

Predictive Characterization Model for Impact Cushioning Curves: Configuring the Predictive Characterization Model

S.-W. Lye and S. Chuchom

Engineers and designers utilize mechanical properties and material behavior to assist in the design and manufacture of products. The material data obtained from standard tables tend to be general and may not correlate well with the actual material being used. To meet the design specifications, a larger number of iterative experimental tests than planned are usually conducted. This paper explores the use of neural networks as a predictive approach to characterize the impact cushioning curves so as to reduce the number of experimental tests required. Key design considerations in configuring a neural network for optimal performance are also highlighted. This approach is able to predict the points on the curves quite accurately but does have some limitations. To develop an effective predictive characterization model, the neural networks need to couple with appropriate algorithms so as to obtain a set of randomly distributed training data and generate the requisite points for curve characterization. Two algorithms are developed and found to be suitable for this purpose.

Keywords
expanded polystyrene, impact properties, neural network

1. Introduction

THE MECHANICAL PROPERTIES and behaviors of various materials can be found in engineering tables and curves. To obtain most of these data, a large number of repetitive experimental setups and tests are required. Engineers and designers use the information to assist in the design and manufacture of products and components. Nevertheless, such tables and curves have inherent limitations owing to their generality. The designed product and the test specimens may be different in terms of (a) the composition and mechanical properties of material used; (b) the varying testing parameters and conditions adopted, and (c) the manufacturing operations to produce them. For most material end users, a common industrial practice is that whenever product designers make use of engineering tables or curves, the batch of manufactured products has to be subjected to a series of iterative and laborious tests (usually the original number of tests is exceeded) in order that the final product will conform to the desired specifications. This practice is costly and can easily be improved if designers are given a more accurate and up-to-date set of material data and properties from the materials suppliers. This is easier said than done as material manufacturers and suppliers have to be concerned about their own profits and goals. Besides, the number of new and modified materials is constantly evolving. Most manufacturers would conduct their own set of tests so as to establish a set of proprietary data or curves for product differentiation and evaluation.

The material characterization for product protection from impact shock is one such example. The amount of current data available on protective packaging materials such as expandable polystyrene (EPS) (Ref 1, 2), paper pulp (Ref 3), and polyurethane foam (Ref 4) is restricted. Little work has also been done to characterize buffer materials containing recycled materials (Ref 5). Most cushioning buffers are made of expandable polystyrene positioned at the ends, edges, or corners of the product and then packed into a corrugated box. Current approaches in designing these cushioning buffers are quite well discussed in a number of published articles that rely mainly on historical material data and properties found in the set of cushioning curves (Ref 1-6). In some cases, data are not available, and attempts to estimate the material properties might need to be made.

S.-W. Lye, Nanyang Technological University, Singapore; and **S. Chuchom,** Prince of Songkla University, Thailand.

2. Current Practice of Establishing EPS Cushioning Curves

Figure 1 shows a typical set of impact cushioning curves for expandable polystyrene, Styropor (BASFAktiengesellschaft, Ludwigshafen, Germany) of a particular material density. Each

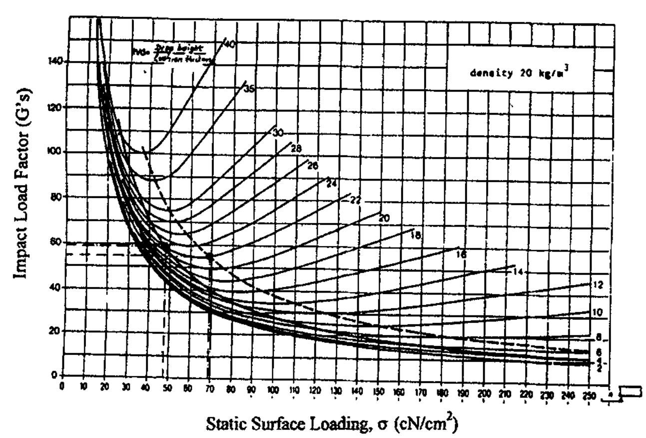

Fig. 1 Cushioning curves for expanded Styropor

shock curve describes the material in terms of its impact G values at different static stresses. The impact G value is computed based on the ratio of the deceleration transmitted to the product at impact with the surface over the gravitational acceleration. For static stress, the value can be obtained by dividing the product weight over the cushioning area as illustrated in Fig. 2. Figure 1 shows most cushion curves tend to exhibit a "U" relationship. This is because at low static stress, the weight of the product is not able to deflect the material at impact. The result is that the material does not function as an effective cushioning medium. As the static stress value is increased, the product weight can deflect the material causing it to act like a shock absorber. The effectiveness of the material to act as a cushioning medium reaches an optimum static stress value after which any further deflection bottoms out leading to a higher acceleration level being transmitted.

