An inverse method for identification of continuously varying material properties in post-manufactured structures through neural networks

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Abstract

Determination of material properties is essential for structural design, optimization and prediction of the mechanical behavior of the structures. Currently, the material properties are measured after the material is produced using standard specimen. However, the material properties at some parts of the structure can change non-uniformly as the results of plastic deformation and hardening during the manufacturing processes, such as metal forming processes. Therefore, the material properties of the manufactured structure components become nonhomogeneous, can vary continuously, and can be very much different than those evaluated based on the specimen measurements. This paper presents an inverse method to systematically determine the variation of the material properties in post-manufactured structure components via, for example, a metal forming process. Our inverse technique uses ABAQUS to simulate the mechanical behavior of the structure, and then the responses are used to train a radial basis function (RBF) neural network (NN). The material properties at any point of the structure can then be obtained rapidly and accurately by measuring the structure responses. Our technique is validated using a hat-shaped plate formed by stamping. It is found from a simulated measurement data that the average error of the inversely identified is less than 2%, which is sufficient for most of the engineering applications.

Keywords: **Material properties; Inverse problem; Inverse identification; RBF neural network; Metal forming**

Introduction

In structural design, optimization or safety analyses, the accuracy of material properties directly determines the reliability of the results [1,2]. Currently, most of the material parameter identification methods are applied to materials without considering the effects of manufacturing processes, and hence the obtained results are effectively the equivalent parameters that omits the spatial inhomogeneity. In actual fact, however, due to the non-uniform loading and plastic deformation in the structure during manufacturing processes such as forming processes, there are significant discrepancy in the material properties at different parts of the structure [3,4,5]. To overcome this shortcoming, an inverse method is proposed in this paper which allows the material properties changes continuously in space manufactured structures.

Description of the problem

The material properties are assumed vary continuously spatially. In the space over which the material properties change, it can be divided into a number of key regions using discrete points. Then, the material properties of the structure's region are obtained by interpolating values at these discrete points. Finally, only the material properties at these key points are needed to be identified, thus it can reduce the number of inversion parameters. Radial basis function neural networks and finite element methods are used in the present method for solving the inverse problem and collecting training data needed for neural networks. The task of this work is to establish such a method that can systematically and rapidly Identifies continuously distributed material properties. In order to develop an effective and practical procedure for continuously distributed material properties, we employ the following strategies:

- Use the well-established FEM (in particular ABAQUS®) as the forward model. This is because the material properties in any element in a FEM model can be different from the others. In addition, ABAQUS is mature and reliable, and can compute structural responses very fast for a given distribution of materials for a structure.
- The ABAQUS models are then used to train a neural network (NN), so that during the inverse analysis, we can infer the material parameters in real-time without calling for time-consuming ABAQUS.
- In training of the neural networks, we use radial basis functions (RBF). This is because the moment matrices using RBF is always investible and hence the training process becomes reliable and effective. Our RBF-NN is expected offering a real-time inverse solver for identifying the continuous distribution of material properties of post-manufactured structures.

Finite element model

This method is applied to the material parameter identification of hat-shaped structure. Due to the symmetry of the plate, only the one-half model is selected for modeling shown in Fig. 3.1. The left end of the one-half model is completely fixed and the load in z direction is applied to the right end of the structure.

The material used for the model is stainless steel SUS201, which has an initial Young's modulus of 207000 MPa. In fact, after stamping process, the Young's modulus of material is continuously variable throughout the entire structure, even the Young's modulus in some local areas of the structure may reach twice of the original Young's modulus [6,7]. Therefore, the model is firstly divided into four blocks by five measuring points 1, 5, 8, 9, 12 as shown in Fig. 3.1 and each block is then divided into several equal-sized areas. The whole model is divided into 254 areas with different Young's modulus, and the Young's modulus of each area is obtained by interpolating from that of the measurement points at both ends of the block. As long as the Young's modulus of the measuring points (5, 8, 9, 12) is determined, the Young's modulus at other positions is obtained. To avoid stress singularity, appropriate triangular meshes is applied. The total number of elements in the model is 101600 and the number of nodes is 51255.

