Airbag Fabric Material Modeling of Nylon and Polyester Fabrics Using a Very Simple Neural Network Architecture

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SYNOPSIS

The material properties of engineering fabrics that are used to manufacture airbags can not be modeled easily by the available nonlinear elastic–plastic shell elements. A nonlinear membrane element that incorporates an elaborate tissue material model has been widely used by the auto industry for the airbag simulation studies. This model is highly computation intensive and does not differentiate between the various physical properties of the fabrics like fiber denier, the polymer fiber, and weave pattern. This paper introduces a new modeling technique that uses artificial neural networks. Experimental permeability data for fabrics under biaxial strain conditions were obtained through a blister-inflation technique and were used to train the proposed network architecture. In this training environment, various properties of the fabric can be incorporated and the network can be trained to generalize relative to the environment. Once trained, the cause–effect pattern is assimilated by the network with appropriate weights to produce a desired output. Fabrics tested in this study included nylon 66 fabrics with three different fabric deniers: 420, 630, & 840 and two types of weave, and two 650-denier polyester fabrics having different calendering effects. The predictions obtained from this neural network model agreed very well with the experimental data. This indicates that neural nets can be considered as a serious design tool use in determining permeability and biaxial stress–strain relationships for textile fabrics used in airbags. © 1996 John Wiley & Sons, Inc.

INTRODUCTION

Safety airbags rely on permeable woven fabrics as their principal material of construction. In this regard, the material properties of the fabric can significantly contribute to the safety of the vehicle occupant as he interacts with the deployed airbag. The two properties that contribute to the energy-absorbing capabilities of the fabric are its permeability and its biaxial stress–strain characteristics in the plane of the fabric.[1,2] The most obvious feature of fabrics is that they have almost no bending strength, and, hence, exhibit an inability to support compressive loads. This inability to support compressive loads introduces a strong nonlinearity into any attempt to approximate a fabric as an isotropic or orthotropic continua. An additional complicating factor is that the fibers that make up a fabric interact in a complex manner that can deviate considerably from continuum behavior. Under uniaxial tension, most of the nonlinear response is due to the kinematic interaction between the warp and weft threads and their undulation in the unstressed state. However, this effect is greatly reduced under biaxial tensile conditions.

Recently, artificial neural networks have become the focus of attention because of their wide range of applicability and their unique ability to handle complex nonlinear problems. They have enormous processing power with the ability to make sensible selections and the potential to learn by training experience. This paper is the result of ongoing investigations in our laboratory on modeling of fluid flow through woven airbag fabrics. The purpose of this paper is to demonstrate how a simple neural network

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approach was used to model complex physical behavior such as airbag fabric inflation temperature–pressure drop relationships. This paper highlights and compares the performance of nylon fabrics with polyester. Both these fabrics were trained and tested together in the same neural network model. The prediction of the proposed neural network model was in excellent agreement with the experimental data.

AIRBAG PRESSURE–TIME HISTORY

The airbag pressure–time history is the basis for the occupant restraint provided by an airbag, and, hence, influences the level of restraint performance. Many researchers have attempted to simulate airbag inflation, including the overall airbag wave form, by using airbag inflation models constructed around thermodynamic and hydrodynamic theories. However, most of these airbag models employ complicated theoretical equations that are based on simplifying assumptions. Consequently, even though these simulation programs may compute an airbag pressure wave form that corresponds reasonably well to specific experimental results, performance of the fabric material during deployment is usually completely ignored because of the complexities involved in modeling fabric deformations.

Typical airbag pressure wave form showing the comparison between inflation in isolation and inflation followed with an impactor/dummy[3] is depicted in Figure 1. When the airbag is inflated in isolation, an initial peak bag-pressure is reached. After reaching this initial peak, a momentary negative pressure is sensed by the transducer, followed by subsequent normal repressurization. A second pressure peak arises within approximately 30 ms, after which the pressure gradually decreases again until it reaches atmospheric pressure. In comparison, the inflation with an impactor/dummy causes the bag to be compressed by contact, producing a secondary increase in the bag pressure. In theory, the contact with the slowly deflating airbag accelerates gaseous outflow from the bag and, thereby, helps it dissipate the kinetic energy of the passenger. A fraction of the occupant's energy can also be absorbed by mechanical stretching of the fabric's fibers. However, the fabric's permeability and/or designed vent system is of primary importance to energy dissipation.[2] In practice the secondary bag-pressure increase is typically in the range of 68 kPa to 107 kPa. The permeability and biaxial performance of the fabrics for this pressure range were investigated in this paper at five

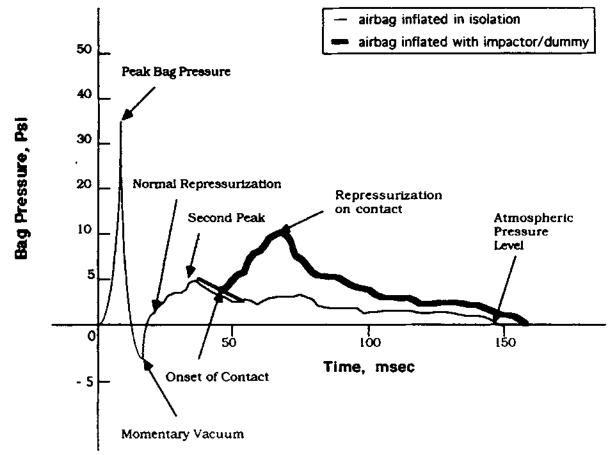

Figure 1 Pressure–time history of an airbag inflation in isolation and with an impactor/dummy.

different isothermal temperature levels ranging from 281 K to 383 K.

