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Prediction of Hardness Distribution in Forged Steel by Neural Network Model

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Abstract

A prediction system for hardness distribution in forged steel has been developed by adapting FEM with the hierarchical type neural network. This system consists of two parts: the FEM-computer simulation of metal forming during forging process; and the neural network prediction for hardness distribution in steel after forging and cooling. This report presents details of the system and an example of an application to the forging process of a knuckle arm.

1. Introduction

The reduction of the weight of automotive parts is required from the standpoint of improving the fuel efficiency of automobiles, and the same is true of automotive steel parts. In order to reduce the weight of an automotive part, it is an effective method to increase the part's strength so as to permit the decreasing of its wall thickness and therefore its weight. This method has already been applied to the frames, outside sheets, etc. of automobiles. At present, R&D is being conducted on higher-strength forging steels which would be applicable to the undercarriage, and engine parts. On the other hand, the design modification made necessary by use of a higher-strength steel takes much more time and labor since it requires repeating the process of creating a prototype, testing its material and feeding the test results back to the steel composition. However, if the material distribution of a forged part can be estimated with fair accuracy, it should be possible to determine the weakest point of the part, reflect it in the design and speed up the development of a suitable steel material.

Concerning the estimation of material characteristic[1-10], studies in the fields of sheets and plates, in particular, have advanced significantly. In many of those studies, the method of calculation called a physical model is employed. This is a method of estimation by sequential calculations. In this method, heated γ grain size is first estimated from the heating temperature, heating time and condition of precipitation. Next, from the estimated γ grain size and rolling pass schedule, recrystallized or non-recrystallized γ grain size and residual dislocation density are estimated. Then, from the estimated grain size and dislocation density and the cooling conditions, the factors of metallurgy structure that influence the material characteristic (phase fraction, grain size and shape, etc.) during transformation are estimated. Finally, the overall material characteristic is estimated from those factors. Since this method of estimation sequentially simulates the metallurgical phenomena involved in the process, it allows the determining of factors that influence the material characteristic easily. On the other hand, in the process of sequential estimation, errors tend to accumulate easily. Besides, at the stage of estimation of the material characteristic, even the slightest variation in the estimated factors of structure can significantly influence the estimation result. Thus, the accuracy of estimation with this method is clearly limited.

As another method of estimating material quality, the use of a neural network has been reported[11-14]. There are several types of neural networks. The most popular of them is the hierarchical type. In this type of neural network, nonlinear operators called units are provided in each of the input, intermediate and output layers, and the input is related to the output by adjusting the link loads that describe the transmissions between the units. The advantage of the neural network is that it can be applied to even nonlinear phenomena and phenomena in which many parameters are related to one another in a complicated manner. It should be noted, however, that the neural network itself is a sort of black box. In the case of a multilayer neural network, in particular, it is extremely difficult to define the physical meanings of the link loads. **Table 1** compares a physical model and a neural network model for estimation of material quality.

We estimated material hardness by using a neural network model

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Table 1 Comparison of physics model and neural networks model

	Neural networks model	Physics model
Outline	Quality of the material is estimated by using the complicated regression equation that can describe every function. Accuracy of estimation improves by accumulating the result of the simplified experiment.	It is based on the metallurgy phenomenon. Phase fraction and grain diameter are estimated from dislocation density, nuclearation rate and growth rate. Quality of the material is estimated by these value.
Advantage	Even quality of the material of the complicated system that is not formulated in a physics model is predictable. It can be estimated even if bainite or martensite is mixed in ferrite and pearlite.	The factor which influences quality of the material is specified easy.
Disadvantage	Much experimental data is necessary. The meaning of the coefficient is weak in comparison with physics model.	An error is easy to bring about because it is the accumulation of the estimation. The transformation model of bainite and martensite isn't established.

which has the characteristics mentioned above. In addition, we estimated hardness distribution in forged parts by using the model incorporated as a user subroutine in the forging FEM analysis software DEFORM-3D which is available on the market. This paper describes the results of the estimations.

