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# Estimation of pressure drop in venturi scrubbers based on annular two-phase flow model, artificial neural networks and genetic algorithm

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ABSTRACT

Pressure drop is the most important factor affecting the dust collection efficiency in venturi scrubbers. The model described by Viswanathan et al. [S. Viswanathan, A.W. Gnyp, C.C. St. Pierre, Annular flow pressure drop model for Pease–Anthony type venturi scrubbers, AIChE J. 31 (1985) 1947–1958] predicts pressure drop according to an annular two-phase flow model, but there is a parameter lacking in order to implement this model. In this work, some correlations are suggested for use in Viswanathan's model. The results are compared with experimental data extracted from two different venturi scrubbers with different conditions. In these ranges of conditions, good agreement between the results of this modified model and experimental data shows the ability of the model to predict pressure drop. In the next step, artificial neural network was used to predict pressure drop in venturi scrubbers and acceptable results were obtained. For increasing the efficiency of neural networks, genetic algorithm was used to optimize parameters of the neural network such as the number of neurons in the hidden layer, the momentum rate and the learning rate. Finally, the model of neural network optimized by genetic algorithm was selected as the best model due to its agreement with experimental data and greater flexibility compared to mathematical models.



## 1. Introduction

The control of air pollution is one of the most important concerns for industrialized countries. Venturi scrubber is a popular gas cleaning device through its high efficiency for removing fine particles and soluble gas pollutants from gas. Venturi scrubbers consist of convergence, throat and divergence parts. Scrubbing liquid is injected from the beginning of the throat section, or entered as a film layer from the convergence. Liquid is atomized to very small droplets facing to gas stream that have a high kinetic energy at the beginning of the throat. These droplets remove pollutants from gas by impaction and interception mechanisms. Growing the gas velocity in the convergence section, friction and also energy transferred to droplets from gas in order to increase their momentum, cause pressure drop in venturi scrubbers. This pressure drop is very high compared to other air pollution controlling devices, so in spite of many advantages that venturi scrubbers have, they need a very high running cost to secure the pressure. Therefore pressure drop is an important designing factor in venturi scrubbers.

Many researches have been performed in order to predict this factor. The model of Calvert [2] is a popular model to predict pressure drop in venturi scrubbers due to its simplicity. Calvert [2] assumed that all the liquid is atomized and droplets are accelerated to reach the velocity of gas at the end of the throat. In this model wall friction and pressure recovery in the diffuser were neglected. Yung et al. [3] improved the model of Calvert by the assumption that droplets do not always reach the gas velocity at the end of the throat. Leith et al. [4] extended the model of Yung et al. [3] in order to include the pressure recovery due to the deceleration of droplets in the diffuser. Boll [5] developed a mathematical model based on momentum balance along the scrubber that include three mechanisms causing pressure drop namely the acceleration of the gas, the acceleration of droplets and friction. In this model complete atomization of the liquid was assumed.

Azzopardi and Govan [6] observed that there are some similarities between hydrodynamics in venturi scrubbers and an annular two-phase flow pattern and developed a model based on it. In this model droplet exchange between gas core and liquid film was considered. The model of Azzopardi and Govan resulted well up to the end of the throat, but it underestimated the pressure drop in the diffuser, so Azzopardi et al. [7] took into account the effect of the growth of the boundary layer in this part to reduce the pressure recovery. The results of this model were acceptable but it needs many equations and complicated algorithms. Viswanathan et al. [1] followed the idea of Azzopardi and Govan to describe the flow of gas and liquid in a venturi scrubber similar to annular two-phase

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**Nomenclature**

| | |
|---|---|
| $A$ | cross-sectional area ($m^2$) |
| $A_s$ | lateral area ($m^2$) |
| $C_D$ | drag coefficient |
| $D$ | diameter (m) |
| $D_H$ | hydraulic diameter (m) |
| $f$ | friction factor |
| $G$ | gas volumetric flow rate ($m^3/s$) |
| $H$ | half of the width of the throat (m) |
| $L$ | liquid volumetric flow rate ($m^3/s$) |
| $\dot{m}_d$ | mass flux of drops ($kg/m^2 s$) |
| $P$ | pressure (KPa) |
| $Q$ | volumetric flow rate ($m^3/s$) |
| $Re$ | Reynolds number |
| $V$ | velocity (m/s) |
| $V_s$ | superficial velocity (m/s) |
| $W$ | mass flow rate (kg/s) |
| $We$ | Weber number |
| $z$ | axial coordinate (m) |
| $\delta$ | film thickness (m) |
| $\rho$ | density ($kg/m^3$) |
| $\mu$ | viscosity (kg/m s) |
| $\tau_w$ | shear stress ($N/m^2$) |

*Subscripts*

| | |
|---|---|
| $c$ | core |
| $d$ | drop |
| $f$ | liquid film |
| $g$ | gas |
| $l$ | liquid |
| $o$ | nuzzle |
| $th$ | throat |

flow. Their model seems to perform reasonable but did not provide a correlation to estimate the fraction of water flowing on the wall; actually they used their experimental data to include this term to the model. Therefore, except for the cases that experimental data are available, it is not possible to implement this model accurately.