In order to quantify the contribution to energy dissipation due to the fabric, the permeability of the expansible fabric was correlated with the biaxial stress–strain behavior of the fabric.[2,4] Measurement of this relationship was accomplished by a special blister-inflation technique.[2–6] In our earlier publications[2] it was demonstrated that for isothermal conditions, fabric permeability as determined by this approach is a linear function of the pressure drop across the fabric for pressures up to 206 kPa (30 psi).

The blister-inflation technique for measuring fabric permeability provides a convenient analog for stretching behavior that is very similar to that which the actual bag must undergo during deployment. When an expansible fabric is stretched biaxially by inflation into a spherical segment or "blister," the fabric's structure opens up and becomes more permeable, just as the fabric in an airbag does when it is inflated. In this study the performances of both nylon 66 and polyester fabrics were examined by blister inflation. The effects of fabric denier on permeability in the case of nylons and the influence of calendering in the case of polyester were also investigated.

THEORY

Blister Inflation

Inelastic fiber stretching and viscous air flow through the fabric or vents in the fabric is the two mechanisms by which the energy is adsorbed by a deployed airbag.[4] Both of these mechanisms, fiber stretching and airflow through the fabric, can be quantified by a novel blister-inflation technique.[2–6]

With respect to fiber stretching, the approach Tock and Nusholtz used for the calculation of the biaxial stress and strain in distended fabrics is based on the relationships derived by Denson and coworkers for solid plastic films.[7–11] In both instances biaxial tensile stress is calculated by the following equation:

$$\sigma_b = \frac{PD}{d_0}\left[4\left(\frac{h}{D}\right)^3 + 2\left(\frac{h}{D}\right) + \left(\frac{1}{4}\right)\left(\frac{D}{h}\right)\right] \quad (1)$$

The amount of biaxial strain is given by eq. (2)

$$\varepsilon_b = \ln\left[\left[\cos^{-1}\left(\frac{1-4(h/D)^2}{1+4(h/D)^2}\right)\right]\left(\frac{h}{D}+\frac{1}{4}\left(\frac{D}{h}\right)\right)\right] \quad (2)$$

In these equations the variables in SI units are

σ_b = biaxial tensile stress in the fabric, Pa
P = pressure drop across the fabric, Pa
d_0 = the original fabric thickness, m
h = height of the blister, m
D = blister diameter, m
ε_b = biaxial strain in the fabric.

Equations (1) and (2) were derived based on the assumption that a constant volume of the polymer sheet used in the test deforms from a flat configuration into a spherical segment. This same assumption applies to the woven fabric samples used in this study.

Neural Networks

A neural network is an organized mesh of nodes and connections. The basic processing elements of a network are known as neurons. The neurons operate collectively and simultaneously on most or all data, and are configured in regular architectures. They "learn" by extracting preexisting information from the data that describe the relationship between the inputs and the outputs. Hence, in the learning process, the network actually acquires knowledge or information from the environment. As a result of the interrelationships, the network assimilates information that can be recalled later. Neural networks that are capable of handling complex and nonlinear problems, process information rapidly, and can reduce the engineering effort required in developing highly computation intensive modeling, such as nonlinear FEA. Neural networks also come in a variety of types, and each has their distinct architectural differences and reasons for their usage.[12]

The type of neural network used in this work is known as a feed-forward network. The information flows only in the forward direction, i.e., from input to output. A general structure of a feed-forward network is shown in Figure 2.

Neural networks are organized in layers and typically consist of at least three layers: an input layer, one or more hidden layers, and an output layer. The input and output layers serve as interfaces that perform appropriate scaling relationship between the actual and the network data. Hidden layers are so termed because their neurons are hidden from the actual data. The connections are the means for information flow. Each connection has as associated weight factor, w_i, expressed by a numerical value that can be adjusted. The weight is an indication of the connection strength between two neurons.

The neurons in the hidden and output layers perform summing and nonlinear mapping functions. The functions carried by each neuron is illustrated in Figure 3. The inputs from other nodes are first summed up. This summing of the weighted inputs is carried out by a processor within the neuron. The sum that is obtained is called the activation of the neuron. For example, if the output from the ith neuron with pattern p is designated as $x_{i,p}$, then the input to the jth neuron from the ith neuron is $x_{i,p}w_i$.