2. Structure of Neural Network Used for Material Estimation Model

Fig. 1 shows the structure of the neural network used for our material estimation model. The network consists of one input layer, two intermediate layers and one output layer. Process conditions (heating temperature, forging temperature, strain, cooling rate, etc.) and steel chemical composition, are provided to the input layer and the output layer is provided with hardness. Thus, the system is such, that when the relevant data is input to the input layer, the calculated hardness is output to the output layer. The input and output values were standardized based on their maximum and minimum values. As the transfer function of each of the units, a sigmoid function was used. The input values for each of the units were simply added up.

$$x = \Sigma\, w_i\, h_i \qquad (1)$$

$$y = 1 / (1 - \exp(-x)) \qquad (2)$$

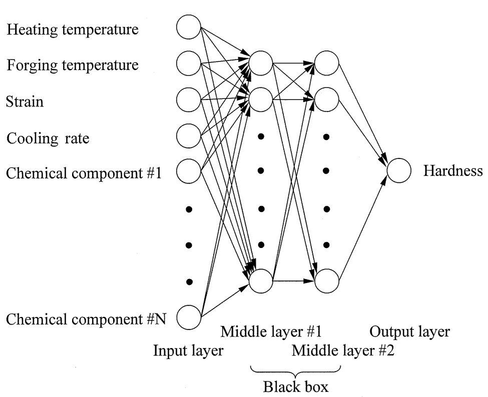

Fig. 1 Structure of neural networks

Where, w_i denotes link load; h_i, value of output from each unit in before layer; and y, value of output from this unit.

3. Learning Method and Teaching Data

The process of relating input data to output data in such a way that a specific output is obtained from a specific input, (determining coupling coefficient (link loads) between the units in a neural network) is called learning, and reference input/output data which are previously given for learning are called teaching data. The purpose of learning is to minimize the sum of squares of the differences between teaching output data and neural network calculation output data. In the learning, an optimum value is searched for by varying the link loads. There are several methods of learning. For example, the back propagation method applies Newton's method to the learning rules, and the extended Karman filter method applies the Karman filter to the learning rules. In the present study, the extended Karman filter method[15] was used for learning.

Small specimens 8 mm in diameter and 12 mm in length were used to collect teaching data. They were subjected to hot working which simulated hot forging. The hardness of each of the specimens was measured after cooling. A total of 1,055 sets of data were collected under varying test conditions. The ranges of the collected data are shown in **Table 2**.

As mentioned earlier, the neural network has a very flexible structure and by increasing the number of units provided in its intermediate layer, the neural network can adapt to any functions. When experimental values are used as the teaching data, it is necessary to estimate their accuracy. In the present study, the experimental error was assumed to be 5% for the purpose of the learning. Learning was deemed to be completed when the maximum error of the difference between the experimental value and the result of repetitive calculation for learning became 5% or less. For example, in the program step that compares teaching data and learning data during the repetitive calculation for learning, if the hardness data indicating maximum error was HV400, the learning was assumed to be completed when the learning data entered the range HV380 to HV420. Similarly, if the hardness data indicating maximum error was HV100, the learning was assumed to be completed when the learning data entered the range HV95 to HV105.

Table 2 Teaching data for estimation of hardness

	Min.	Max.	Ave.
C (mass%)	0.0017	0.6	0.313
Si (mass%)	0.009	1.63	0.940
Mn (mass%)	0.15	2	1.387
P (mass%)	0.0017	0.021	0.0152
S (mass%)	0.0029	0.1	0.0159
Ni (mass%)	0	0.503	0.034
Cr (mass%)	0	1	0.314
Cu (mass%)	0	0.29	0.035
Mo (mass%)	0	1.01	0.091
V (mass%)	0	0.51	0.0915
t-Nb (mass%)	0	0.031	0.0023
t-Al (mass%)	0	0.039	0.0270
t-Ti (mass%)	0	0.5	0.0237
Zr (mass%)	0	0.002	0.0000
Pb (mass%)	0	0.17	0.0027
Ca (mass%)	0	0.0024	0.0001
t-B (mass%)	0	0.0011	0.0001
t-N (mass%)	0.0014	0.016	0.0097
Heating temperature (℃)	680	1300	1111
Forging temperature (℃)	640	1300	897
Strain	0	2.42	1.52
Strain rate (1/s)	0	12.25	8.00
Cooling rate (℃/s)	0.5	10	0.64
Hardness (HV)	59	603	288

4. Results of Learning

Fig. 2 compares all the teaching data (measured values) used for the learning and all the learning data (calculated values). Over a wide hardness range, the measured and calculated values fall within the 5% error at the end of the learning.