In this study at the first step it is tried to use some correlations for film flow rate, core and film friction factor in the model of Viswanathan to get better results. In our previous work [8], artificial neural networks were applied to predict pressure drop in venturi scrubbers. In the present work different types of venturi scrubbers have been used for training data set and the inputs of the ANNs are increased. Also, genetic algorithm is used to optimize the parameters of the ANNs to improve the results. Taheri and Mohebbi [9] used the same procedure to predict collection efficiency in venturi scrubbers.

## 2. Mathematical modeling

As mentioned before the model proposed by Viswanathan et al. [1] is based on an annular two-phase flow. This is a pattern that is described as a flow of gas including liquid drops in the core, and a flow of liquid film on the wall of the equipment.

Fig. 1 defines the control volume and related variables for a differential length of the venturi scrubber. A force balance on this element may be written as

$$d(PA) + W_g dV_g + W_d dV_d + W_f dV_f + d(AP_{TP}) = 0 \tag{1}$$

The second, third and fourth terms are considered momentum change of the gas, drops and liquid film, respectively. $P_{TP}$ is two-phase frictional pressure drop which is obtained from homogenous

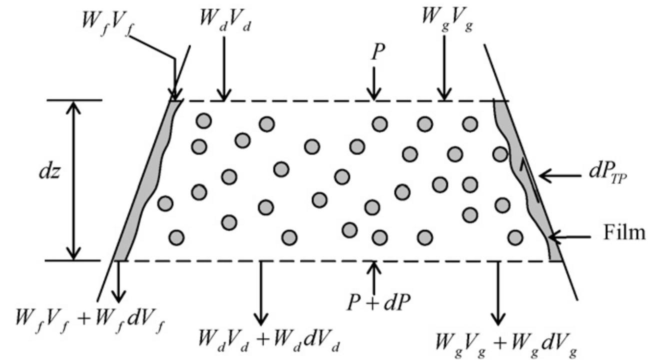


**Fig. 1.** Force balance on a differential element.

pressure gradient and two-phase friction factor. It is obvious that for the regions before liquid injection point, because there is no liquid droplet or film, the third and fourth terms will be omitted and the fifth term will be replaced by $d(A_s\tau_w)$, in order to include dry frictional pressure drop.

To calculate pressure drop, Eq. (1) and an equation for droplet velocity should be solved simultaneously. Droplet velocity can be determined from a force balance for droplet as Boll [5] obtained:

$$\frac{dV_d}{dt} = \frac{3}{4}\frac{\mu_g}{\rho_d}\frac{(V_g - V_d)}{D_d^2} C_{DN} \tag{2}$$

$C_{DN}$ is modified drag coefficient defined as

$$C_{DN} = Re_d C_D \tag{3}$$

Boll obtained drag coefficient, $C_D$, from standard curve. In this work it is observed that using the modified drag coefficient proposed by Talaie et al. [10] makes prediction of pressure drop significantly better, especially in the throat part of venturi scrubber. This coefficient is as follows:

$$C_{DN} = 18.65 Re_d^{0.16} \tag{4}$$

To solve Eq. (1), liquid film flow rate, core and film friction factor are required. Viswanathan et al. [1] determined the value of film flow rate from the experimental data. The correlations were used for defining core and film friction factor were not specified in Viswanathan's work. In this work to calculate pressure drop from Eq. (1), the following two correlations were applied to obtain the fraction of water flowing on the wall:

(1) Viswanathan et al.'s correlation [11]:

$$\frac{Q_f}{L} = \frac{89.379}{\left(\frac{L}{G} \times 1000 \times \frac{H}{D_o}\right)^{1.007} V_{gth}^{0.888}} \tag{5}$$

(2) Griffith and Wallis' correlation [12]:

$$\begin{aligned} \frac{Q_f}{L} &= 1 & V_{sl} &\leq 0.0304\,\text{m/s} \\ \frac{Q_f}{L} &= 0.0042 V_{sl}^{-1.5} & 0.0304 &< V_{sl} < 0.912\,\text{m/s} \\ \frac{Q_f}{L} &= 0.005 & V_{sl} &\geq 0.912\,\text{m/s} \end{aligned} \tag{6}$$

As can be seen in spite of the correlation of Griffith and Wallis that is used in both venturi scrubbers with rectangular and circular cross-sections, Viswanathan's correlation is just used in rectangular one.

Aziz et al. [13] established a method for defining core and film friction factor in annular two-phase flow. In this method the core friction factor is calculated from following equations:

$$f_c = (0.0014 + 0.125 Re_c^{-0.32})\left(1 + \frac{300\delta}{D_H}\right) \tag{7}$$

$$V_c = \frac{4(G + Q_d)}{\pi (D_H - 2\delta)^2} \tag{8}$$

where $\delta$ is the liquid film thickness which is calculated from Ishii and Grolmes [14] correlations by trial and error method.

