An Artificial Neural Network Approach to Plastic Collapse of Oval Boiler Tubes

Author:
Zarrabi, Khosrow; Basu, Abheek

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Zarrabi K.[1], Basu A[2].

[1]School of Mechanical and Manufacturing Engineering, UNSW, Sydney, NSW 2052, Australia

[2] Strand7 Pty Ltd, Suite 1, Level 5, 65 York Street, Sydney NSW 2000

[1] k.zarrabi@unsw.edu.au

Abstract. Boilers in power, refinery and chemical processing plants contain extensive range of tube bends. Tube bends are manufactured by bending a straight-section tube. As a result, the cross-section of a tube bend becomes oval. Using the finite element analysis (FEA) and artificial neural network (ANN), the paper presents the relationships between the plastic collapse pressures and tube bend dimensions with various degrees of ovality. It is found that as ovality increases the plastic collapse pressure decreases. Also, the reduction of plastic collapse pressure with ovality is small for a thick tube bend when compared with that for a thin tube bend.

Introduction

Since the development of the first power plants in the 1880s, electricity has proven to be the most convenient and flexible medium in which to transfer power from its source to where it is required. Much of the world's electric power is generated from burning fossil fuels such as coal or oil. In view of the many environmental concerns associated with these processes, a great deal of effort has been devoted to developing alternative energy sources, including the nuclear power, water power (i.e. hydro-electricity), solar energy, wind energy and geothermal energy. However, for economic reasons, power generation via fossil fuel power plants still dominates the market. Within Australia, over 85% of the total electricity generated is produced by fossil fuel power plants.

On of the major units in a power plant is a boiler where internal energy in the fossil fuel is converted to thermal energy in the superheated steam. One of the major problems associated with fossil fuel power plants is the failure of boiler tubes. With hot water or steam running through the inside and hot combustion gases flowing over their outside surfaces, and with operating pressures and temperatures being extremely high and often fluctuating, boiler tubes experience an operational environment that is among the most severe for any large engineered structure. It is therefore no surprise that boiler tube failure accounts for the majority of unscheduled shutdowns in fossil fuel power plants. The first author and his research team have previously developed effective life assessment paradigms for straight section of boiler tubes, see for example [1].

Tube bends are extensively used in a boiler of a plant. These tubes are subjected to high temperatures and prone to plastic/ creep rupture. More generalised changes in geometry occur as a result of boiler tube manufacture. When a boiler tube bend is fabricated, two phenomena occur due to the nature of the fabrication process, ovality and wall thickness variation. Ovality is the flattening of the cross section of a tube due to the forces it is subjected to in the process of forming a bend from a straight section of tube. During the same bending process, thinning occurs as a result of the difference in arc length on the outer surface (extrados) and inner surface (intrados) of the bend. Due to the longer arc length on the extrados the tube is stretched and thinned. At the intrados, where the arc length is shortened, the tube is compressed and thickens.

This research concentrates on the effect of ovality on the tube plastic collapse pressures and uses a finite element method and artificial neural network to develop a paradigm.

Plastic Collapse Pressures of Tube Bends

The objective of the analysis is to generate relationships that give the plastic collapse pressure of a boiler-tube-bend with various degree of ovality. Previously it has been shown that when the internal pressure is dominant loading, the stresses in a toroidal vessel (Figs 1, 2 and 3) obtained using an elastic-plastic analysis are an accurate representation of those occurring in a tube bend [2, 3].
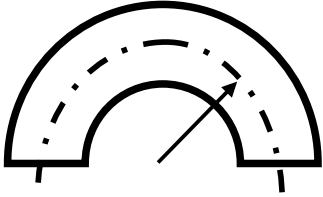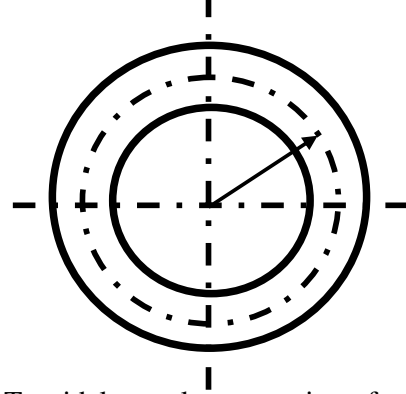

Fig. 1 – A tube bend section

Fig. 2 – Toroidal vessel presentation of a tube bend section

In the present study, elastic-plastic finite element analysis (FEA) is used to compute the plastic collapse pressures for the toroidal vessel shown in Figures 2 and 3. In doing so, the following assumptions are made:

1. The vessel (tube) is subjected to uniform internal pressure only.
2. It is assumed that the material of the vessel follows the elastic-perfectly plastic behaviour. This reduces the computational cost noting that the plastic collapse pressure is not sensitive to stress and strain levels in the elastic-plastic transition region. Note that because there is no strain-hardening, then the hardening rule does not affect the plastic collapse pressures.
3. There is no residual stress. Plastic deformation releases any residual stresses. Therefore, plastic collapse pressure is not affected by the initial state of residual stresses.