Fig. 3 shows the results of over-learning with the teaching data hardness range narrowed down to HV117 - HV422, the number of data sets reduced to 959 and the error at the end of learning set at 0.1%. The variance in measurement is reproduced even though the teaching data and learning data completely agree with each other as shown in **Fig. 4**. Thus, over-learning is unsuitable for practical use.

In the present study, a link weighing set created from the learning shown in Fig. 2 was built in our FEM forging analysis system.

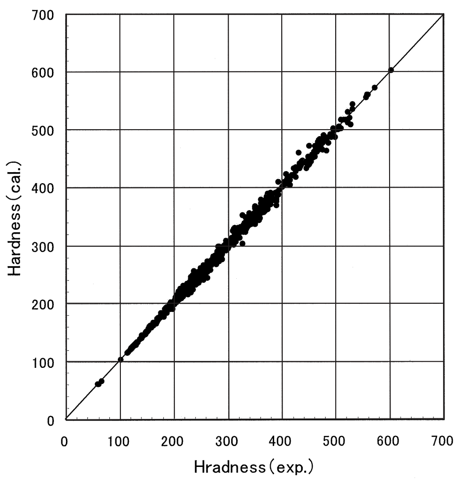

Fig. 2 Comparison of the experimentation and the calculation

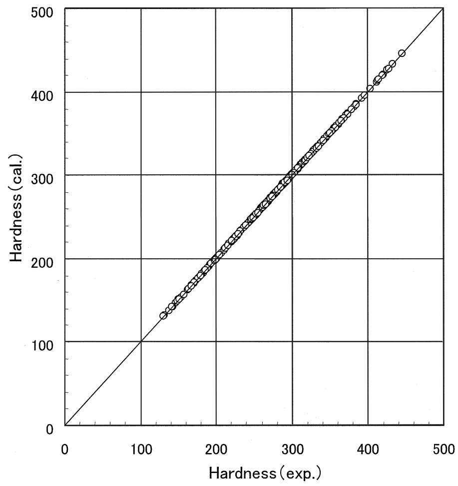

Fig. 3 Comparison of the experimentation and the calculation

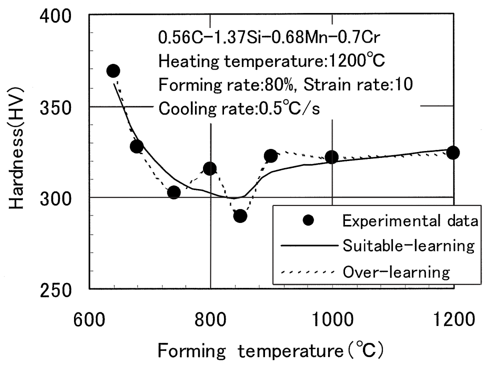

Fig. 4 Comparison of the estimated value of suitable-leaning and over-leaning

5. Configuration of Forging Material Quality Estimation System

As mentioned already, the analysis of forging itself was made using the FEM software "DEFORM3-D" which is available on the market. With this software, it is possible to simulate forging and cooling by setting shape data (specimen shape, die shape, etc.), heating conditions (furnace temperature, heating time, etc.), forging conditions (forging speed, die temperature, contact heat transfer coefficient, etc.) and cooling conditions (definitions of contact surfaces with various types of coolants, heat transfer coefficients, etc.).

The FEM calculation is performed in increments of time. For all the elements of the FEM mesh cut in the forging element in each time increment, temperature, strain, etc. are calculated. Based on the calculated time, temperature and strain data, the data necessary for estimation of hardness were extracted. In order to estimate hardness, it is necessary that chemical composition, heating temperature, forging temperature, strain, strain rate and cooling rate must be given. We