Also liquid film friction factor is obtained from the following correlations:

$$\begin{aligned} f_f &= \frac{24}{Re_f} \qquad Re_f \le 2100 \\ f_f &= \frac{0.0913}{Re_f^{0.263}} \qquad Re_f > 2100 \end{aligned} \tag{9}$$

In order to increase the accuracy of the model, the elevation term of pressure drop is added:

$$\left(\frac{dP}{dz}\right)_{ele} = g\left(\frac{L}{L+G}\rho_l + \left(1 - \frac{L}{L+G}\right)\rho_g\right) \tag{10}$$

In the model described by Viswanathan et al. [1], the correlation of Nukiyama and Tanasawa [15] was used for calculating liquid droplet diameter that can be used just in Pease–Anthony venturi scrubbers. For the wetted wall venturi scrubbers the Azzopardi's correlation [16] can be used:

$$\frac{D_d}{D_{Hth}} = 1.91 \frac{Re_g^{0.1}}{We^{0.6}}\left(\frac{\rho_g}{\rho_l}\right)^{0.6} + 0.4 \frac{\dot{m}_d}{\rho_l V_{gth}} \tag{11}$$

According to these modifications, Eqs. (1) and (2) were solved numerically and pressure drop was obtained for two different venturi scrubbers and compared with experimental data.

## 3. Results of mathematical model

In Figs. 2–6 the pressure drop along venturi scrubber obtained with the proposed model are compared with the experimental data obtained by Viswanathan et al. [1] from a pilot Pease–Anthony venturi scrubber with a rectangular cross-section for five different liquid to gas flow rate ratios and three throat gas velocities. The correlation of Nukiyama and Tanasawa [15] for droplet diameter and Viswanathan's correlation for liquid film flow rate were used in the model.

We found that for calculating pressure drop along venturi scrubber for low values of the liquid to gas flow rate ratio, the correlations given by Griffith and Wallis for liquid film flow rate and Azzopardi for droplet diameter give a better result, which is shown in Fig. 7.

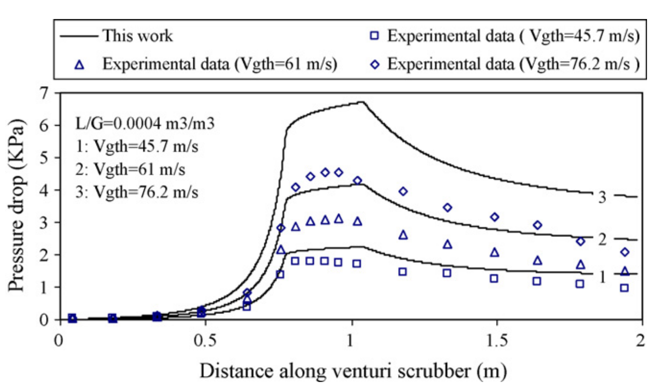


**Fig. 2.** The comparison of modeling results of this work with the experimental data reported by Viswanathan et al. [1] for $L/G = 0.0004\,m^3/m^3$.

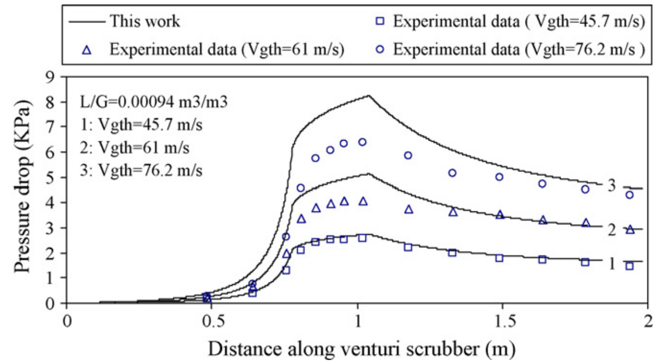


**Fig. 3.** The comparison of modeling results of this work with the experimental data reported by Viswanathan et al. [1] for $L/G = 0.00094\,m^3/m^3$.

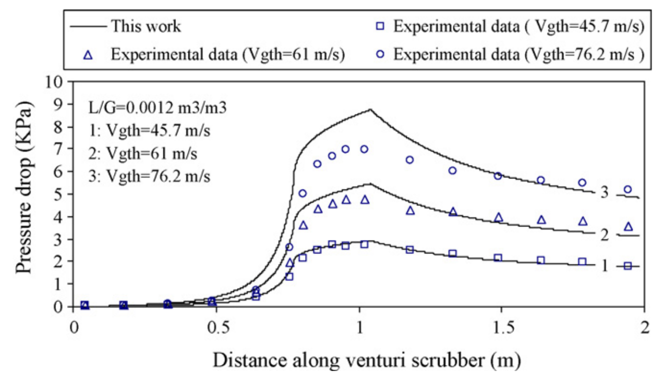


**Fig. 4.** The comparison of modeling results of this work with the experimental data reported by Viswanathan et al. [1] for $L/G = 0.0012\,m^3/m^3$.

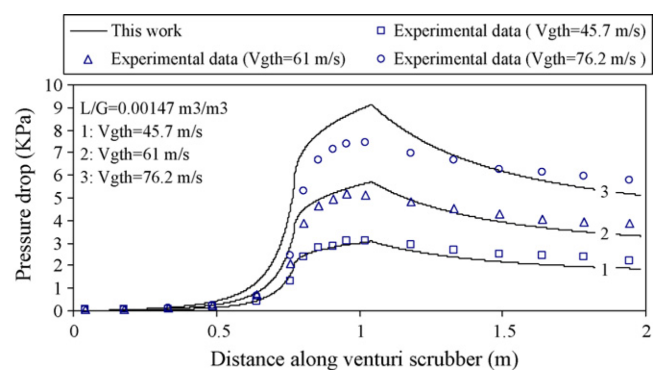


**Fig. 5.** The comparison of modeling results of this work with the experimental data reported by Viswanathan et al. [1] for $L/G = 0.00148\,m^3/m^3$.

