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Composite Hydrogen Storage Cylinders

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UTC
R165

University Transportation Center Program

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Technical Report Documentation Page

1. Report No. UTC R165	2. Government Accession No.	3. Recipient's Catalog No.	
4. Title and Subtitle Composite Hydrogen Storage Cylinders	5. Report Date July 2007		
	6. Performing Organization Code		
7. Author/s K. Chandrashekhara	8. Performing Organization Report No.		
9. Performing Organization Name and Address Center for Infrastructure Engineering Studies/UTC program University of Missouri - Rolla 223 Engineering Research Lab Rolla, MO 65409	10. Work Unit No. (TRAIS)		
	11. Contract or Grant No. DTRS98-G-0021		
12. Sponsoring Organization Name and Address U.S. Department of Transportation Research and Special Programs Administration 400 7 th Street, SW Washington, DC 20590-0001	13. Type of Report and Period Covered Final		
	14. Sponsoring Agency Code		
15. Supplementary Notes			
16. Abstract Composite high-pressure cylinders have potential application for hydrogen storage in automotive and transportation systems. Safe installation and operation of these cylinders is of primary concern. A neural network model has been developed for predicting the failure of composite storage cylinders subjected to thermo-mechanical loading. A Back-propagation Neural Network model is developed to predict composite cylinder failure. The inputs of the neural network model are the laminate thickness, winding angle, and temperatures. The output of the model is the failure pressure. The finite element model of the cylinder is based on laminated shell theory accounting for transverse shear deformation and geometric nonlinearity. A composite failure model is used to evaluate the failure under various thermo-mechanical loadings. The neural network is trained using failure results of simulation under different thermal loadings and lay-up. The developed neural network model is found to be quite successful in determining the failure of hydrogen storage cylinders.			
17. Key Words Composite Hydrogen Storage Cylinders	18. Distribution Statement No restrictions. This document is available to the public through the National Technical Information Service, Springfield, Virginia 22161.		
19. Security Classification (of this report) unclassified	20. Security Classification (of this page) unclassified	21. No. Of Pages 7	22. Price

Composite Hydrogen Storage Cylinders

by

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Project Summary (Year 1)

Composite high-pressure cylinders have potential application for hydrogen storage in automotive and transportation systems. Safe installation and operation of these cylinders is of primary concern. A neural network model has been developed for predicting the failure of composite storage cylinders subjected to thermo-mechanical loading. A Back-propagation Neural Network model is developed to predict composite cylinder failure. The inputs of the neural network model are the laminate thickness, winding angle, and temperatures. The output of the model is the failure pressure. The finite element model of the cylinder is based on laminated shell theory accounting for transverse shear deformation and geometric nonlinearity. A composite failure model is used to evaluate the failure under various thermo-mechanical loadings. The neural network is trained using failure results of simulation under different thermal loadings and lay-up. The developed neural network model is found to be quite successful in determining the failure of hydrogen storage cylinders.

Introduction

The composite high-pressure cylinder is made with a high molecular weight polymer or aluminum liner that serves as a hydrogen gas permeation barrier. A filament-wound, carbon/epoxy composite laminate over-wrapped outside of the liner provides the desired pressure load bearing capacity. The cylinder is capable of sustaining pressures of 5000 psi or higher by taking advantage of high modulus, high strength and low specific weight of modern high performance composite. To design composite high-pressure cylinders with the most possible safety, reliability and minimum weight considerations, the failure of composite structures under various mechanical and thermal loadings need to be well understood.

To account for complex composite wall structure and environmental temperature influence, a comprehensive finite element model is developed and implemented in commercial finite element code ABAQUS to analyze the failure of the composite cylinder. Due to a large number of parameters such as varying thermal loads, winding angles, cylinder dimensions and lay up configurations, it is a tremendous task to optimize the cylinder design and predict cylinder failure pressure through case-by-case finite element analysis simulation. A Back-propagation Neural Network (NNk) model is employed to predict the failure pressure using the results obtained from a few finite element simulation cases. Three sets of simulation results with various winding angles and thermal loadings are applied for Neural Network training. The trained NNk model can be used as a tool to predict the failure pressure of the hydrogen storage cylinder under a given set of loads.

Finite Element Simulation of Composite Hydrogen Cylinder

A typical structure scheme of hydrogen storage cylinder is shown in Fig. 1. The inner aluminum liner is subject to mechanical pressure and temperature. In many current designs, a glass/epoxy layer is placed over the carbon/epoxy laminate to provide impact and damage resistance. The doubly curved shell theory accounting for out of plane shear deformations and geometric nonlinearity is used for the analysis of composite hydrogen storage cylinders.