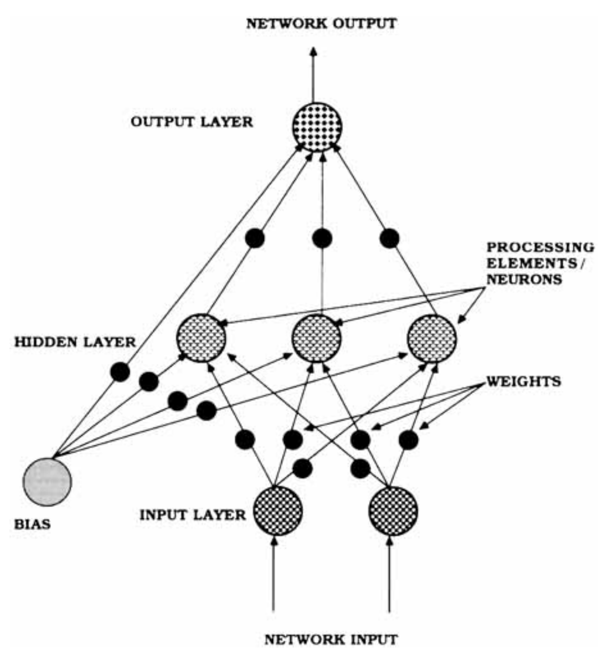

Figure 2 A general structure of feed-forward neural network.

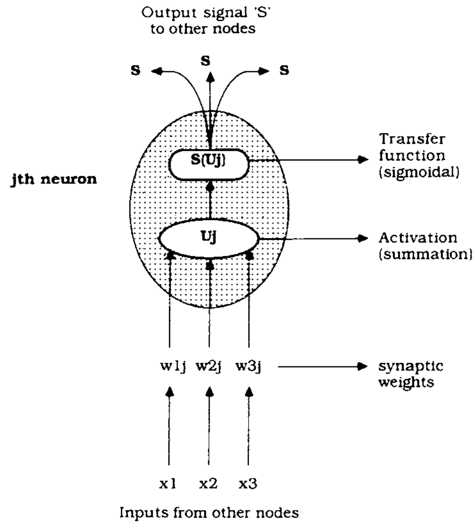

Figure 3 Microstructure of a typical neuron.

Summing the weighted inputs to the jth neuron can be represented as

$$u_{i,p} = \sum_i x_{i,p} w_{ij} - w_{B,j}\theta_j \tag{3}$$

Where θ_j is a bias term and $w_{B,j}$ is the weight of the connection from the bias neuron on to the jth neuron. The bias weight is adjusted in very much the same way as the other connection weights are adjusted during the network training. The summed total is then modified by a mapping function, also known as a transfer function/threshold function. A transfer function commonly used is the "sigmoid," which is expressed as

$$S_{i,p} = \frac{1}{[1 + e^{(-u_{i,p})}]} \tag{4}$$

A sigmoid (S-shaped) function is a monotonically increasing function, where $S_{i,p}$ is the transformed output ($0 \le S_{i,p} \le 1$) and $u_{i,p}$ is the summed total of the inputs ($-\infty \le u_{i,p} \le +\infty$) with a pattern p. Hence, when the neural network is presented with a set of input data, each neuron sums up all the inputs modified by the corresponding connection weights and applies the transfer function to the summed total. This process is repeated until finally the network outputs are obtained.

"Training" a Neural Network

Once the network architecture is selected and the characteristics of the neurons and the initial weights are specified, the network has to be taught to associate new patterns and new functional dependencies. Learning corresponds to adjustment of the weights in order to obtain satisfactory input–output mapping. Since neural networks do not use *a priori* information about the process to be modeled and learning is experiential, it is necessary to have data that adequately represent the relationship between the process input and output.

Nonlinear Optimization Routine

Several different learning rules have been proposed by various researchers,[12] but the aim of every learning process is to adjust the weights in order to minimize the error between the network predicted output and the actual output. The optimization problem can be defined if the model to be fitted to the data is written as follows:

$$\begin{aligned} F(y) &= f(\alpha_1, \alpha_2, \ldots, \alpha_m; \beta_1, \beta_2, \ldots, \beta_k) \\ &= f(\alpha, \beta) \end{aligned} \tag{5}$$

Where $\alpha_1, \alpha_2, \ldots, \alpha_m$ are independent variables, $\beta_1, \beta_2, \ldots, \beta_k$ are the population values of k parameter and $F(y)$ is the expected value of the independent variable y. Then the data points can be denoted by

$$(Y_i, X_{1i}, X_{2i}, \ldots, X_{mi}) \quad i = 1, 2, \ldots, n \tag{6}$$

The problem is to compute those estimates of the parameter which will minimize the following objective function

$$\phi = \sum_{i=1}^{n} [Y_i - \hat{Y}_i]^2 \tag{7}$$

Where $\hat{Y}_i$ is the value of y predicted by the model at the ith data point. The parameter to be determined in our case is the strength of the connections, i.e., the weights, $w_{i,j}$. The advantages and quickness of this training routine in its comparison to traditional back-propagation algorithm were shown in our earlier publication in the same journal.[13] More details of the Levenberg–Marquardt method are found elsewhere.[14] The optimization procedure updated weights at every connection and yielded rapid and robust training. The weights were initialized to values in the range ± 0.1 by random assignment.