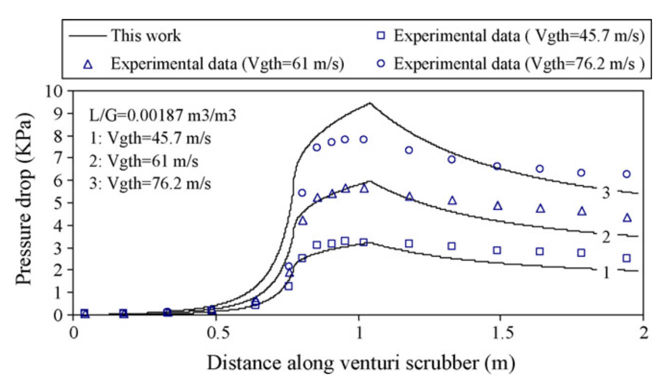


**Fig. 6.** The comparison of modeling results of this work with the experimental data reported by Viswanathan et al. [1] for $L/G = 0.00187\,m^3/m^3$.

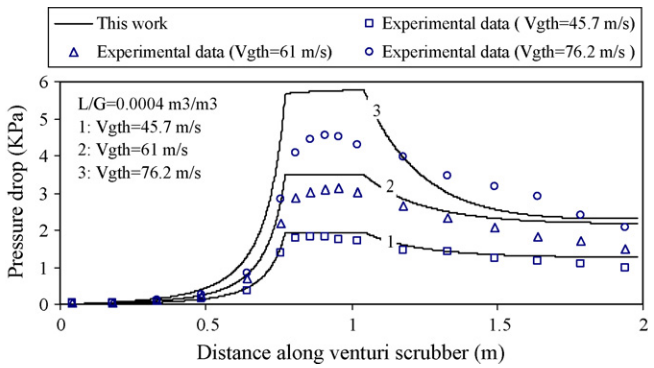


**Fig. 7.** The comparison of modeling results of this work with the experimental data reported by Viswanathan et al. [1] for $L/G = 0.0004\,m^3/m^3$ using the film flow rate of Griffith and Wallis [12] and the droplet diameter of Azzopardi [16].

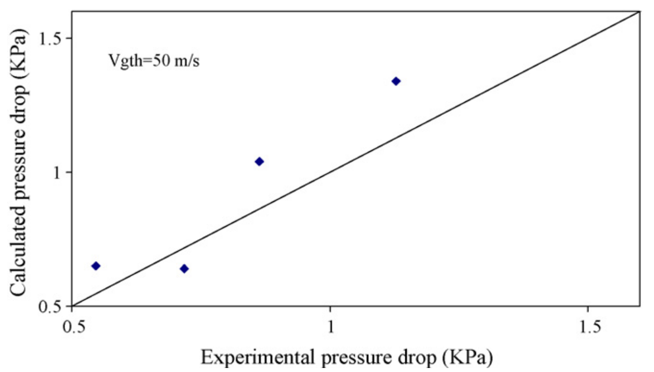


**Fig. 8.** The comparison of modeling results of this work with the experimental data reported by Goncalves et al. [17] for $V_{gth} = 50\,m/s$.

The experimental data reported by Goncalves et al. [17] for a small, circular, wetted wall venturi scrubber were used to test the validity of the proposed model. The correlations of Azzopardi for droplet diameter and Griffith and Wallis for liquid film flow rate were used. The comparison between the results of the model and Goncalves' experimental data are shown in Figs. 8–10 for three different throat gas velocities. Figs. 2–10 show that in most of the cases the results obtained with Viswanathan's model as modified in this work are in good agreement with experimental data obtained in the conditions described above. As can be seen, the agreement is better for lower throat gas velocities.

This model like other mathematical models has limitations and is not suitable for all physical conditions. So in the next step, artificial neural networks were applied to predict pressure drop in venturi scrubbers as a more general model.

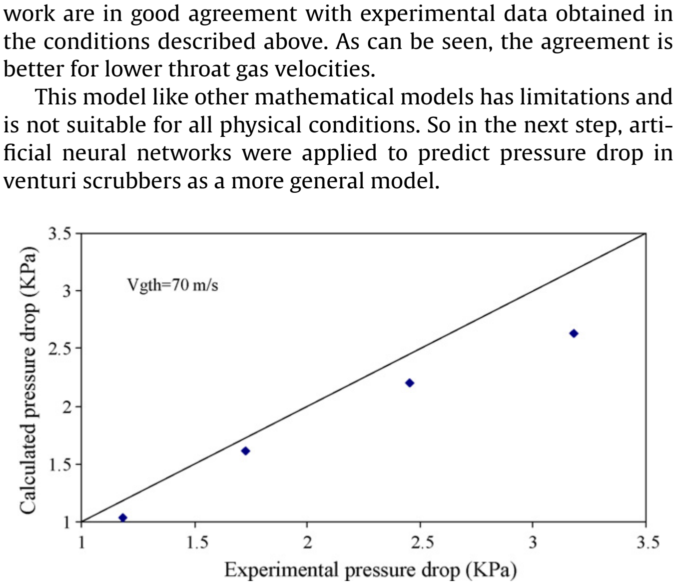


**Fig. 9.** The comparison of modeling results of this work with the experimental data reported by Goncalves et al. [17] for $V_{gth} = 70\,m/s$.

