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Predicting the buckling Capacity of Steel Cylindrical Shells with Rectangular Stringers under Axial Loading by using Artificial Neural Networks

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A B S T R A C T

A parametric study was carried out in order to investigate the buckling capacity of the vertically stiffened cylindrical shells. To this end, ANSYS software was used. Cylindrical steel shells with different yield stresses, diameter-to-thickness ratios (D/t) and number of stiffeners were modeled and their buckling capacities calculated by displacement control nonlinear static analysis. Radial basis function (RBF) neural networks were used to predict the buckling capacity of shells. Herein, 70 percent of the results of numerical analyses were used to train the neural network and the remainders to test and validate the results. Results of this study showed that RBF neural networks are useful tools to predict the buckling capacity of vertically stiffened cylindrical shells. It was also shown that buckling capacities of stiffened shells exponentially vary by distance of adjacent stiffeners (unstiffened length).

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1. INTRODUCTION

Buckling is one of the major failure modes of the thin walled cylindrical shells. Hence, there is a worldwide interest in investigating the buckling capacity of these types of structures. Cylindrical shells are one of the most common thin walled structures. The buckling capacity of cylindrical shells was investigated by Timoshenko in early 1900s. Since then the buckling of cylindrical shells has been investigated by several researchers [1]. Buckling of cylindrical shells depends on several parameters such as geometric specifications, boundary conditions, inelastic behavior and imperfections [1, 2]. Such parameters may cause shell buckling to occur in stresses below the classical buckling stress presented by Timoshenko [2]. Rotter and Teng [3] investigated the effects of weld depressions on buckling capacity of cylindrical shells. Arbocz and Bobcock [4] studied the effects of imperfections on buckling of cylindrical shells. Furthermore, several valuable studies on buckling of cylindrical shells are available [5-8].

Several techniques are used to increase the buckling capacity of cylindrical shells. The effects of vertical stiffeners (stringers) on buckling of cylindrical shells have been investigated by researchers all around the word [9-14]. Razzaghi and Karimi [10] showed that although the stringers increase the axial buckling capacity of cylindrical shells, they may decrease the buckling capacity of shells due to global shear.

During the recent decades, numerical analysis has been carried out to investigate the buckling and post buckling behavior of shells [15-17]. Numerical analysis is a fast and easy method for parametric study of buckling of shells, especially in inelastic problems. The most important shortcoming of numerical analysis of shells is convergence difficulties associated with nonlinear problems. Soft computing techniques such as artificial neural networks are useful tools to decrease the number of analyses in parametric studies [18]. Regarding to the remarkable capability of artificial neural networks, several researchers have implemented artificial neural networks in many engineering problems such as concrete technology [19], structural engineering

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[20], earthquake engineering [21] and offshore structures [22]. In this study inelastic buckling capacity of cylindrical steel shells with stringers was investigated. Because of high degrees of material and geometric nonlinearity, noticeable convergence difficulties may happen during numerical analysis. Hence, a parametric study on buckling capacity of such a structure is time consuming, and sometimes impossible. On the other hand, calculating the inelastic buckling capacity of stiffened shells via solving nonlinear partial differential equations for various shells is dramatically difficult. Thus, there is a remarkable need to investigate the buckling capacity of such structures using a reliable simpler method. Artificial neural networks maybe a suitable approach for approximate solution of complex problems. It should be noted that although neural predicting techniques are usually simple for implementation, a deep attention is required to obtain reliable results. To this end, in this study nonlinear numerical analysis was used. Moreover, radial basis function (RBF) neural networks were used in order to predict the buckling capacity of vertically stiffened shells.