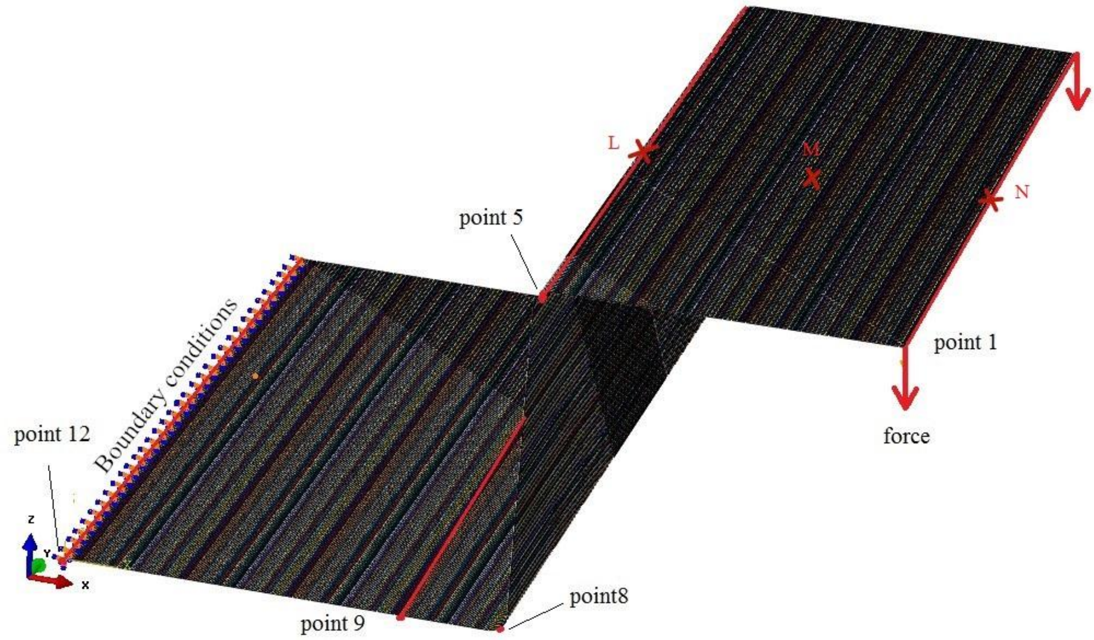

Fig. 0.1 One-half model of hat-shaped structure

Sensitivity analysis and establishment of neural networks

In the process of material properties inversion, there should be a strong sensitivity between the parameters to be reversed and the measured response of the load, in order to guarantee the existence and solvability of the inverse solution [,8,9,10,11,12]. After sensitivity analysis, it is found that the z-direction and the x-direction displacement of positioning points L, M, and N are sensitive to the change in material parameters as shown in Fig. 3.1 and Table 0.1. The displacement responses are represented by U_{Lx}, U_{Lz}, U_{Mx}, U_{Mz}, U_{Nx}, U_{Nz}, where U represents the displacement response, L, M, and N are the names of the positioning points, and x and z represent the direction of the displacement. It can be seen in Table 0.2 that the displacement responses of the three positioning points (L, M, N) are less sensitive to the change of Young's modulus at point 5 while they are highly sensitive to the change of Young's modulus at points 9 and 12. Because the deformation of the structure always occurs firstly in the position with a lower Young's modulus when the structure withstands external forces. The Young's modulus at point 9 and point 12 are smaller than that of point 5 and point 8, thus, the displacement is likely to be more sensitive to here. Based on the results of sensitivity analysis, with these six displacement responses of the points (L, M, N) as inputs, the material parameters of the five measuring points are outputs, the inverse problem neural network is established, and appropriate training and error analysis are performed.

Table 0.3 The sensitivity coefficient of displacement responses of points L, M, and N to the changes of Young's modulus of the measuring points

point	U_{Lx}	U_{Lz}	U_{Mx}	U_{Mz}	U_{Nx}	U_{Nz}
5	4.44%	1.04%	4.44%	8.27%	4.44%	12.02%
8	21.37%	4.00%	21.37%	13.33%	21.37%	16.44%
9	40.07%	38.61%	40.07%	35.96%	40.07%	34.42%
12	39.09%	58.52%	39.09%	46.30%	39.09%	41.10%

Conclusions

In this work, a novel method of continuous inverse identification of material properties was proposed to accurately obtained the material properties at arbitrary position of structure. It is found that the average error of the inversely identified result is less than 2%, compared with a simulated measurement data. The radial basis function neural network is used to solve the inverse of the positive problem because of its advantages in solving complex nonlinear problems. The method of approximating the material properties at any position of the structure by interpolating material properties of key positions of the structure reduces the number of outputs and simplifies the solution of inverse problem. In addition, this method separates the simulation from the solution and it is more convenient for engineering applications.

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