Finally, training is incomplete without proper validation of the trained model. Therefore, the trained network should be tested with data that it has not seen before during training. This procedure was followed in this study by first training the network on one data set and then testing it on a second data set.

EXPERIMENTAL

Fabric Materials

Traditionally, nylon 66 has been the material of choice for fabrics used in safety airbag construction. In this paper the performances of nylon 66 and thermoplastic polyester fabrics were considered in the neural network model. The effect of denier of the fiber on the performance, both in terms of permeability and biaxial stress–strain, was considered in the case of the nylon 66 material. In the case of polyester the effect of calendering was investigated. In addition to the good engineering properties of their constituent fibers, fabrics must be compatible with the design constraints required in the construction and performance of airbags. The general characteristics of these fabrics are tabulated in Table I.

Blister Inflation Technique

The blister-inflation technique is a quasi-steady-state measurement in which a blister is created by a pressure drop across the fabric and is maintained while data on permeability and biaxial strain are recorded. These biaxial characteristics are important since they directly impact on the permeability of a distended fabric. The difference between a biaxial stress–strain behavior and a uniaxial behavior in either warp or weft direction is that, in the former the stress–strain behavior is nearly linear as was shown in Figure 4. It is important to note that the blister inflation technique does not attempt to extend to fabric rupture.

Table I Physical Characteristics to Test Fabrics

Material	Denier	Weave Count	Weave Type/ Process
Nylon 66	420	72 × 46	Plain
	630	42 × 42	Plain
	840	32 × 32	Ripstop
Polyester	650	42 × 42	Plain/uncalendered
	650	42 × 42	Calendered

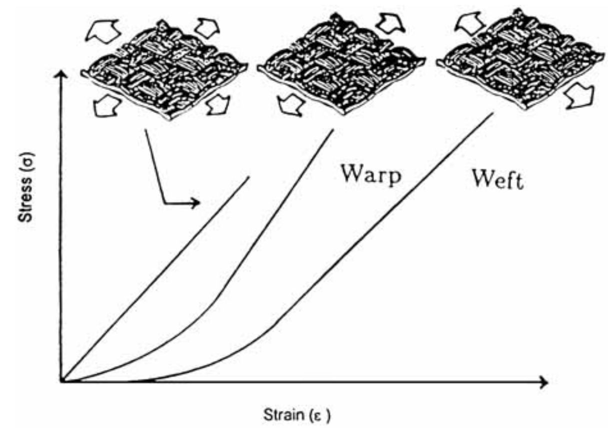

Figure 4 Comparison of the biaxial and uniaxial tensile stress–strain behavior of a typical woven fabric.

Apparatus for "Blister-Inflation"

In this experiment, a flat sheet of test fabric was deformed with compressed air into an expanded blister.[2,15] A schematic diagram of the experimental apparatus is shown in Figure 5. The basic component of the apparatus is the blister-jig assembly. The sample jig itself consisted of two metal plates, both with a centered, beveled hole of diameter, $D = 0.075$ m. The test fabric of thickness, d_0, was clamped between the plates that were then bolted together to form a tight seal at the edge of the hole. As shown, the compressed air that was used to form the blister passed through a pressure regulator, a manual valve, a Speedaire moisture trap, and a heat exchanger prior to entering the blister-jig assembly. A pressure gauge to determine P was positioned in the line downstream of the moisture trap. The blister height h was measured manually. The volumetric flow rate of air passing through a given test fabric for a given differential pressure drop was measured with a Taylor anemometer. This was corrected to STP based on the recorded temperature of the flowing air.

RESULTS AND DISCUSSIONS

Permeability Variation with Temperature and Pressure Drop across the Fabric

As mentioned earlier, the nylon 66 fabrics consisted of three different denier fibers, i.e., 420D, 630D, and 840D, while the two polyester fabrics had the same fiber denier, 650D, but differed in their finish, i.e., calendering. The weave type in all the fabrics was plain except for the "ripstop" 840D nylon fabric. Their respective weave counts are given in Table I.