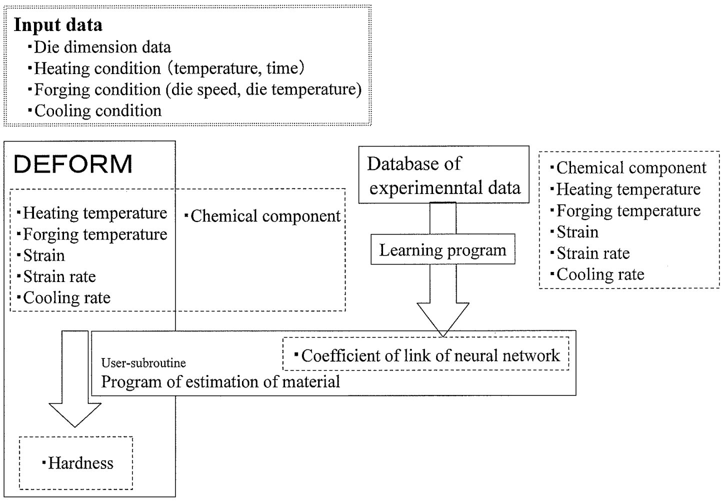

Fig. 5 Estimation system of material distribution of forged part

assumed the maximum temperature at the time when the strain before forging was zero as the heating temperature, the time-strain average temperature while a strain was applied (Equation 3) as the forging temperature, the cumulative strain as the strain, the average strain rate (Equation 4) as the strain rate, and the average cooling rate from 800℃ to 500℃ as the cooling rate.

External file 1 was created which described the chemical composition of the specimen steel since the forging software had no input term for chemical composition. On the basis of the heating temperature, forging temperature, strain, strain rate and cooling rate, calculated for each element throughout the forging and cooling process, and the chemical composition data provided by external file 1, the authors calculated the hardness for each element at the end of the cooling at which the FEM calculation was finished. The calculation of hardness was performed by using external file 2 that described the learned link weighing set. In order to secure the applicability of the neural network even if it is restructured in the future, external file 2 describes the number of inputs, the number of outputs, the number of intermediate layers and the number of units in each of the intermediate layers, all of which define the structure of the neural network.

Fig. 5 shows the configuration of our forging material quality estimation system.

$$T = \left(\sum_{i=m}^{n} (t_i - t_{i-1})(\varepsilon_i - \varepsilon_{i-1}) T_i \right) / (t_n - t_m)\, \varepsilon_n \tag{3}$$

$$\dot{\varepsilon} = \left(\sum_{i=m}^{n} (t_i - t_{i-1})(\dot{\varepsilon}_i - \dot{\varepsilon}_{i-1}) \right) / (t_n - t_m) = \frac{\varepsilon_n}{t_n - t_m} \tag{4}$$

Where, T denotes average forging temperature; t_m, time at which forging starts; t_n, time at which forging ends; ε_m, initial strain (= 0); and ε_n, cumulative strain.

6. Forging Calculation Example

Here, the forging of a knuckle arm is discussed as an example of calculation using our system. The calculation was performed under the following conditions.

Material chemical composition: 0.33C - 1.2Si - 1.6Mn - 0.1V
Material shape: 68 mmφ × 210 mm
Heating condition: Material evenly heated at 1,200℃
Forging condition: Forging speed 300 mm/s
Cooling condition: Air cooling after forging

Fig. 6 shows the temperature distributions in the work in the forging and cooling processes. Multiple steps were carried out in the forging process. However, since the inter-pass time was comparatively short, one-pass forging was judged possible for the simulation and hence, the calculation was performed with one-pass forging. The

