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Neural network approach for prediction of deflection of clamped beams struck by a mass

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ABSTRACT

The purpose of this work is to establish an empirical relationship and neural network for the prediction of deflection of clamped metallic beams struck by mass and causing large inelastic deformations. A multivariable power series was selected as the form of the regression model to develop the empirical relationship. Material properties and geometry of both the striker and beam were selected as the independent variables of this model to predict the deflection in beam. Good agreement between the experimental results and the prediction of maximum deflections for various impact energies has been obtained. The data used in the development of statistical model was reanalyzed for the prediction of maximum deflection by employing the technique of neural networks with a view towards seeing if better predictions are possible. The neural network models resulted in very low errors and high correlation coefficients as compared to the regression based models.

1. Introduction

In an early experimental study, Menkes and Opat [1] investigated the dynamic plastic response and failure of fully clamped metal beams which were subjected to uniformly distributed velocities over the entire span. The experimental results of Menkes and Opat [1] were later analysed by Jones [2] using the rigid-plastic method. A systematic and exhaustive study on the deformation and failure of fully clamped ductile beams struck by a mass has been conducted by Liu and Jones [3–6] and Yu and Jones [7,8]. Two modes of failure – Tensile tearing and shear failure modes – were observed in experiments [3] depending on the uniaxial rupture strain of the materials, the location of impact point and support conditions of beam. The experiments on aluminum beams showed that the geometry changes for finite deflection play an important role in the dynamic response of beams. Further, higher modal dynamic plastic response of the beams is more efficient in absorbing kinetic energy than single modal response [9].

In a rigid-plastic structure, Shen and Jones [10] assumed that the rupture occurs when the absorption of plastic work per unit volume reached a critical value. To calculate the actual plastic work in beams, a hinge length was estimated from experimental data obtained by Menkes and Opat [1] on impulsively loaded aluminum beams. Continuum damage mechanics has been used recently [11,12] for predicting the static and dynamic failure of beams, but the method requires the values for several parameters, some of which are difficult to obtain. Wen et al. [13] studied the phenomenon of deformation and failure of clamped beams under low speed impact loading (quasi static) at any point on the span by a heavy mass to estimate the dynamic plastic response and failure of clamped beams. Based on the principle of virtual work they obtained the load displacement relationship.

In the present study, a multivariable empirical power series relationship has been established for the prediction of deflection caused in a series of experimental tests on clamped metal beams struck by mass with sufficient initial kinetic energy to produce large inelastic deformations. The data used in the development of statistical models was reanalyzed for the prediction of maximum deflection by employing the technique of neural networks with a view towards seeing if better predictions are possible. The neural network models resulted in very low errors and high correlation coefficients as compared to the regression based models.

2. Deflection of beams under impact load

The analysis of metallic beams impacted by projectile at velocity less than the ballistic limit has been carried out earlier by Liu and Jones [3]. The maximum permanent deflection, W, of

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clamped beam of span, l_1+l_2, struck by a projectile of mass m_p at a distance l_1 from clamped end predicted by their analysis is given by [3]:

$$\frac{W}{H}=\frac{1}{2}\left[-1+\sqrt{1+\frac{8\lambda}{(1+r)}}\right] \tag{1}$$

where,

$$\lambda=\frac{m_pV^2l_1}{8M_PH},r=\frac{l_1}{l_2} \tag{2a, b}$$

where, M_P is the plastic bending moment of fully clamped beam; H is the thickness of beam; and V is the striking velocity of striker.

The above relation incorporates the influence of finite transverse displacements, axial restraints and bending moments, but disregards material elasticity and the influence of the transverse shear force in the yield condition.

3. Experimental data

In this paper the drop mass experiments reported in Ref. [3] are used. The drop has a variable drop height and achieved an impact velocity of 0.178 to 11.65 m/s. A total of two-hundred flat specimens of aluminum alloy and steel were tested. In all cases, the beam width and span were 10.16 mm and 101.6 mm, respectively, while the beam thicknesses H varied from 3.81 to7.62 mm. Out of the 200 beams, 38 beams either fractured, cracked or there was slippage at the clamps, thus leaving 162 beams which underwent nonlinear deflection. Thus the test results of these 162 beams have been used in this study. The range of different basic and non-dimensional parameters involved in these experiments are reported in Table 1.