2. NUMERICAL ANALYSIS

In order to calculate the inelastic buckling capacity of cylindrical steel shells with stringers, numerical analysis was used. To this end, ANSYS finite element software was used [23]. More than 160 cylindrical shells of various geometrical specifications and material properties were modeled (see Table 1). It should be noted that the cross section of all of the stringers were rectangular and their width was10 cm. Furthermore, the heights of all of the models were 15m. It is worth mentioning that all of the degrees of freedom were restrained at bottom and were released at top of all of the shells. Four node SHELL 181 elements having six degrees of freedom at each node were used to model cylindrical shells and stringers. The elements are capable of considering material nonlinearity and large deformation effects. Material nonlinearity of steel was accounted for based on Von Mises yield criterion. Kinematic hardening rule was used to define the material property in these elements. Bilinear stress-strain model were considered for cylindrical shell and stringers. The elastic modulus of shell and stiffeners was 2.1×10^5 MPa and the tangent modulus was assumed to be 4200 MPa. Figure 1 indicates a finite element model of one of the stiffened shells. In order to calculate the buckling capacity of shells, pure axial displacements were incrementally applied to the top of the shells. In order to calculate the buckling capacity of shells variations of axial load versus axial shortening of shells were plotted. The bifurcation point of the axial load-shortening graph of shell was considered as buckling load of a particular shell. It should be noted that the element tests and validation of models were carefully conducted according to techniques provided by Cook [24]. Several buckling modes may occur in stiffened shells (e.g. local buckling of shell, in-panel buckling of shell, global buckling and stringer buckling). In this study both in panel and global buckling mode of the shell were considered. In other words, local buckling modes of shell and/or stiffeners were not taken into account.

Results of numerical analyses revealed that the buckling capacity of a particular shell increases by decreasing the unstiffened length of the shell. The unstiffened length of the shell is defined as distance between the adjacent stiffeners and can be calculated as follows: $d = \pi \mathrm{D}/\mathrm{n}$ (1), where d is an unstiffened length of the shell, D diameter the cylindrical shell and n the number of stringers. In unstiffened shells d is the perimeter of the cross section of the shell.

Variation of buckling capacity of shells with d is indicated in Figures 2-7. As indicated in Figures 2-7, the relation of dimensionless buckling capacities of shells (P_{cr}/Pc_{r0}) and d can be expressed by a power function. Dimensionless buckling capacity of shell is defined as the ratio of the buckling capacity of a stiffened shell to that of the same unstiffened one. The above mentioned figures also show that the yield stress has low influence on buckling capacity of shells with large unstiffened lengths. This happens because the stiffened shells, especially those with large number of stiffeners, experience noticeable nonlinear behavior prior to buckling. The unstiffened length of the cylinders plays a role in buckling mode of the shells. In most of the shells with large numbers of stiffeners in-panel mode of buckling or combination of in-panel and stringer buckling took place; but, in other shells global buckling was the major failure mode.

TABLE 1. Specifications of the models

Item	Diameter (m)	Stringer thickness (mm)	Shell thickness (mm)	Yield stress (MPa)	Number of stringers
1	10	1, 1.2, 2	1, 1.2, 2	250, 300, 370	0-4-8-16-32-64
2	15	1, 1.2, 2	1, 1.2, 2	250, 300, 370	0-4-8-16-32-64
3	20	1, 1.2, 2	1, 1.2, 2	250, 300, 370	0-4-8-16-32-64

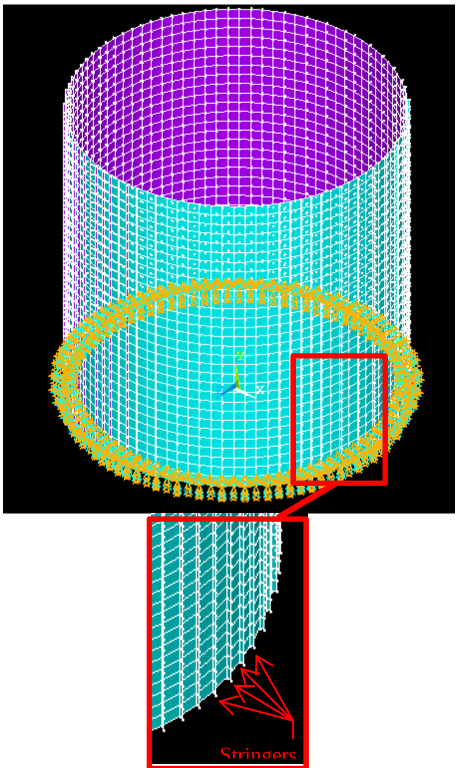

Figure 1. FEM model of a stringer stiffened shell

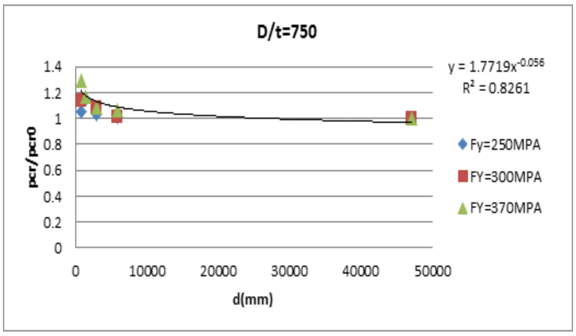

Figure 2. Variation of dimensionless buckling capacity of shells with their unstiffened length (D/t = 750)