To establish a set of impact cushioning curves, numerous drop tests according to ASTM standard (Ref 7) need to be conducted at various drop heights of different material densities and thicknesses. This is usually done using a standard drop test machine where a flat dropping head, having a larger surface area than the test specimen, is vertically raised and dropped onto a test specimen laid on a massive anvil surface parallel to the head. An accelerometer, usually mounted to the rigid portion of the product near the center of gravity, is used to monitor the acceleration level transmitted through the cushioning material into the product. An oscillograph is used to record the acceleration level calibrated to obtain the G factor. For each point on the curve, five repeated tests from a particular drop height are made. The average of the G values recorded from the last four of these drops is the value used in plotting each cushion curve point. Thus, if one needs to establish a set of 17 cushioning curves as shown in Fig. 1, 510 tests (assuming 6 points per curve) will need to be carried out for one material density only. For points that do not lie on these curves, one would need to interpolate to obtain the result. Generally, material manufacturers need to supply the cushioning data for a discrete number of densities. This step is costly, tedious, and time consuming to the material manufacturers faced with the need to constantly develop new and better materials over a period of time. One effective solution is to develop an approach that could substantially reduce the number of experimental data required and yet not compromise the accuracy or quality in matching the actual curve profiles, which is the focus of the following section.

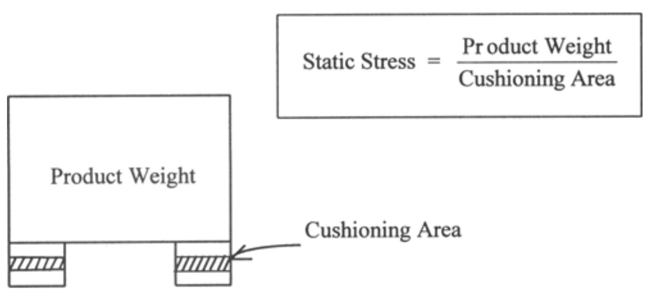

Fig. 2 Determination of static stress

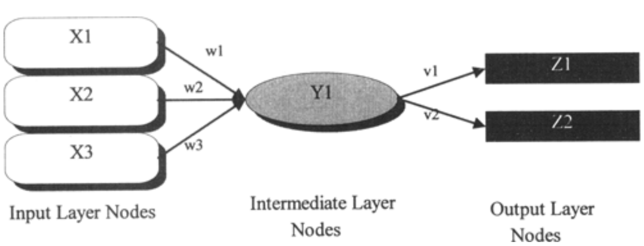

Fig. 3 A simple neural network

3. Neural Network for Predicting Cushioning Curve Characteristics

3.1 *Description of a Simple Feedforward Back Propagation Neural Network*

A neural network is an information processing system consisting of many interconnections and nodes organized in a parallel distributed manner (Ref 8). Each connection points from one node to another and is associated with a weight that highlights the importance of the relationship. To design, configure, and optimize the performance of a neural network for an application involves two key phases: training and consultation of the network. Training is forcing the neural network to yield to a particular response to a specific input. Once trained, the network is ready for consultation or use. Although a lot of research work is done in developing appropriate methods for training and consultation, no single method clearly suits all applications (Ref 8-10). Nevertheless, there are certain accepted guidelines for selecting a suitable type of neural network for a particular application. In this work, a multilayered feedforward back propagation neural network for characterizing and predicting the impact G values of a cushioning material for product protection is investigated. The multilayered feedforward back propagation approach was adopted as it was applied successfully in many robust pattern recognition problems (Ref 9). The term feedforward related to the consultation phase, whereas back propagation refers to the training or learning phase of the neural network.