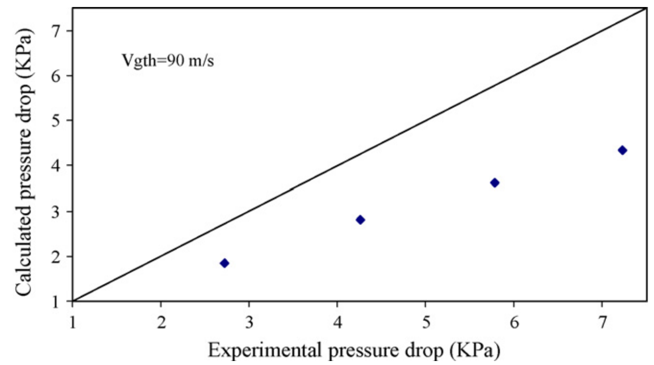


**Fig. 10.** The comparison of modeling results of this work with the experimental data reported by Goncalves et al. [17] for $V_{gth} = 90\,m/s$.

## 4. Artificial neural networks

Artificial neural networks that are mathematical techniques to deal with different types of problems are the networks of interconnected processing elements or neurons. ANNs can be trained to learn the relationship between two sets of input and output data. Multilayer perceptrons (MLPs), the best known type of neural networks, consist of input, hidden and output layers. The number of independent parameters affecting the outputs specifies the number of neurons in the input layer. The number of neurons in the hidden layer has been determined by trial and error or other methods during the training process [18].

Neural networks are trained by learning algorithms. The back propagation algorithm is the most commonly adopted MLP learning algorithm. Each neuron in hidden or output layers sum up its input signals after weighting them with the strengths of the respective connections from the previous layer and calculates its output signal as a function of the sum. The outputs of neurons in output layer are compared with desired values to compute the error. According to this error, weights are updated and this procedure is continued to reach an acceptable error [20]. Well-trained neural network will be able to give accurate outputs corresponding to new inputs.

### 4.1. Methodology

Azzopardi and Govan [6] identified three main parameters affecting pressure drop in venturi scrubbers; gas velocity in the throat ($V_{gth}$), liquid to gas flow rate ratio ($L/G$), and distance along the venturi scrubber ($z$). In our previous work [8], these parameters were the inputs of networks. In this study, two other inputs, throat hydraulic diameter ($D_{Hth}$) and throat length ($L_{th}$), were added to increase the efficiency of the networks.

Two neural networks were designed to estimate the wet pressure drop and the dry pressure drop in venturi scrubbers. The experimental data from seven different venturi scrubbers, including a pilot-scale rectangular Pease–Anthony venturi scrubber [1], a pilot-scale circular venturi scrubber with wetted wall irrigation [19], two pilot-scale ejector venturi scrubbers with different throat diameters [21], two small circular venturi scrubbers with jet and wetted wall approach for introducing the liquid [17], and a pilot-scale circular Pease–Anthony venturi scrubber [22], were used to train and test the networks. The first network with five inputs: $V_{gth}$, $L/G$, $z$, $D_{Hth}$ and $L_{th}$, used the experimental data from all seven venturi scrubbers to predict the wet pressure drop. The second network evaluates the dry pressure drop by including four inputs $V_{gth}$, $z$, $D_{Hth}$ and $L_{th}$ and used the experimental data from five venturi scrubbers. Pressure drop is the output of both networks. The range of inputs and outputs of these two networks is given in Tables 1 and 2.

**Table 1**
The range of experimental data used for training network No. 1.

| Venturi type | $V_{gth}$ (m/s) | $L/G \times 10^3$ ($m^3/m^3$) | $z$ (m) | $D_{Hth}$ (m) | $L_{th}$ (m) | $\Delta P$ (KPa) | Reference |
|---|---|---|---|---|---|---|---|
| Rectangular | 45.7, 61.0, 76.2 | 0.40, 1.23, 1.87 | 0–2 | 0.101 | 0.267 | 0.04–7.82 | [1] |
| Circular | 88.7<br>79.1, 99.5, 110 | 0.61, 0.76, 0.88, 1.01<br>0.2–1.0 | 0–1.415<br>1.415 | 0.16<br>0.16 | 0.206<br>0.206 | 0.65–8.18<br>1.75–6.57 | [19] |
| Circular | 8–24<br>11, 27 | 0–12.75<br>3.573, 7.145, 10.432 | 0.75<br>0–0.75 | 0.15<br>0.15 | 0.1<br>0.1 | 0–0.66<br>0.01–0.61 | [21] |
| Circular | 39 | 2.267, 4.534, 6.620 | 0–0.75 | 0.1 | 0.05 | 0.1–1.63 | [21] |
| Circular | 50, 70, 90 | 0.5–2 | 0.109 | 0.019 | 0.015 | 0.53–7.23 | [17] |
| Circular | 50 | 0.5–2 | 0.109 | 0.019 | 0.015 | 0.55–2.66 | [17] |
| Circular | 70<br>50, 70, 100 | 1.1, 1.65, 2.2, 2.75<br>0.54–2.74 | 0–1.5<br>1.39 | 0.07<br>0.07 | 0.14<br>0.14 | 1.84–11.93<br>0.96–18.87 | [22]<br>[22] |