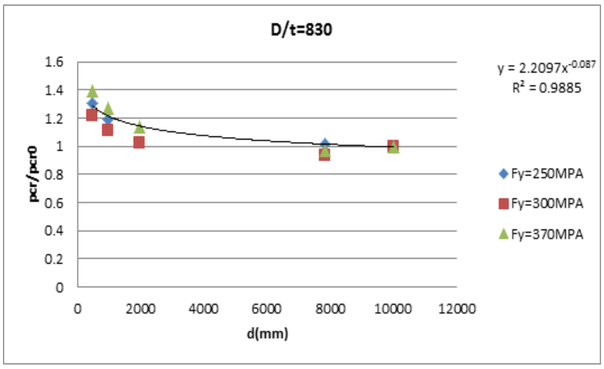

Figure 3. Variation of dimensionless buckling capacity of shells with their unstiffened length (D/t = 830)

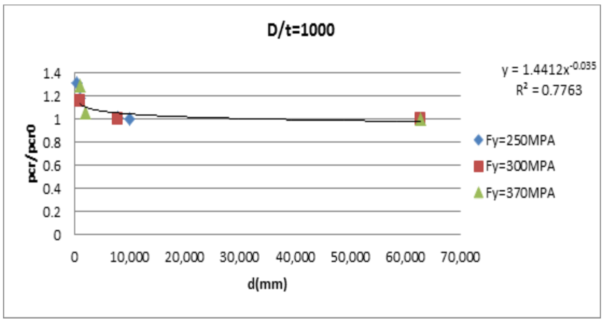

Figure 4. Variation of dimensionless buckling capacity of shells with their unstiffened length (D/t = 1000)

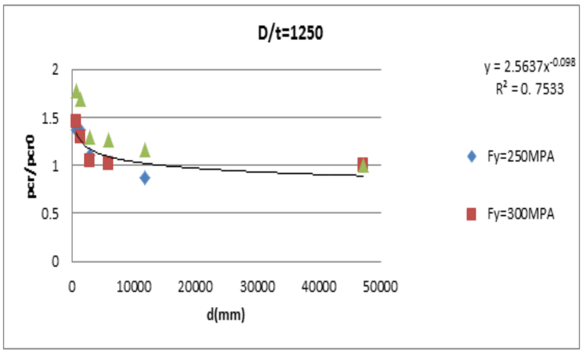

Figure 5. Variation of dimensionless buckling capacity of shells with their unstiffened length (D/t = 1250)

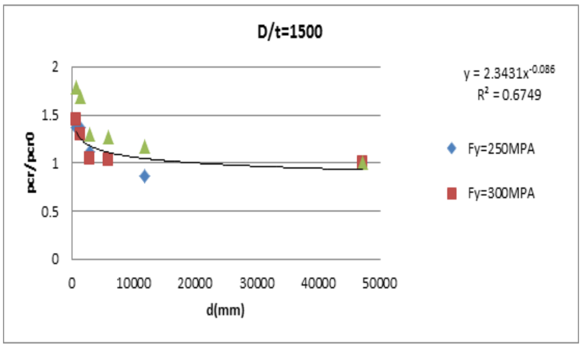

Figure 6. Variation of dimensionless buckling capacity of shells with their unstiffened length (D/t =1500)

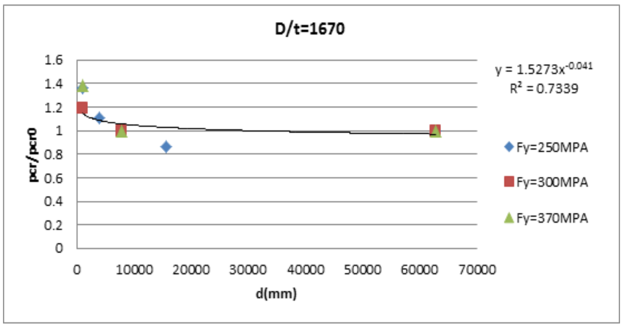

Figure 7. Variation of dimensionless buckling capacity of shells with their unstiffened length (D/t = 1670)