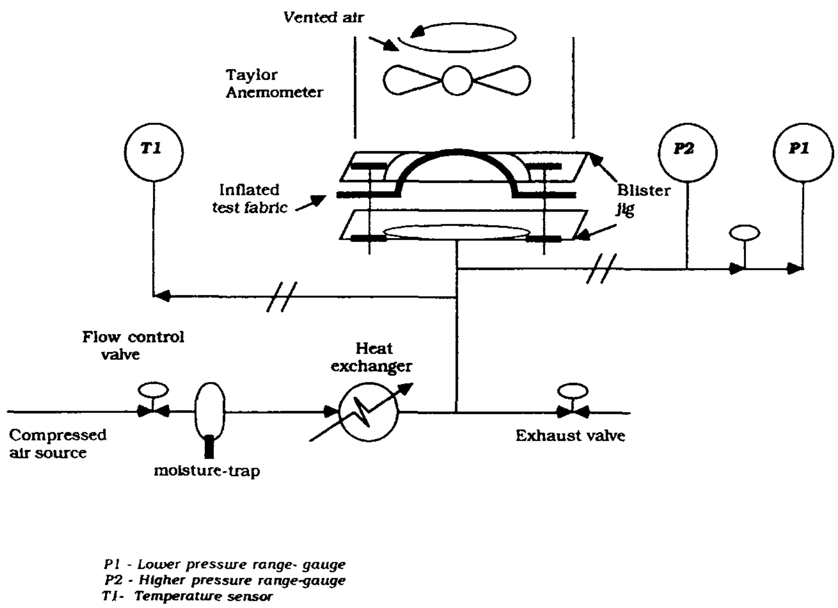

Figure 5 Schematic of the blister inflation apparatus.

The experimental data were reduced for each sample, and the volumetric permeabilities were corrected to STP for the different pressure drops and temperatures. The pressure drop range used in this study covered the re-pressurization range encountered during actual inflation of an airbag, i.e., 3.4 kPa to 103 kPa. The fabrics were tested at five isothermal temperatures; they were 281 K, 298 K, 323 K, 348 K, and 368 K (46°F to 200°F) respectively. These temperatures of the compressed air used for inflation were achieved with the use of a heat exchanger in our experimental apparatus. The observed behavior of the nylon and polyester fabrics that were tested is discussed separately in the following sections.

Nylon 66 Fabrics

Insights into fabric performance were obtained from studies on the variation of permeabilities with temperature when the data are displayed as isobars. For both the 420D and 630D fabrics, permeability could not be detected in the blister-inflation apparatus until a pressure drop of 14 kPa was reached (Figs. 6, 7). The negative slope of the isobars as a function of an increase in temperature showed a gradual decline with an increase in the denier of the fiber as shown in Figures 6, 7, and 8. The permeability isobars for all three fabrics were otherwise linear up to a 20-kPa pressure drop across the fabric. When the temperature was raised above the typical glass transition temperature, T_g (T_g = 323 K at 6.4% moisture and 343 K at 0% moisture for nylons[16]), the permeability was observed to decrease drastically for the smaller denier fabric, i.e., 420D nylon. However, the permeability was observed to increase in this temperature range for both the higher fiber deniers, i.e., 630D and 840D. Both the 420D and 840D fabrics exhibited the extremes of this behavior. This behavior at higher temperatures is an important fabric characteristic, since a reduction of the response time

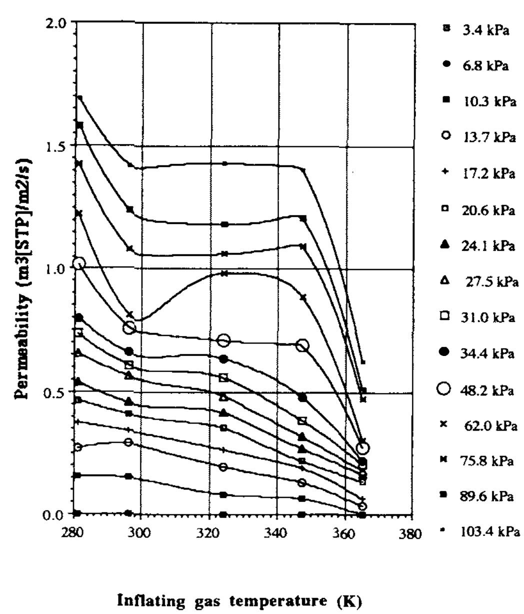

Figure 6 Permeability isobars for the 420-denier nylon 66 fabric.

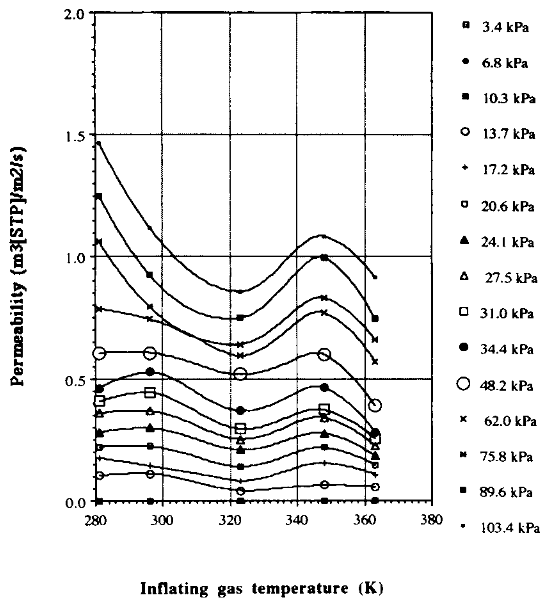

Figure 7 Permeability isobars for the 630-denier nylon 66 fabric.

of the initial peak pressure can be achieved by increasing the temperature of the inflation gases.