**Table 2**
The range of experimental data used for training network No. 2.

| Venturi type | $V_{gth}$ (m/s) | $z$ (m) | $D_{Hth}$ (m) | $L_{th}$ (m) | $\Delta P$ (KPa) | Reference |
|---|---|---|---|---|---|---|
| Rectangular | 45.7, 61, 76.2 | 0–2 | 0.101 | 0.267 | 0.4–3.26 | [1] |
| Circular | 80.3, 94.5, 99.5 | 0–1.415 | 0.16 | 0.206 | 0–6.56 | [19] |
| Circular | 8.303–23.514 | 0.732 | 0.15 | 0.1 | 0.03–0.28 | [21] |
| Circular | 50, 70, 90 | 0.109 | 0.019 | 0.015 | 0.25–0.82 | [17] |
| Circular | 50, 70, 100 | 1.39 | 0.07 | 0.14 | 0.22–1.11 | [22] |

The networks were multilayer perceptron (MLP) type and a back-propagation algorithm was applied for training them. In these two networks, just one hidden layer is considered with 5 and 6 neurons, respectively. These values were determined by trial and error based on the mean square error of the outputs of the testing process. Table 3 gives the results of training and testing processes for two networks based on the mean square error and the $R$-squared ($R^2$) between network outputs and the experimental data. As can be seen from Table 3, the $R^2$ values are close to unity, confirming that neural networks can be used to predict the pressure drop in venturi scrubbers. But the MSE values are still not acceptable and can be decreased using an optimization method, so genetic algorithm is applied for this purpose.

In the next section, genetic algorithm is described briefly and used for improving the performance of two networks.

## 5. Genetic algorithm

A genetic algorithm (GA) is an optimization algorithm based on evolution principles. GA can be a learning algorithm for training MLPs, and in this way the weights of the connections are considered as genes in a chromosome. In this study, the genes in a chromosome are the learning rate, momentum rate and the number of neurons in the hidden layer. The goodness or fitness of a chromosome is related inversely to the mean square error of the MLP outputs. In other words, a chromosome that trains the MLP better has a higher fitness number.

The algorithm starts with a population of chromosomes produced at random and then genetic operators act on them to create a new and fitter population. These operators commonly are selection, crossover and mutation operators. The selection operator chooses chromosomes with higher fitness numbers; the crossover operator selects two chromosomes at random, cuts them at a random position and exchanges the parts following the cut to create two new chromosomes. The mutation operator changes the genes of a chromosome according to a low probability to create a new chromosome. In this way, a fitter population of chromosomes is created. This procedure is repeated to reach a population of chromosomes with an acceptable fitness number [23].

**Table 3**
The results of training and testing of two networks.

| | Training process | | Testing process | |
|---|---|---|---|---|
| | $R$-squared | MSE | $R$-squared | MSE |
| Network 1 | 0.9940 | 0.1091 | 0.9826 | 3.1693 |
| Network 2 | 0.9971 | 0.0215 | 0.9952 | 0.0364 |

According to this approach, two neural networks were created and optimized to predict wet and dry pressure drop in venturi scrubbers, we used NeuroSolution software [24] for this purpose; this is a software that is specialized for optimizing the parameters of ANN by using GA. 80% of data were used for training and cross-validation, and the remainders were used for testing the networks. Many tests were performed with different operators, population and generation sizes based on momentum and Levenberg–Marquardt methods for updating the weights, and the best networks were chosen. Using the Levenberg–Marquardt method, Roulette Wheel selection operator and a two-point crossover operator gave the best results for training two networks. Both networks, with one hidden layer and 5 neurons in each layer, showed the best agreement with the experimental data. Figs. 11 and 12 show the average fitness in each generation for two networks.

Table 4 gives the mean square error (MSE), mean absolute error (MAE), minimum and maximum absolute error, and the $R$-squared