Figure 3 shows a one-layered neural network consisting of three input nodes, one hidden node, and two output nodes. During consultation, all connections point (feedforward) in one direction from the input nodes to the output nodes. The network is activated by introducing values to the three input nodes. (X_1, X_2, X_3), which are then relayed to node Y. At node Y, a selected linear or nonlinear activation transfer function is used to compute the nodal value based on these input values and associated weights. A commonly used activation transfer function is the sigmoid function (Ref 8):

$$Y = \sum_{i}^{3} F(x_i) = \sum_{i=1}^{3} \left(\frac{1}{1 + e^{x_i}} \right)$$

The nodal value at Y is then sent to nodes Z_1 and Z_2. Based on the residing activation transfer function, the nodal values at Z_1 and Z_2 are computed. By adjusting the number of hidden layers, nodes, associated weights, and activation transfer functions at the nodes, the neural network is able hopefully to establish appropriate relationships between the set of input values and the desired output values.

For training, the network is given both the input and output values. The input values are fed forward to obtain their output values. The data are then back propagated or relayed backward to enable the neural network to determine a suitable function by attempting to minimize the errors between the generated and desired values during training. This is done by first calculating the activation values at the output nodes (Z_1 and Z_2) and then comparing them with the desired values to determine the associated errors for that pattern. The error factor is generally computed based on the difference between activation and desired values. These error factors are relayed backward to node Y_1. The nodal value at Y_1 is computed based on the output values, associated weights, error factors, and activation transfer function. In a similar manner, the error factor for node Y_1 is computed and relayed backward to the three input nodes (X_1, X_2, and X_3). After all the error factors are determined, the weights for all layers are adjusted simultaneously based on the error factors and the activation values of the connecting nodes. The weight change is the product between the learning rate or momentum and the error factor in the prior layer. Learning rate is the step size of each learning or iterative cycle; whereas learning momentum refers to the curve gradient of change. A neural network typically might take about 60,000 learning cycles before the data converge to an acceptable level.

3.2 *Design Considerations in Configuring a Neural Network*

This section discusses three key considerations in configuring an appropriate feedforward back propagation neural network used for predicting the impact cushioning curves. They are the network properties, the nature of the input data, and data convergence.

3.2.1 Network Properties

A basic network structure that consists of three input nodes, multiple intermediate layers having varying number of nodes, (as highlighted in Table 1) and one output node is investigated. The three input nodes are the parameters of static stress, ratio of drop height/cushioning thickness required (h/d), and the material density as found in the impact cushioning curve. The output node registers the desired impact G factor. To train each neural network structure, 100 data points obtained from the various BASF impact cushioning curves for material densities of 20, 25, and 30 kg/m^3 are used. The neural network adopts the back propagation approach for training. The activation transfer function for the first connection layer is based on the tangent sigmoid function, whereas the remaining connection layers use the log sigmoid function. The neural network consisting of three input nodes, two intermediate layers having eight and two nodes, respectively, and one output node (G-value) yields the least RMS error variance of 1.5%. Therefore, the neural network is able to predict quite accurately the points on the impact cushioning curves and thus be adopted for this work. If a more accurate value is required, one might need to try out alternative network structures, introduce bias weights, or adopt other transfer functions until a suitable one is obtained on a trial-and-error basis.

3.2.2 Nature of Input Data

Another design consideration is the effect different clustered input data patterns have on the integrity of the neural network in predicting the desired output values accurately. Four sets of tests were conducted using eight h/d cushioning curves. The data obtained were either randomly distributed, randomly distributed in clusters, or right clustered and left clustered as highlighted in Fig. 4. Each test was conducted using 48 points from eight h/d curves for a material density of 20 kg/m^3. The neural network model is based on the above basic structure having 3 input nodes: 2 intermediate layers of 8 and 2 nodes, respectively, and one output node. This network configuration is adopted here.

Table 2 shows the results of the four different clustered data patterns. If the data were randomly distributed, the network would be able to predict more accurately the actual curve characteristics than the other clustered data patterns. This result is consistent with conventional curve-fitting approaches, as the back propagation approach adopts a certain learning function that is also dependent on the appropriateness of the inputs. The results highlight the importance of selecting the right initial set of training data that would best describe the actual material properties and behavioral pattern. Therefore, an algorithm has to be developed to ensure that the experimental points derived for network are random and well-distributed in characterizing a set of cushioning curves for a new material.