When the pressure drop in the apparatus exceeded 34 kPa, the 630D fabric showed a distinct maximum in permeability around the, T_g of the nylon. This behavior of nylons was reported in our earlier publications.[2,5,6] The permeability of all three fabrics exhibited an increase following a reduction of temperature to below room temperature, i.e., 291 K (46°F). This behavior became much more distinctive for the higher pressure drops as seen in Figures 6, 7, and 8. We believe that with a reduction of temperature, the individual fiber bundles in the fabrics tend to contract and, hence, lose their compactness and increase the fabric porosity. An inverse of this behavior was expected to occur from expansion/swelling caused by increases in temperature above the T_g.

In general, the permeability of the nylon fabrics increased with respect to increases in temperature and pressure drop in the following order, 840D > 420D > 630D. For these nylon materials, the measured cover factors of the fabrics did not appear to correlate with the observed behavior. Therefore, this order of performance may be attributed to the number of fibers in individual bundles and the amount of twist employed in them. This order of permeability between the tested nylon fabrics is also validated later in this paper through characterization of the biaxial stress–strain behavior of the fabrics.

Polyester Fabrics

Two 650D fiber polyester fabrics with a plain weave were analyzed for comparison with the nylon fabrics. Also, since polyester can be calendered, the effect of calendering on permeability performance was investigated. Calendering causes the permanent flattening of the fiber bundles and, hence an increase in the fabric's cover factors. With an increase in cover factor, a drop in the initial porosity of the fabric is expected. The experiments indicated that for the calendered polyester, permeability was not discernible until a pressure drop of 17 kPa was reached as shown in Figure 9. In comparison to Figure 10 for the uncalendered polyester, the calendering effect as expected resulted in a reduction of the permeability of this fabric. The decrease was in the range of 0.5 to 1.5 ($m^3/m^2(STP)/s$) depending on the pressure drop across the fabric.

The performance of the 650D-uncalendered polyester was comparable to that of the 840D nylons, especially in the temperature range of 323 K to 368 K (122°F to 203°F). Also, a permeability increase with a reduction in temperature below room temperature was also observed in this case. The degree of increase in permeability at 281 K (46°F) compared with room temperature permeability was similar for both nylons and polyesters.

Biaxial Stress–Strain Behavior

The biaxial stress–strain characteristics of the five fabric samples were determined by the blister-infla-

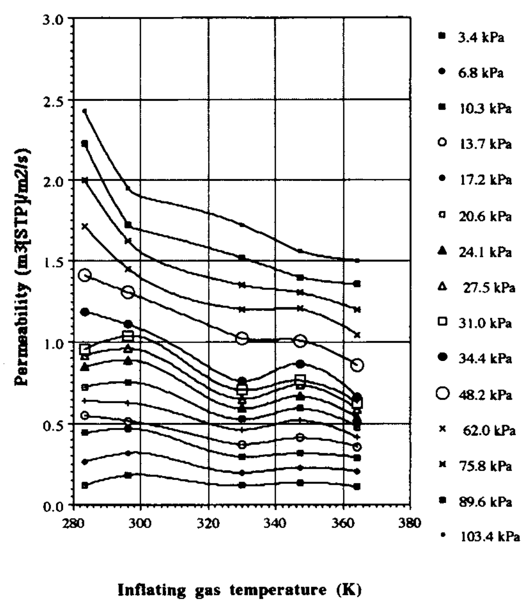

Figure 8 Permeability isobars for the 840-denier nylon 66 fabric.

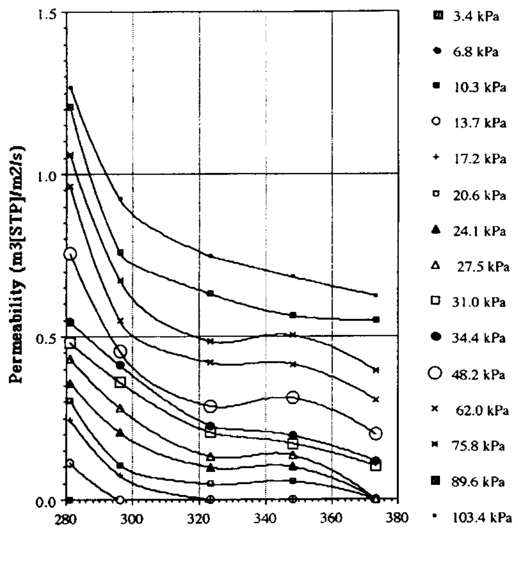

Figure 9 Permeability isobars for the 650-denier calendered polyester fabric.