A cross-section of the toroidal vessel subjected to uniform internal pressure P is schematically shown in Fig. 3. The vessel is axisymmetric and the section labeled as ABC in Fig. 3 is modelled for FEA as shown in Fig. 4. PATRAN [4] is used to generate finite element models. Because of its convenience, an in-house finite element software was used for elastic-plastic analysis using 4 node elements allowing linear displacement variation within each element. A number of models are generated. Each model has 6 elements through the vessel thickness. This is thought to be sufficient to model any through thickness bending state. Referring to Figs 3 and 4, ovality (o in %) is defined as:

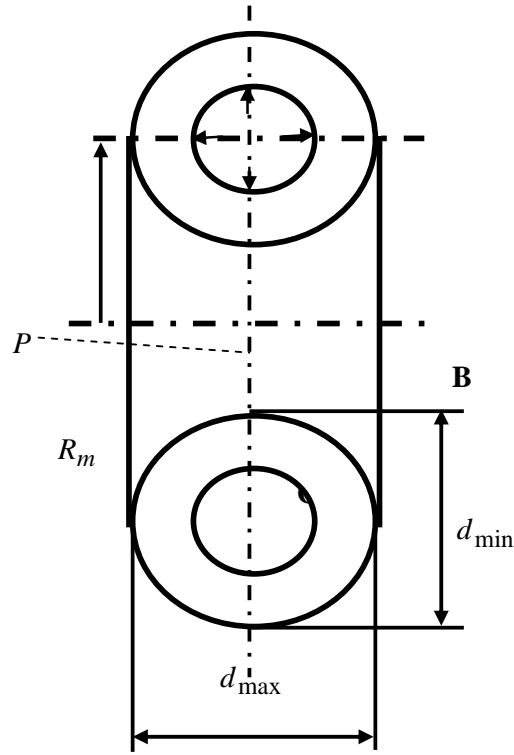$$O = \frac{2\,(\,d_{\max} - d_{\min}\,)}{d_{\max} + d_{\min}}\,x100 \tag{1}$$

A

Fig. 3 – A cross-section of the toroidal vessel (tube bend) subjected to uniform internal pressure P
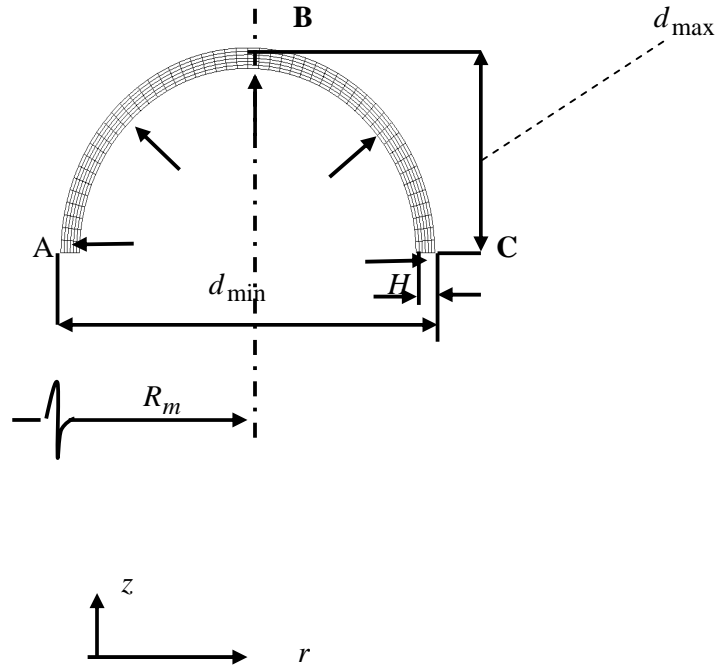

Fig. 4 – Axisymmetric finite element model of the toroidal vessel (tube bend)