The composite hydrogen storage cylinder is modeled and meshed using ABAQUS commercial Finite Element Analysis code (Fig. 2). A laminated shell element (S8R), based on doubly curved shell theory, including membrane bending and transverse shear effects, is used for modeling the cylinder. In order to estimate the failure pressure of the cylinder, it is necessary to include failure criterion. Tsai-Wu failure theory is utilized to check and report the ply-by-ply laminate failure by using user subroutine UARM. In addition, temperature dependent material properties are incorporated in the model by using user subroutine USDFLD so that, at each integration point, the material properties are determined by the given temperature. The orientation of each element at every ply is handled by subroutine ORIENT according to winding pattern. The comprehensive model is then solved by using ABAQUS/standard solver with geometric nonlinearity considered. The dimensions considered in the present cylinder analysis are based on a typical design from literature. The outer radius of the cylinder is taken as $R_{out} = 0.235$ m and inner radius $R_{in} = 0.22$ m (Fig. 1). The pressure bearing carbon/epoxy laminate consists of 24 plies with a total thickness of 28 mm. The protective glass/epoxy layer and liner are 2 mm and 2.5 mm thick respectively. The cylinder is subjected to an internal pressure that gradually increases until the first ply failure occurs. To manufacture closed cylinders, two types of winding patterns are usually used: hoop winding and helical/polar winding. The thickness ratio R (total thickness of helical laminate/total thickness of hoop laminate) affects the failure pressure of the cylinder and a range of 0.1 to 2.0 is considered. Winding angle of laminae also affects the failure pressure of the cylinder and a range of 10° to 30° for helical winding and 89° for hoop winding has been considered based on the manufacturing feasibility. The plies in the protection laminate are oriented as 45° angle ply.

Failure Model for Composite Hydrogen Storage Cylinders by Feedforward Back-propagation Neural Network

Feed-forward back propagation Neural Network is used to predict the failure pressure of hydrogen cylinder. The schematic of the NNk is shown in Fig. 3. The relationship of failure pressure and the inputs (thickness ratio R, temperature inside of the cylinder T_{in} , temperature outside of the cylinder T_{out} , and filament winding angle θ) is modeled by a two-layer (hidden layer and output layer) network. Each layer consists of a number of processing units, known as neurons (Fig. 3). To obtain an easy training and a robust NNk model, inputs are scaled to a desirable range by a designed transfer function f_{in}^T before entering the input layer. Inputs are then passed through weighted connections to the hidden layer and then to the output layer. The output P' is, finally, scaled back to failure pressure P by a designed transfer function f_{out}^T . The number of neurons in the hidden layer and the characterizing weights and biases in the model are determined by training the NNk.

The input Transfer function

$$f_{in}^T(I_i) = I_i \cdot a_i + b_i \text{ and } I'_i = f_{in}^T(I_i) \quad (1)$$

where I_i are input variables (corresponding to $\{R, T_{in}, T_{out}, \theta\}$ respectively)

I'_i are normalized input variables

$$a_i = \frac{n_{\max} - n_{\min}}{\bar{I}_{i\max} - \bar{I}_{i\min}}, b_i = n_{\min} - \text{Min}\{a_i \cdot \bar{I}_i\}, i = 1, 2, 3, \text{ and } 4$$

$[n_{\min} \ n_{\max}]$ is the desired scale range (Here, taken as [-1 1])

and \bar{I}_i are input training pattern vectors.

The activation function in the hidden layer is the Log-sigmoid function

$$f^h(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

The activation function in the output layer is the Pureline function

$$f^o(x) = x \quad (3)$$

The relationship of normalized input and output of NNk

$$P' = \sum_{j=1}^N W_{1j}^o f^h \left(\sum_{i=1}^4 W_{ji}^h I'_i + {}^h b_j \right) + {}^o b \quad (4)$$

where N is number of neurons in the hidden layer

W_{1j}^o are weights in the second (output) layer

W_{ji}^h are weights in the hidden layer

b^o is bias in the second (output) layer

b_j^h are biases in the hidden layer

and P' is the normalized output burst pressure.

The output Transfer function

$$f_{out}^T(I_i) = (P' - b) / a \text{ and } P = f_{out}^T(P') \quad (5)$$

where P is the final output burst pressure

$$a = \frac{n_{\max} - n_{\min}}{\bar{P}_{\max} - \bar{P}_{\min}}, i = 1, 2, 3, \text{ and } 4$$

$$b = n_{\min} - \text{Min}\{a_u \cdot \bar{P}\}, i = 1, 2, 3, \text{ and } 4$$

and \bar{P} is the output training pattern vector.