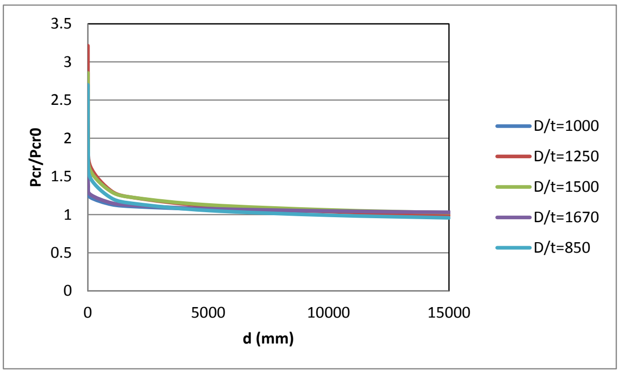

Figure 8. The effects of D/t on buckling capacity of stiffened shells

Variation of dimensionless buckling capacity of shells with unstiffened length for various D/t ratios and constant f_y is shown in Figure 8. As indicated in Figure 8, there is not a meaningful relationship among the results of the buckling capacities stiffened shells and D/t (especially in shorter unstiffened lengths).

3. ARTIFICIAL NEURAL NETWORKS (ANN)

3. 1. Theoretical Background Artificial neural networks are simple computer model of the human brain. They are capable of mapping a relation between information in input and output layer. Several types of ANNs (e.g. Multi-layer perceptron, RBF, etc.) are available. Multi-layer perceptron (MLP) and Radial basis function (RBF) neural network are two of the most common neural networks which use to solve engineering problems. The MLP neural networks include a single input layer, one or more hidden layer(s) and an output layer. As indicated in Figure 2, each layer includes one or more artificial neuron(s). All neurons are fully connected to the neurons of the neighboring layer; but neurons within a same layer are not connected together. The RBF neural networks have simple structures with three distinct layers [25-28]. The information is collected by the first layer (input layer) and formulated the input vector. The second layer is a hidden layer which performs a non-linear transformation to the input vector. Finally, the third layer applies a linear transformation from hidden layer to the output space [25-28]. The j^{th} output of a RBF neural network, $y_j(p)$, can be mathematically defined as follows:

$$y_j(x) = \sum_{i=1}^{u} R_i(x) w_{ij} \quad (1)$$

where $R_i(p)$ is the activity of node i which is the Euclidean norm of the difference between the input vector and the node center:

$$R_i(x) = \|x - \hat{x}_i\| \quad (2)$$

where $\hat{x}_i$ is the node center. Several radial basis functions are available; but the Gaussian function is usually preferred [28]. Hence, Equation (3) can be rewritten as follows:

$$R_i(p) = e^{-\frac{\|x-\hat{x}_i\|^2}{\sigma_i^2}} \quad (3)$$

where σ_i is a scalar width of the i^{th} RBF unit.

3. 2. Network Architecture Radial Basis Function (RBF) networks have simple structure that includes a hidden layer with radial nonlinear functions and an output layer with linear transfer functions. They need to have more neurons compared to back propagation networks, but they have simpler training method than MLP networks [29]. Hence these networks usually have more efficiency when much training vectors are available.

In this study, RBF neural networks were used in order to predict the buckling capacity of stiffened cylindrical shells. To this end, 70% of the results of numerical analyses were selected to train the artificial neural networks. Various architectures were selected and examined. Generally, there is not a unique method to select the optimum architecture for neural networks [30]. In this study, the squared correlation coefficient (R^2) and mean squared error (MSE) are the criteria for selecting the appropriate network. In other words, the neural network which had the least mean square error (MSE) and the maximum correlation factor (R^2) were selected as the most suitable neural network. Thickness of shell and stiffeners, number of stiffeners, yield stress and the diameter of the shells were considered as input vectors and the dimensionless buckling capacity was considered as an output of the network.

Figure 9 indicates the performance curve of the selected RBF network. It is shown that the selected network reaches the performance of 2.56×10^{-6} in 99 epochs which is a reasonable performance. Comparison of the prediction of the neural network with results of numerical analysis is shown in Figure 10. As shown in Figure 10, the RBF network has an acceptable potential to predict the buckling capacity of stiffened shells. In order to estimate the accuracy of the ANN predictions, the ratio of results of ANN to those estimated by numerical analysis were calculated for 108 samples (See Figure 11).

To this end, 108 new geometric-material specifications were simulated by the selected neural network and simultaneously analyzed by FEM. Figure 11 indicates that the maximum error in ANN prediction is less than 20%. Furthermore in most of the cases (more than of 80% of the samples) the error is less than 10%.