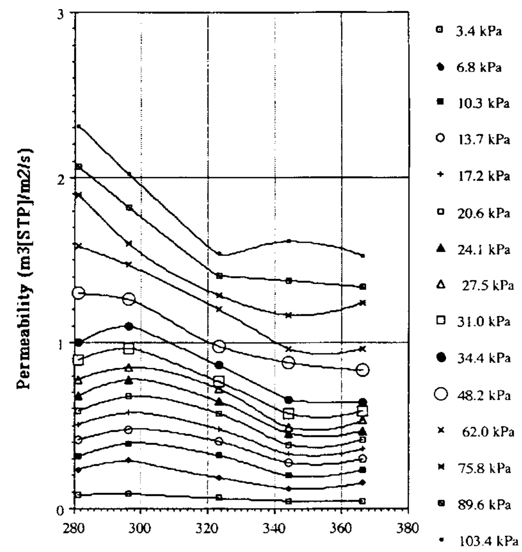

Figure 10 Permeability isobars for the 650-denier uncalendered polyester fabric.

tion technique. This is a quasi-steady-state measurement in which the blister is created by a pressure drop across the fabric. This technique is more sensitive in the lower biaxial strain region (ε = 3% to 5%) which is encountered by the fabric during inflation of an airbag. The biaxial stress–strain behavior as determined by the blister-inflation technique is shown in Figure 11 for all the five fabrics. All of the experimental data points are shown connected by interpolation. On the basis of this figure the permeability order for the different nylons becomes more apparent. Among the nylons, the 840D fabric exhibited the steepest slope, indicating a greater fabric stiffness for this material. Hence, an overall stiffness (modulus) correlates with permeability and also with the fabric's ability to be folded into compact bundles.

The effect of calendering on the stiffness of the polyester fabric is also obvious in Figure 11. Moreover, the divergence in behavior for the two polyesters increased with pressure drop ($\Delta P >$ 27.5 kPa/4.0 psi) for the samples tested in this study. This is indicative of the potential role that fiber movement within the yarn bundles can have on the fabric's openness as it is stretched biaxially.

Permeability Predictions of the Proposed Neural Network Model

The main purpose here is to develop a model that can be used to predict the changes in permeability with inflation temperature and internal pressure drop. The network used in the model was a: 3-input node, 4-hidden node, 1-output node (abbreviated as 3-4-1 network) architecture. The permeability data were divided into two data sets, the training data set was at three temperature levels: namely 281 K, 323 K, and 373 K. This covered the whole range of operating conditions for the fifteen different isobaric pressure drops. The second or test data set, was the

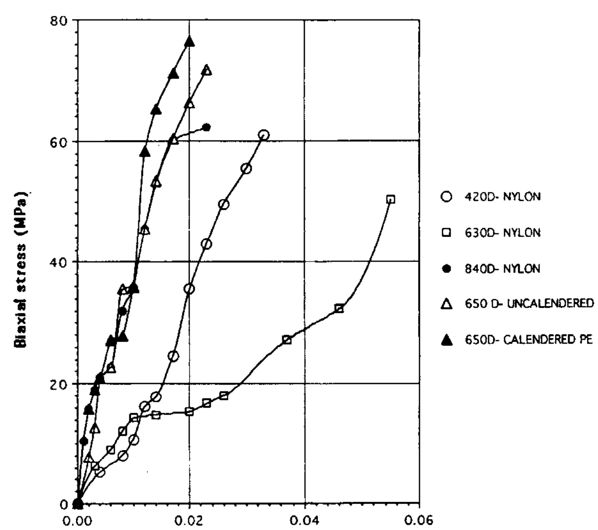

Figure 11 Biaxial stress–strain relationship in blister inflation.

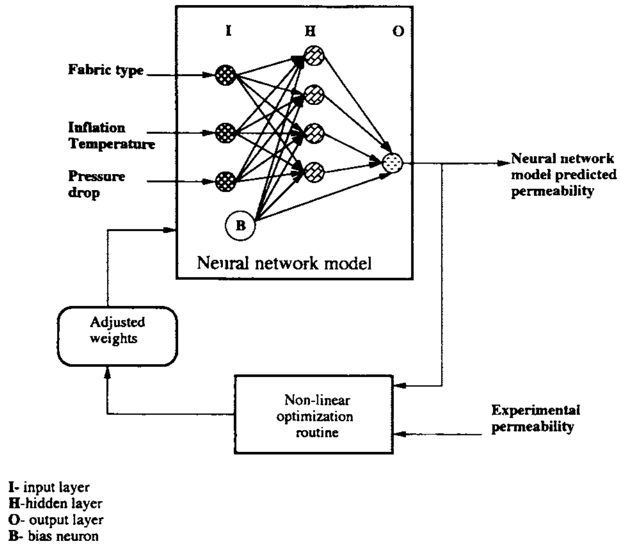

Figure 12 Schematic of the proposed neural-network training for permeability predictions.

permeability obtained at the other two temperature levels: namely 298 K and 348 K. These too covered all 15 different isobaric pressure drop conditions. The fabric characteristics incorporated in the model were the fabric type (fabric deniers, weave type). These were combined with inflation temperature and internal pressure drop. A schematic of this neural network training procedure is shown in Figure 12. However, the nylon 66 fabric and the polyester fabric were trained and tested together. But the results from this model are presented separately in the following sections.

Nylon 66 Fabrics

The training data set consisted of 108 permeability data points at three different inflation temperature levels (281 K, 323 K, and 373 K) and fifteen different pressure drop levels over a pressure range of 3.4 kPa to 103.4 kPa for the three nylon fabrics: namely 420D, 630D, and 840D fabrics. The test data set consisted of 72 permeability data points at two different temperatures' levels that the network has not seen before: namely 298 K and 348 K and at fifteen different pressure drop levels.