Training consists of providing a set of known input-output pairs (or patterns) to the network. During the backward propagation, weights in each node are iteratively adjusted based on the errors using the gradient descent equations. The procedure is repeated until convergence is achieved. In this study, the input-output sets are obtained from finite element simulation results.

The model is trained in MATLAB NNk tool box. The fast training Levenberg-Marquardt algorithm is adopted for the training process.

Curve Fitting

The network is trained by using the simulation results from three cases shown in Table 1. There are 12 neurons used in the neural network (NNk) model and the learning parameter is set to 0.01. After convergence is achieved, the network model is capable of predicting the failure pressure for a given cylinder thickness ratio (R), temperature distribution (T_{in} and T_{out}) and winding pattern (θ). To evaluate the performance of NNk prediction, six test cases (shown in Table 2) are studied. The test data from ABAQUS simulation results, for winding angles not included in the training (15° and 25°), are used to compare the predicted results from the trained neural network. The performance of the NNk is then illustrated in Fig. 4 and Fig. 5, and the maximum errors are reported for each case in Table 2. The test case 1 (T40-40) implies $T_{in}=40^\circ\text{C}$ and $T_{out} = 40^\circ\text{C}$. It can be seen that the simulation results are in good agreement with the results predicted by NNk model.

Conclusions

A comprehensive finite element model is developed for composite hydrogen cylinder. Taking parameters determining the failure behavior of cylinder as inputs and failure pressure as output, a 2-layered backpropagation neural network model is developed and used to predict the failure pressure. The performance of the trained neural network is then evaluated by comparing the predicted values with test cases. The results are in good agreement.

Acknowledgements

The project is sponsored by the US. Department of Transportation and University Transportation Center.

Publication

J. Chen, J. Hu, V.G.K. Menta and K. Chandrashekhara, "Neural Network Based Failure Prediction Model for Composite Hydrogen Storage Cylinders," Proceedings of the ANNIE Conference, St. Louis, MO, November 11-14, 2007.(to appear).

Table 1: Lay-up configurations for various winding patterns

Case No.	Lay-up Pattern	Description
1	$[\pm 20^\circ/\pm 89^\circ]_6$	24 layers with total thickness of 28 mm $T_{in}=[25\ 50\ 75\ 100\ 120\ 140]^\circ\text{C}$ $T_{out}=[25\ 50\ 75\ 100\ 120\ 140]^\circ\text{C}$
2	$[\pm 10^\circ/\pm 89^\circ]_6$	
3	$[\pm 30^\circ/\pm 89^\circ]_6$	

Table 2: Testing cases and maximum error of prediction

Testing Case	Inputs			Max. Error (%)
	T_{in} ($^\circ\text{C}$)	T_{out} ($^\circ\text{C}$)	θ (Degree)	
1	40	40	15	1.32
2	30	80	15	-1.54
3	130	40	15	1.23
4	40	40	25	1.11
5	30	80	25	-2.40
6	130	40	25	-1.00