To cover a wide range of the vessel geometries from a thin to a thick vessels, dimensions of the model are varied so that: $0 \leq O \leq 10\%$, $\dfrac{R_m}{d_{\min}} = 3$, 4.5 or 6, $\dfrac{d_{\min}}{H} = 6$ (a thick tube) or 20 (a thin tube) with $d_{\min} = 120\,mm$ and $H = 6\,mm\ or\ 20\,mm$. For each model the pressure versus the maximum displacement in the r-direction (that occurred at point B, see Figs 2 and 3 for position of

point B) is noted from which the plastic collapse pressure is calculated. A typical graph is shown in Fig. 5. Various methods of determining the plastic collapse pressure from a graph such that shown in Fig. 5 are described by Kitching and Zarrabi [5].
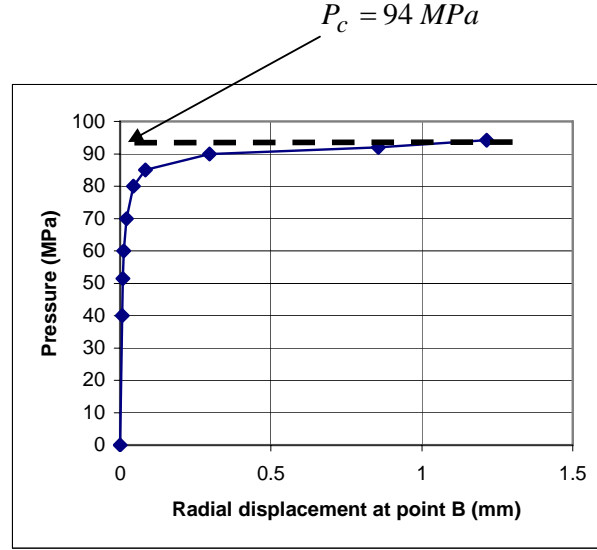
$$P_c = 94\ MPa$$

Fig. 5 – Internal pressure versus maximum displacement in the r-direction when $\dfrac{R_m}{d_{\min}} = 4.5$ and

$$\frac{d_{\min}}{H} = 6$$

Artificial Neural Network (ANN) and Results

The objective is to represent the non-dimensional computed plastic collapse pressures, viz., σ_y / P_c where σ_y is the yield strength, as a function of non-dimensional geometrical parameters and ovality so that:

$$\frac{\sigma_y}{P_c} = f(O, \frac{R_m}{d_{\min}}, \frac{d_{\min}}{H}) \tag{2}$$

To determine the function 'f' in Eq. (2), the present investigation uses an artificial neural network (ANN) similar to that developed by Zarrabi [6]. When data are assumed to fit a mathematical distribution, we are adding information that helps us to model the available data. This, however, may be misleading if we have chosen the wrong distribution. An ANN consists of a training stage and a simulation stage. ANN models the data that are presented to it during the training stage without assuming a particular distribution. After the network is trained it is used to simulate or predict plastic collapse pressures using the tube dimensions and ovality data as input. More specifically the inputs to ANN are: $O, \dfrac{R_m}{d_{\min}}, \dfrac{d_{\min}}{H}$ and the output is: $\dfrac{\sigma_y}{P_c}$. ANN has a parallel processing architecture that is composed of many non-linear computational elements (neurons). It is naturally suited to tackle complex and non-linear problems. The elements or neurons in ANN are arranged in patterns reminiscent of biological brain cells. The present investigation uses a back propagation, feed forward ANN with input, hidden, and output layers [6]. In operation, ANN learns a predefined set of input-output example pairs by using a two-phase propagate-adapt cycle. As

mentioned before, the development of ANN consists of two stages, viz., a learning and a prediction stages. During the learning stage, first, the inputs are supplied to the input layer where they are acted upon by input transfer functions, weights and biases at each neuron; then they propagate through hidden and output layers. At hidden and output layers the variables are acted upon by the corresponding transform functions, weights, and biases. Biases are normally set to unity for all three layers. At the output layer, the variables are combined to produce an output. This output is then compared with the desired output (Computed $\dfrac{P_c}{\sigma_y}$ using FEA) and an error signal (ER) is computed. ER is then minimized with respects to weights and the process is iterated until ER is less than a desired value. The final weights are used in the predication stage to compute the desired output variable. Before the training of the network both input and output variables (V) are normalized within the range 0–1 using:

$$V_n = \frac{2V - V_{\max} - V_{\min}}{V_{\max} - V_{\min}} \tag{3}$$

where V_n is the normalized value of variable V, $V_{\max}$ is the maximum value of the variable and $V_{\min}$ is the minimum value of the variable. Having determined the plastic collapse pressures for various bends, they are plotted in Figs 6 (a thick tube) and 7 (a thin tube). In general, as might be expected, Figs 6 and 7 show that as ovality increases the plastic collapse pressure decrease (i.e., $\dfrac{\sigma_y}{P_c}$ increases). Also, when the tube is thick (Fig. 6), it is too stiff to be affected by the through-thickness bending stresses and therefore the reduction in P_c with ovality is relatively small. This is not so for the thin tube when it is more flexible (Fig. 7).
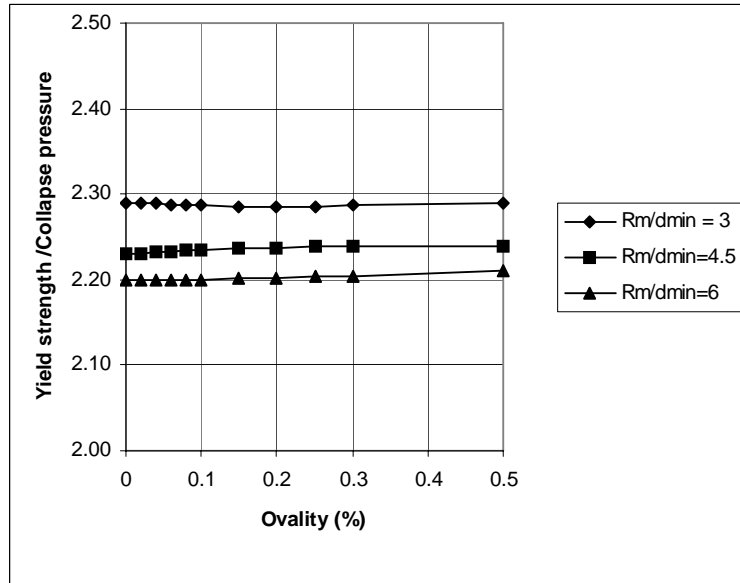

Fig. 6 – $\dfrac{\sigma_y}{P_c}$ versus ovality for various $\dfrac{R_m}{d_{\min}}$ when $\dfrac{d_{\min}}{H} = 6$ (a thick tube bend)
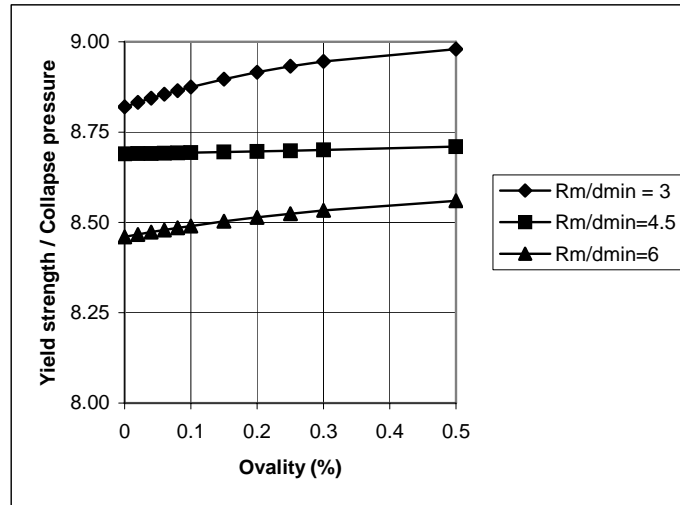
Fig. 7 – $\dfrac{\sigma_y}{P_c}$ versus ovality for various $\dfrac{R_m}{d_{\min}}$ when $\dfrac{d_{\min}}{H} = 20$ (a thin tube bend)

Conclusions

Plastic collapse pressures for the boiler tube bends with various degree of ovality are computed using FEA. ANN is then applied to the computed results in order to establish a relationship between the computed plastic collapse pressures and ovality and tube dimensions. In doing so, non-dimensional parameters are employed so that ANN will cover a wide range of tube dimensions and materials. It is found that: (1) the plastic collapse pressure decreases as ovality increases due to increase of through thickness bending stresses and (2) the variation of the plastic collapse pressure with ovality is relatively small for the thick tube bend.

References

[1] K. Zarrabi K and H. Zhang, *A model for integrity assessment of boiler tubes containing complex shaped scars,* the ASME/JSME Joint Pressure Vessels and Piping Conference, San Diego, California, July 26-30, (1998) PVP-Vol. 368, "Analysis and Design of Composite, Process, and Power Piping and Vessels", Edited by: D. K. Williams (1998), PP 3-8, ISBN No.: 0-7918-1864-0.

[2] Basu, A., *The Finite Element Analysis of Damaged Boiler Tubes,* PhD Thesis, The University of New South Wales, Sydney, Australia (2002).

[3] Zarrabi K and Basu A, *A finite volume formulation for solution of elastic axisymmetric pressurized components,* International Journal of Pressure Vessels and Piping, Vol. 77, No 8, pp 479-484, Nov (2000).

[4] PATRAN, PDA Engineering, Release 2.5, Oct (1990).

[5] Kitching R and Zarrabi K, *Limit and Burst Pressures for a Cylindrical Shell with a Part-through Slot,* International Journal of Pressure Vessels and Piping, Vol. 10, No 4, (1982).

[6] Zarrabi K, *Estimating the plane-strain fracture toughness under mode I from the uniaxial tensile data,* Proceedings of the Structural Integrity & Failure conference, CD-ROM, Sydney, Australia, 27 – 29 September (2006), ISBN: 1 876855 26 6.