3.2.3 Data Convergence

Accuracy is a crucial factor if the neural network is to be used as a predictive tool since the values generated by the network are unlikely to match exactly the desired values. Nonconvergence of the data can occur due to inappropriate selection of the learning algorithms adopted. Researchers have developed many learning algorithms for neural applications (Ref 8-11). The result is that the final error between the generated and desired values is too large to be of use. Another concern is if the

Table 1 The RMS errors obtained for different number of nodes for multiple intermediate layers

Nodes in the intermediate levels		RMS output error
First	Second	after 60,000 training cycles
6	2	1.85
8	2	1.51
6	3	1.62
9	3	1.85
4	0	3.49
7	0	3.33

Table 2 RMS errors of various clustered data patterns

Group patterns	No. of trained data points	RMS output error, %
Random distributed	48	2.06
Cluster distributed	48	5.04
Left cluster	48	18.08
Right cluster	48	9.55

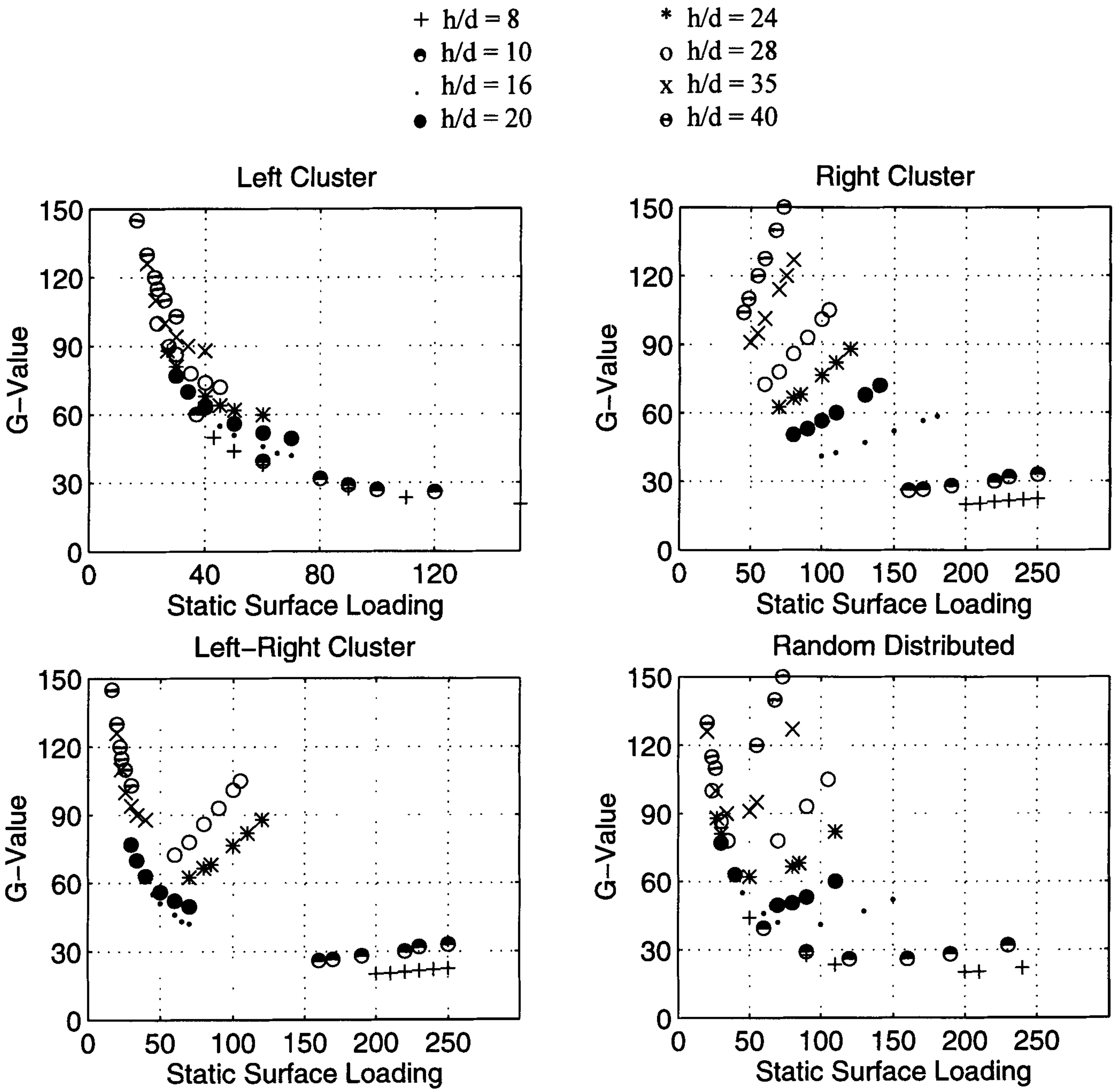

Fig. 4 The effect of group patterns in training neural networks

data converge too slowly and the training process has to be aborted. Therefore, the data introduced into the network must converge to an acceptable error range during training. Based on the adopted neural network configuration, the sum of squares error (SSE) is set at 0.001, which is the error criterion to be satisfied. For training, the network adopts the momentum with learning rate approach (Ref 11), in which adjustment to the weights of the network are based not only on the rate value of between 0 and 5 but also on the gradient change of the learning curve. After 60,000 cycles, the neural network was found to satisfy the error criterion. A section of the learning curve can be found in Fig. 5.

3.3 *Limitations of the Neural Network*

A neural network structure has been established that is able to predict quite accurately the points on the curve. For this work, three limitations were observed:

- The performance of the neural network in terms of its accuracy, learning rate, and convergence may not be optimum. Much effort in adjusting the network properties or adopting more complex algorithms is required if one needs to attain a very high order of accuracy (SSE < 0.001).
- As highlighted earlier, the neural network is dependent on a good set of training data.