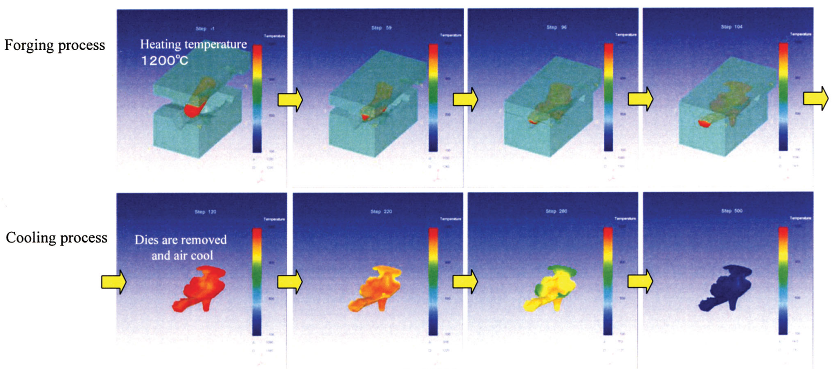

Fig. 6 Temperature distribution of forging and cooling process

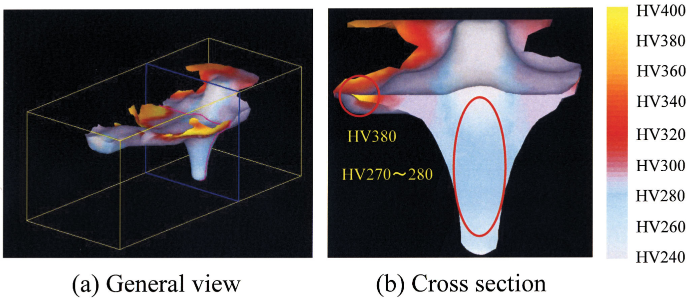

Fig. 7 Hardness distribution of forged part

hardness distribution in the forged part at the end of cooling is shown in **Fig. 7**. According to the calculation results, the hardness of the flash is high, whereas that of the stem is low. However, the calculated hardness matches fairly well with the hardness of the actual forged part. The higher hardness of the flash is considered due to the fact that the flash was subjected to a higher rate of forging and a higher rate of cooling. The flash of the actual forged part were of bainite structure, suggesting that our estimation model would be applicable not only to a ferrite-pearlite structure but also to a bainite structure.

7. Problems to Solve in the Future

The hardness estimation model that has been described so far produces fairly good results when it is applied to steel materials of ordinary chemical composition and simple processes of heating, forging and cooling. However, when the variance in steel chemical composition is fairly wide or when the steel material is subjected to a rather more complicated process (e.g., repetitions of heating and cooling), the model does not produce satisfactory results. At present, the following problems have been noted with the hardness estimation model.

One problem is that although estimation by interpolation produces a relatively accurate result, estimation by extrapolation is inaccurate (there are cases where it produces a ludicrous result). At present, there is a current discussion taking place regarding whether this phenomenon is inherent in material quality estimation using a neural network. As a possible solution to this problem, an attempt has been made to improve the accuracy of estimation through extrapolation by standardizing the teaching data using the range 0.25 to 0.75 instead of the ordinary range 0 to 1. However, the attempt has not been very successful. A definitive solution would be to collect extensive teaching data and apply estimation by interpolation exclusively. At present, testing is being conducted to increase the volume of teaching data. At the same time, there has been consideration given to introducing to the learning process the basic laws of material quality (e.g., the material hardness increases when the carbon content is increased or the cooling rate is raised).

Another problem is that as the process factors determine the material quality greatly but only the heating temperature, strain, strain rate and cooling rate are considered (other factors are left out of consideration). For example, the strain is introduced as a substitute for the dislocation density, which is a physical factor. However, in multi-pass forging, dislocation recovery and recrystallization occur in each pass, causing the dislocation density to decrease. Therefore, there is a possibility that the relationship between cumulative strain and dislocation density will change significantly in this case. In addition, some new phenomena, such as precipitation, can take place when the work temperature is retained or raised in the cooling process. These phenomena are left out of consideration in the teaching data. With the present estimation model, it is impossible to estimate these factors. All this is considered due to the absence of a factor which indicates the time integral of temperature. At present, consideration is being made to adding time-serial temperature factors, such as temper parameter.

Still another problem concerns the accuracy of teaching data. The present learning is based on the 5% accuracy rule. However, there is no guarantee that all the teaching data falls within this accuracy. This means that there is the possibility of over-learning. The poor accuracy of estimation by extrapolation cited as the first problem might be ascribable to over-learning. This is considered due to the fact that test data obtained in the past was directly used as learning data. In this respect, it is necessary to carefully examine the origin of the data in the future.

8. Conclusion

On the premise that a neural network would be applicable to a situation in which several phenomena, such as metallurgical ones, are involved in a complicated manner, a material quality estimation model was created using a neural network. In addition, a forging material quality estimation system was built by incorporating the model in forging FEM analysis software. The simulation results concur fairly well with the measurement results. On the other hand, in the course of the study, several problems with the system were revealed. It is important to solve them in the future.

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