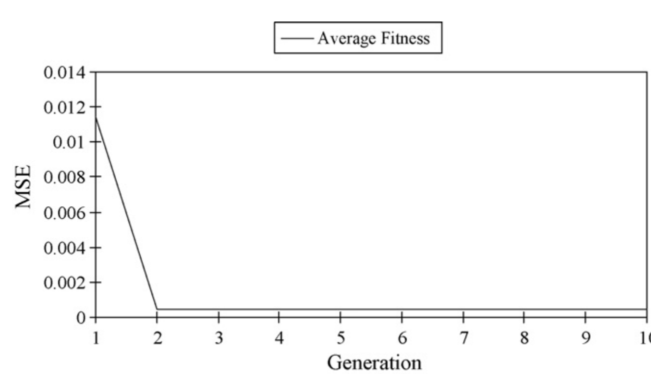


**Fig. 11.** Average fitness in each generation for network 1.

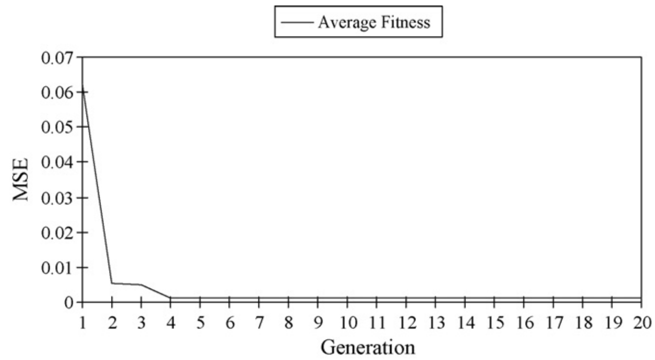


**Fig. 12.** Average fitness in each generation for network 2.

**Table 4**
The results of testing the networks.

| | Network 1 | Network 2 |
|---|---|---|
| MSE | 0.1529 | 0.0087 |
| MAE | 0.2780 | 0.0757 |
| Min Abs Error | 0.0035 | 0.0186 |
| Max Abs Error | 1.5064 | 0.1865 |
| *R*-squared | 0.9912 | 0.9987 |

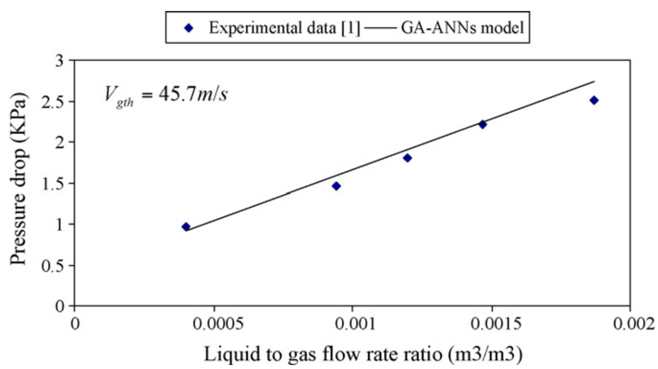


**Fig. 13.** The effect of liquid to gas flow rate ratio on the total pressure drop in the venturi scrubber of Viswanathan et al. [1] (ANN No. 1).

between the outputs of the networks and the experimental data for the testing process. A comparison of Tables 3 and 4 shows that GA makes a great improvement in the performance of the neural networks.

The effect of the main parameters on pressure drop in venturi scrubbers predicted by the GA–ANNs model is illustrated by Figs. 13–15, which also represent the accuracy of the model.

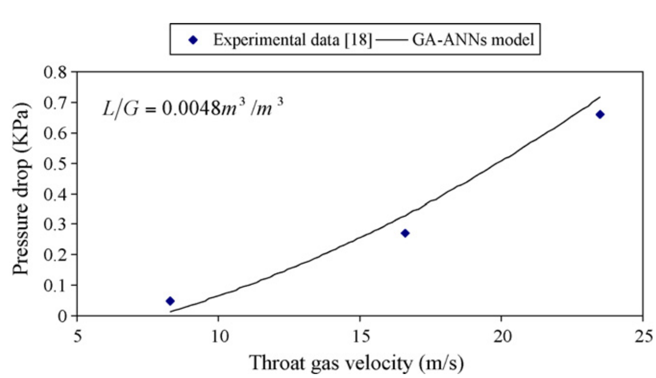


**Fig. 14.** The effect of throat gas velocity on the total pressure drop in the venturi scrubber of Gamisans et al. [21] (ANN No. 1).

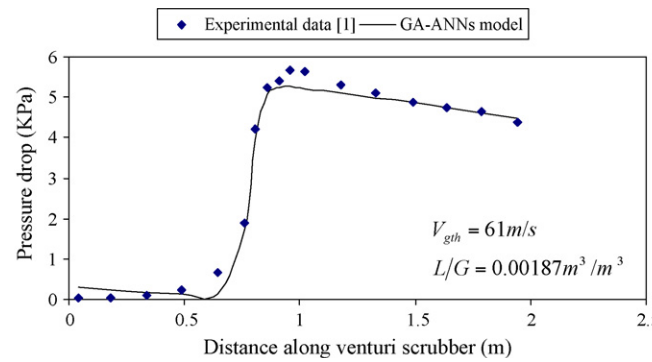


**Fig. 15.** The effect of distance along venturi on the total pressure drop in the venturi scrubber of Viswanathan et al. [1] (ANN No. 1).

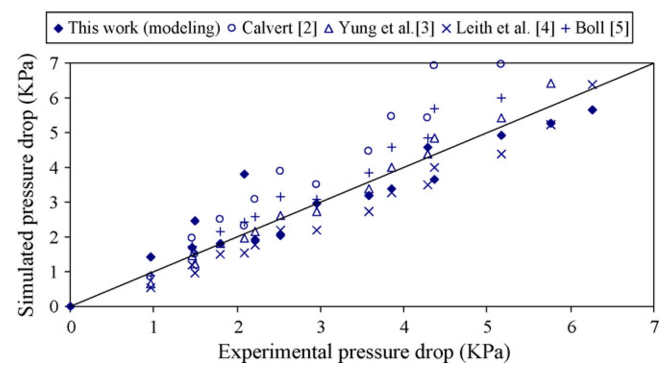


**Fig. 16.** The comparison of results of different models with the experimental data reported by Viswanathan et al. [1].