The training and testing results from the neural network model is shown in Figure 13. The model prediction for permeability was within ± 0.2 m^3 (STP)/m^2/s ($\pm 6\%$ error). This agreement is very good considering the nature of this experiment, and also, this level of error constitutes a relatively small level of energy dissipation by viscose flow through the airbag.

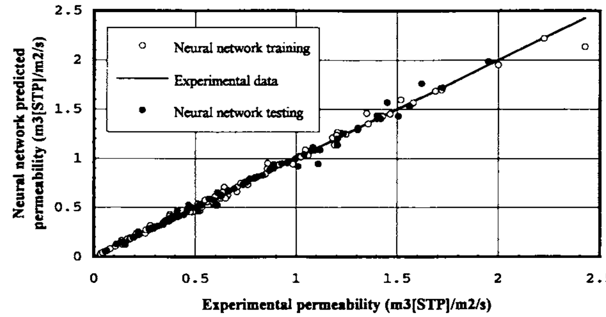

Figure 13 Neural-network training (281, 323, and 373°K) and testing (298 and 348°K) of the permeability data for nylon 66 fabrics.

Polyester Fabrics

The training data set for the polyester fabric consisted of both the uncalendered and calendered fabric data. Both the fabrics were of the same denier (650D) so calendering was introduced as an input layer. The same 3-4-1 network architecture used for the nylon fabrics was again used here. The training data set consisted of 66 permeability data points, and the test data set consisted of 44 permeability data points. The training and testing results of the model is shown in Figure 14. Overall, the predictions provided by the neural network model were better for the polyester fabrics than they were for the nylon fabrics over the inflation temperature and pressure drop ranges investigated. The model predictions were within ± 0.01 m^3(STP)/m^2/s ($\pm 0.1\%$ error).

Biaxial Stress–Strain Predictions of the Proposed Neural Network Model

The experimental data in this instance were randomly separated into two data sets of 32 data points each with different levels of the fabrics' biaxial strain. The effects of the type of the fabric, i.e., den-

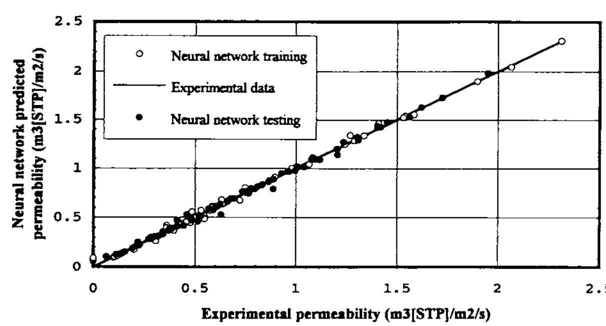

Figure 14 Neural-network training (281, 323, and 373°K) and testing (298 and 348°K) of the permeability data for polyester fabrics.

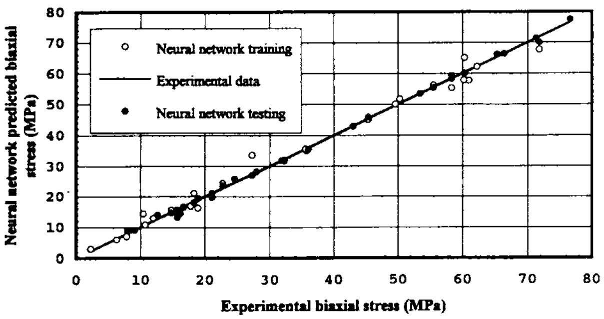

Figure 15 Neural-network training and testing of the biaxial stress–strain data.

ier and weave type, with nylons and calendering in case of polyester, biaxial strain, biaxial stress, and pressure drop were considered in the model. However, since the change in biaxial stress–strain relationship with inflation temperature was not significant, this effect was ignored. The predicted variable was the biaxial stress of the fabric under a biaxial deformation. The same 3-4-1 network architecture was again used here. The training and testing results from the model is shown in Figure 15. The predictions agreed very well with the experimental data as can be seen in this figure. The model prediction was within a ±3-MPa error limit.

CONCLUSIONS

The work presented here extends the novel approach that used neural networks to model[13] and predict the very important fabric permeability characteristics of nylon 66 fabrics to polyester fabrics. Permeability was predicted as a function of temperature and pressure drop for actual airbag fabrics under biaxial stress conditions. The proposed neural network model is conceptually simple, but its generated predictions were very good: well within reasonable error limits considering the complexities involved. The versatility of this model is demonstrated by predicting fabric permeability of both nylon and polyester fabrics as a function of temperature, whose overall effect may be negative or positive.

Finally, the proposed model is computationally simple compared to the nonlinear FEA based approach, and still incorporates the important fabric characteristics that the FEA does not. Once trained, the neural network model yields extremely fast predictions (within a second) and has the potential to used for on-line simulation of airbag deployment studies.

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