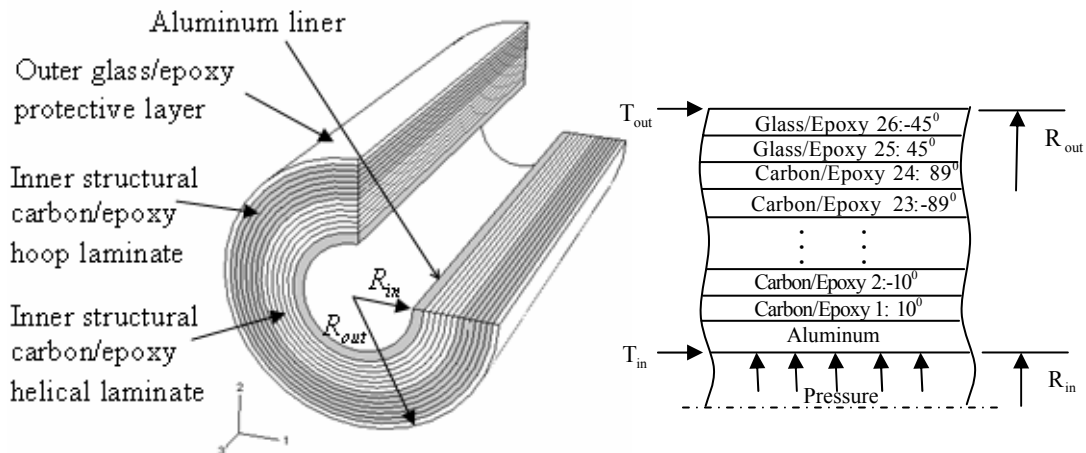


Figure 1 Structure scheme of hydrogen storage cylinder

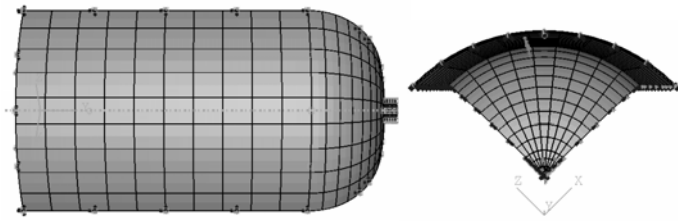


Figure 2 Finite element model of hydrogen cylinder

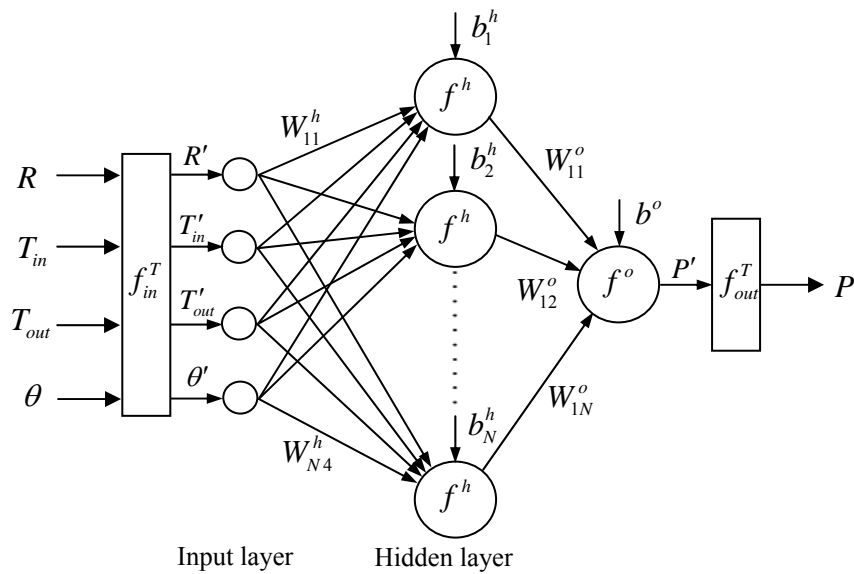


Figure 3 Feedforward Back-propagation Neural Network architecture

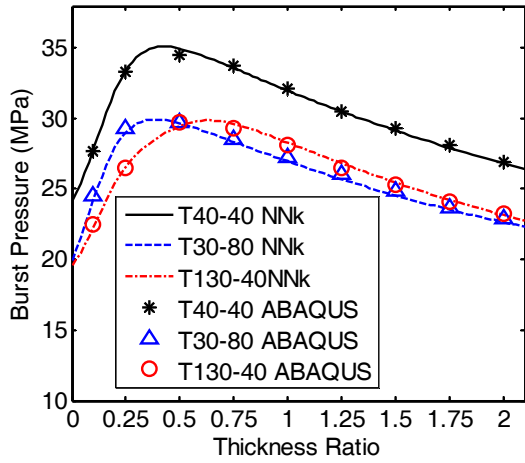


Figure 4 Comparison of burst pressures from NNk and ABAQUS at $\theta = 15^\circ$

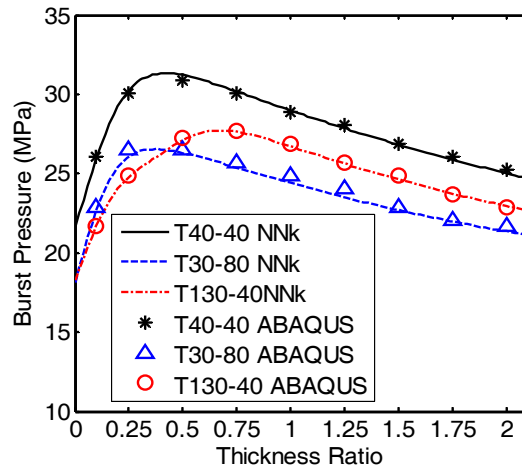


Figure 5 Comparison of burst pressures from NNk and ABAQUS at $\theta = 25^\circ$