4. Regression model

The empirical model selected is a generic multivariable power function with the independent and dependent variables applied to the model in such a manner as to maintain non-dimensionality. Failure impact event parameters that are needed, as a minimum, to describe the beam deflection are the basic impact geometry (point of impact of the striker; length and thickness of beam), strike velocity, and basic material properties (static flow stress of beam). The static flow stress, σ_0, of beam was chosen as the only material property because it is the only material property involved in the basic shock jump relationship.

Table 1
Range of parameters for the data of experimental details of flat beams (200 data points).

S. No.	Parameter	Range
Basic parameters		
1	Beam deflection,W (mm)	0.30–21.56
2	Beam thickness, H (mm)	0.15–7.62
3	Beam mass, m (kg)	0.01–0.062
4	Striker mass, m_p (kg)	5
5	Static flow stress, σ_0(N/mm^2)	302–412
6	Striker velocity, V (m/s)	1.78–11.65
7	Length of beam from the impact point to the right-hand support (after test), l_1(mm)	5.30–52.30
8	Material of beams	Aluminum and Steel
Non-dimensional parameters		
1	W/H	0.04–5.66
2	$\left(m_pV^2l_1\right)/\left(2BH^3\sigma_0\right)$	0.03–48.63
3	l_1/l_2Z	0.06–1.00
4	m_p/m	80.87–488.97

The dimensionless model used for the prediction of maximum permanent deflection of beams is:

$$\frac{W}{H}=C_1\left(\frac{m_pl_1V^2}{2\sigma_0BH^3}\right)^{P1}\left(\frac{l_1}{l_2}\right)^{P2}+C_2 \tag{3}$$

where, C_1, C_2, $P1$ and $P2$ are the model parameters, B is the width of beam.

The model parameters have been determined independently by regression for data involving (a) aluminum beams only, (b) steel beams only and (c) combined data of both the materials. Thus giving three regression models:

$$\frac{W}{H}=0.841\left(\frac{m_pl_1V^2}{2\sigma_0BH^3}\right)^{0.529}\left(\frac{l_1}{l_2}\right)^{-0.076}-0.226 \quad \text{for aluminum beams} \tag{4}$$

$$\frac{W}{H}=0.841\left(\frac{m_pl_1V^2}{2\sigma_0BH^3}\right)^{0.529}\left(\frac{l_1}{l_2}\right)^{-0.076}-0.170 \quad \text{for steel beams} \tag{5}$$

$$\frac{W}{H}=0.841\left(\frac{m_pl_1V^2}{2\sigma_0BH^3}\right)^{0.529}\left(\frac{l_1}{l_2}\right)^{-0.076}-0.173 \quad \text{for aluminum and steel beams} \tag{6}$$

The above independent models for aluminum and steel beams given by Eqs. (4) and (5) respectively have been developed for assessing the performance of one combined model for both the materials given by Eq. (6).

The mean absolute percent deviation (MAD) in the prediction of results employed for three regression models are given in Table 2. The corresponding mean error for each data set calculated using Eq. (1) [3] is also reported in Table 2. A comparison of the error estimates show that the proposed models are better than the prediction by Eq. (1). Though the independent models for the two materials are better than the model developed for the combined data set but the difference in error being only nominal, the model developed for combined data set as given by Eq. (6) may be used for the prediction of maximum deflection of beams.

5. Neural network model

The manner in which the data are presented for training is the most important aspect of the neural network method. Often this can be done in more than one way, the best configuration being determined by trial-and-error. It can also be beneficial to examine the input/output patterns and data sets that the network finds difficult to learn. This requires a comparison of the performance of the neural network model for these different combinations of data. In order to map the causal relationship related to the deflection, two separate input–output schemes (called Model—A1 and Model—A2) were employed, where the first took the input of raw causal parameters while the second utilized their non-dimensional groupings. This was done in order to see if the use of the grouped variables produced better results? The Model—A1 thus takes the input in the form of causative factors namely, l_1, l_2, B, H, m_p,σ_0 and V yields the output, the deflection, W, while Model—A2 employs the input in the form of grouped dimensionless variables namely, l_1/l_2 and $m_pl_1V^2/2\sigma_0BH^3$ and yields the corresponding dimensionless output W/H. Thus, the two models are:

$$\text{Model}-\text{A1}\ W=f_1(l_1,l_2,B,H,m_p,\sigma_0,V) \tag{7}$$