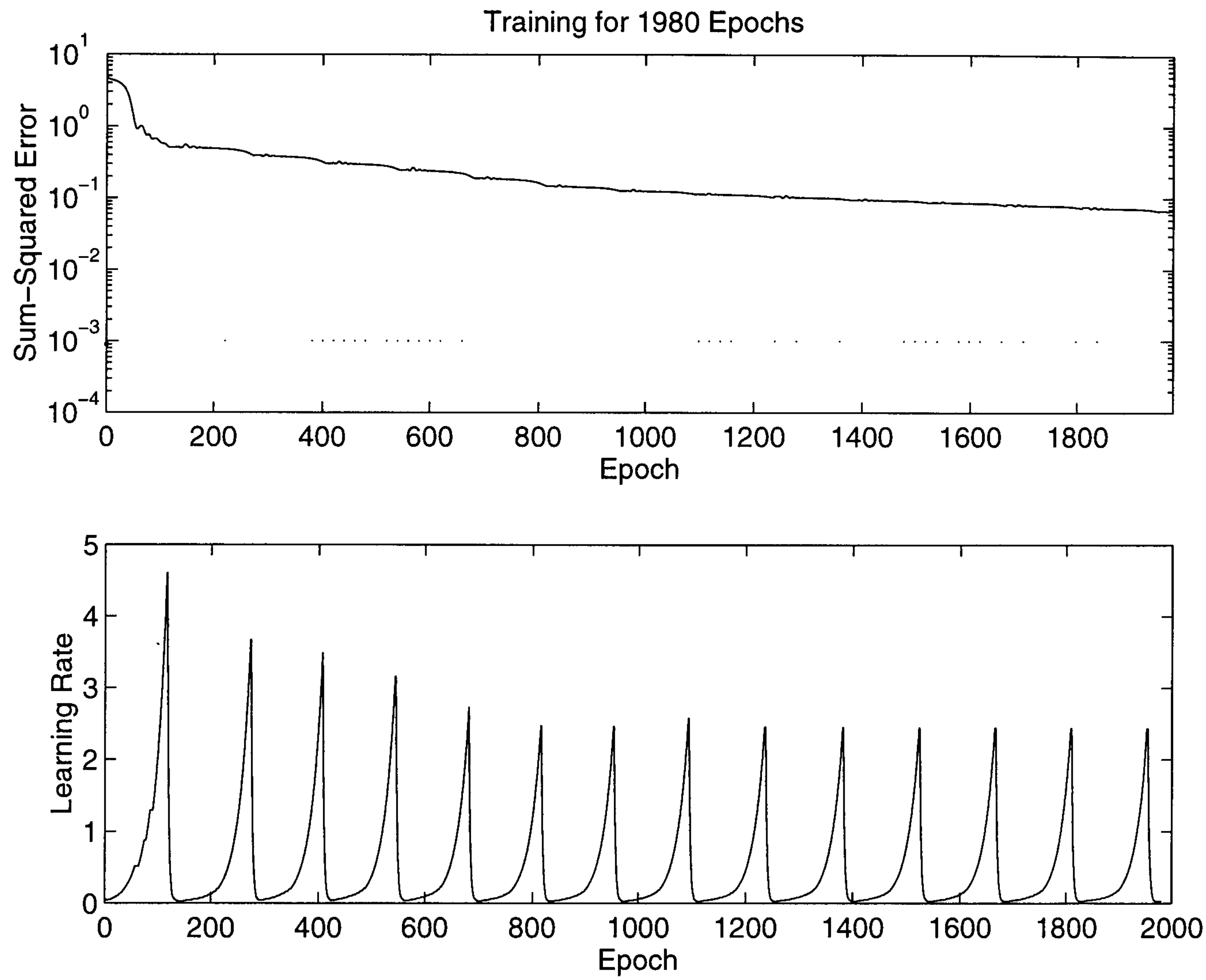

Fig. 5 Momentum with learning rate approach in training neural networks

- The overall function used to predict the points on the impact cushioning curves is not known. Neural networks tend to adopt a black box approach to problem solving. This means that the approach would not be able to properly characterize the h/d and optimal curves found in the set of impact cushioning curves as more points are needed. For the predictive characterization model to construct the impact cushioning curves, a requisite-point-generation (RPG) algorithm needs to be developed that enables the requisite points to be automatically generated and through which an impact cushioning curve can be fitted.

4. Conclusions

A multilayered feedforward back propagation neural network (consisting of three input nodes, two intermediate network levels of eight and two nodes, respectively, and one output node) is able to predict points on the impact cushioning curves. In training the network, the data converge, having an RMS error variance of 1.5. The number of data points required for training the network to facilitate the prediction is substantially smaller than that required if conventional curve-fitting techniques were used. Therefore, fewer experimental data points would be required in characterizing a set of impact cushioning curves for a new material.

