the algorithm is stable with respect to small noise. To simulated noise measurements, noises with Gaussian distribution were added to load-displacement curve. The mean of each distribution is zero, and the standard deviation is a given percent of the mean of the magnitude of the loads. The ability of the inverse procedure was checked for the load-displacement data containing noise from 0.05% to 10%. The estimated errors for D and n are calculated three times. The averaged values are shown in figure 5. The percent errors in both D and n tend to increase monotonically, and the errors in n are larger than those in D for a given amount noise. In the case of data with 5% noise, the errors in D and n are 8.95% and 13.9 %, respectively, and the relative error in flow stress is within 7.44% and its average is 4.29% over the strain range up to 30%. The solution method appears to be stable since small errors in the load-displacement data cause relatively small errors in the estimated parameters.

4.2 Determination of Flow Stress for Experimental Data

The stress-strain curve of SA508 Cl. 3 nuclear pressure vessel steel is fitted by Eq. (1), and the fitting result is expressed in Eq. (5)

$$\varepsilon_p = \left(\frac{\sigma}{892.13}\right)^{7.35} \tag{5}$$

Poor fitting quality shown in the low strain range of figure 6 is due to yield-point phenomenon of low alloy steel. The simulated load-displacement response obtained with Eq (5) stress-strain curve is compared with the measured one in figure 2.

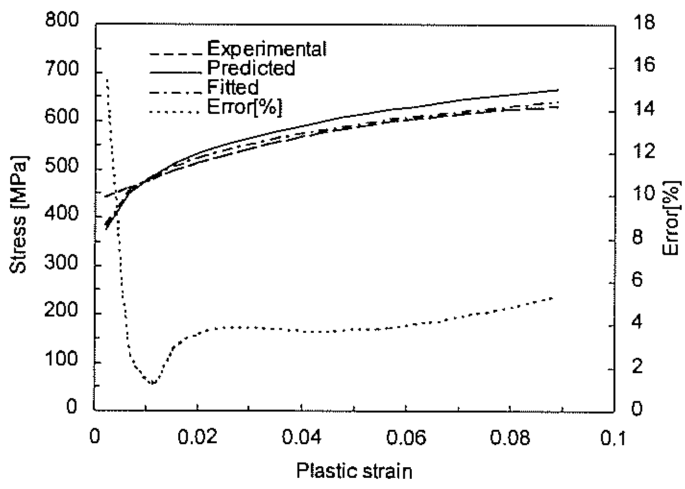


Fig. 6 Determination of flow stress for SA508 Cl. 3 steel.
(Error = |Predicted –Experimental / Experimental| × 100)

For the SA508 Cl. 3 steel, iterations stopped with the parameters, D=964, and n=6.57 at which the load-displacement curve shows good agreement with the measured one as appeared in figure 2. Figure 6 shows the experimental tensile stress-strain curve in comparison with the stress-strain curve calculated using the predicted D and n. The relative errors in flow stress is less than 16%, and the average error appears to be 4.5%. Compared with the predicted results for the numerical data, load-displacement curve experimentally acquired results in larger difference. It is thought that this difference is primarily produced because the experimental stress-strain data can not be expressed in the form of simple power hardening law in the low strain range.

5. CONCLUSION

An inverse algorithm combining simulated annealing method for solving an optimization problem and neural network for calculating load response is proposed to evaluate the flow properties of materials expressed by simple power-hardening relationship. The proposed method is devised to obtain the flow curves using small punch test. The prediction performance is quite good for numerically simulated data. The stability of the prediction method is not affected by artificially generated small noise. The proposed method is extended to apply to the estimation of flow stresses for the SA508 Cl. 3 pressure vessel steel. It is found that the flow stresses predicted using the present method agree well with those obtained by the uniaxial tensile test method except the region where yield-drop phenomenon is manifested.

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