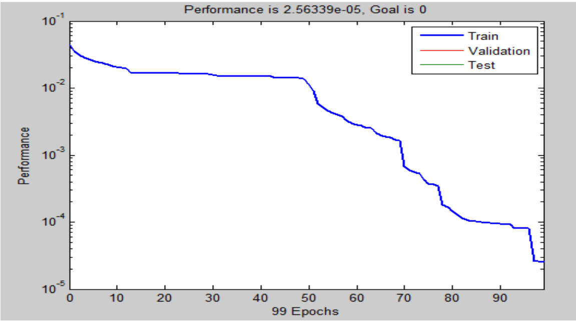

Figure 9. Performance curve of the selected RBF network

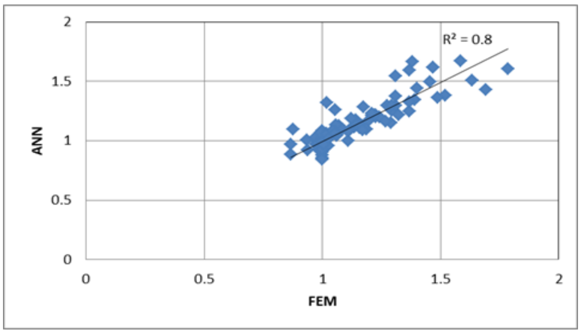

Figure 10. Neural predictions vs. results of FEM analyses

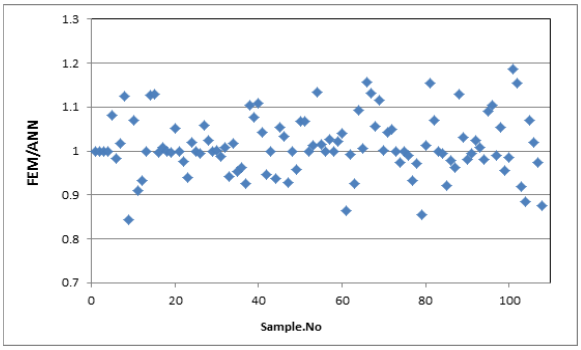

Figure 11. The accuracy of neural predictions in simulated shells

4. CONCLUDING REMARKS

A combination of nonlinear numerical analysis and artificial neural networks were implemented in order to estimate the buckling capacity of cylindrical stiffened shells. To this end, ANSYS software was used for nonlinear FEM analysis and RBF neural networks for neural prediction. Different structures of RBF networks were used and the best network was selected based on the minimized MSE and maximized R^2.

Results of this study revealed that the relation of nonlinear buckling capacities of axially loaded cylindrical stiffened shells and their unstiffened length is approximately a power function. Results of the numerical analyses also revealed that yield stress has low influence in buckling capacity of shells with large unstiffened lengths. It was also shown that RBF neural networks have a noticeable potential in accurate estimation of buckling capacity of stiffened shells. The maximum error in ANN prediction is less than 20%.

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چکیده

به منظور بررسی ظرفیت کمانش پوسته‌های استوانه‌ای با سخت‌کننده‌های قائم، مطالعات پارامتریک به انجام رسید. برای این منظور از نرم افزار ANSYS استفاده شد. پوسته‌های استوانه‌ای فولادی با تنش جاری شدن، نسبت ارتفاع به قطر و تعداد سخت‌کننده‌های گوناگون مدل سازی شدند و ظرفیت کمانش آنها با استفاده از تحلیل استاتیکی غیرخطی با کنترل تغییر مکان محاسبه شد. به منظور پیش‌بینی ظرفیت محوری کمانش از شبکه عصبی RBF استفاده شد. برای این منظور هفتاد درصد از نتایج خروجی تحلیل‌های عددی برای آموزش شبکه استفاده شدند و مابقی برای تست و صحت‌سنجی نتایج کنار گذاشته شدند. نتایج این پژوهش نشان می‌دهد که شبکه‌های عصبی RBF ابزاری مناسب برای پیش‌بینی ظرفیت کمانش پوسته‌های استوانه‌ای با سخت‌کننده قائم هستند. علاوه بر این، نشان داده شد که تغییرات ظرفیت کمانش پوسته‌ها با فاصله سخت‌کننده‌های مجاور (طول مهار نشده) به صورت نمایی تغییر می‌کند.

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