The limitations of a neural network to be used as a predictive characterization model for impact cushioning curves is highlighted. Two algorithms are developed that would enable a randomly distributed set of initial experimental points for network training and requisite points generation for characterization of the impact cushioning curves. Such algorithms better facilitate the automation effort of the predictive characterization model.

References

1. "Technical Information on Packaging with Expanded Styropor," BASF, Ludwigshafen, Germany, 1978
2. "Package Cushion Design," MIL-HDBK-304B, *Military Standardization Handbook,* 1978

3. R.C. Griffin, S. Sacharow, A.L. Brody, *Principles of Package Development*, 2nd ed., AVI Publishing Co., 1982
4. J.F. Hanlon, *Handbook of Package Engineering*, McGraw-Hill Publishing Co., 1971
5. H.Y. Yeong and S.W. Lye, Rotational Microwave Moulding of Expanded Polystyrene, *J. Mater.*, Vol 37, 1993
6. S.W. Lye and H.K. Ho, Knowledge-Based CAD System for Protective Packaging Design, *AIEDAM*, Vol 5 (No. 2), 1991, p 125-134
7. "Standard Test Method for Shock Absorbing Characteristics of Package Cushioning Materials," D 1596-78a, *Annual Book of ASTM Standards*, ASTM, 1985
8. L. Fu, *Neural Networks in Computer Intelligence*, McGraw-Hill Publishing Co., 1994
9. A. Maren, C. Harston, and R. Pap, *Handbook of Neural Computing Applications*, Academic Press, 1990
10. J.M. Zurada, *Introduction to Artificial Neural Systems*, Info Access Distribution Pte Ltd., 1992
11. H. Demuth and M. Beale, *User's Manual: Neural Network Toolbox—For Use with MathLab*, The Math Works Inc., Natick, MA, 1993