## 6. Overall results and discussions

In Fig. 16, Viswanathan's model as modified here, and the models described by Calvert [2], Yung et al. [3], Leith et al. [4] and Boll [5] for predicting pressure drop in venturi scrubbers are compared with Viswanathan's experimental data [1]. Figs. 17–19 illustrate the comparison with Goncalves' experimental data [17]. In order to apply Boll and Yung's models for venturi scrubbers with a film injection system, the correlation of Azzopardi [16] was used to evaluate droplet diameter instead of using Nukiyama and Tanasawa's equation [15].

Figs. 16–19 indicate an acceptable agreement between the results of the model described here and the experimental data. The model proposed by Calvert overestimates pressure drop significantly, probably due to its reliance on a large number of simplifying assumptions. The length of throat in Goncalves' venturi scrubber is

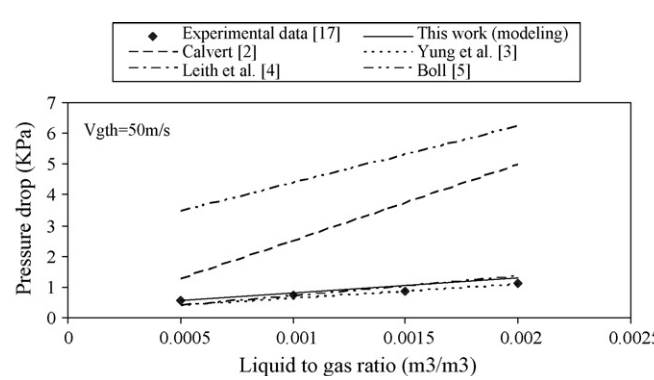


**Fig. 17.** The comparison of results of different models with the experimental data reported by Goncalves et al. [17] for $V_{gth} = 50$ m/s.

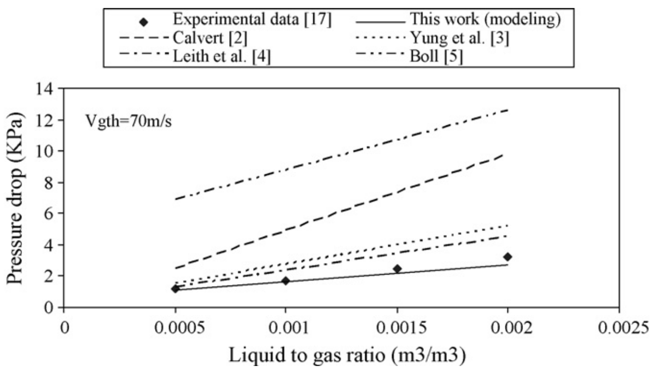


**Fig. 18.** The comparison of results of different models with the experimental data reported by Goncalves et al. [17] for $V_{gth}$ = 70 m/s.

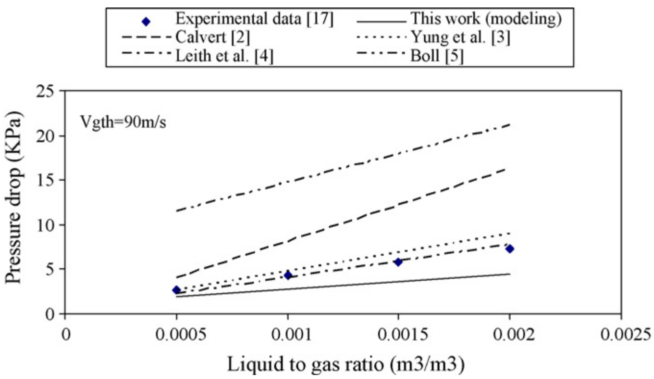


**Fig. 19.** The comparison of results of different models with the experimental data reported by Goncalves et al. [17] for $V_{gth}$ = 90 m/s.

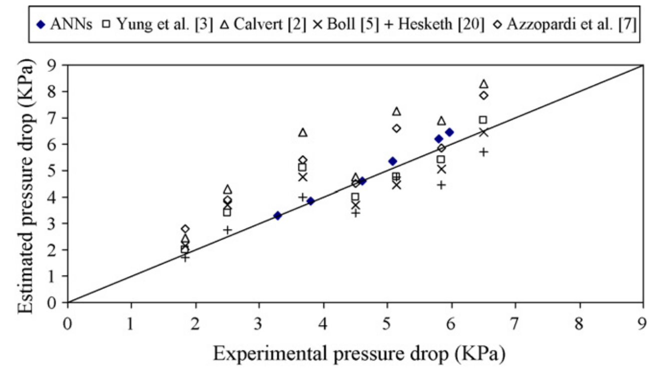


**Fig. 20.** The comparison of different models with the testing results of ANN No. 1 based on experimental data of Allen and van Santen circular venturi scrubber [19].

less than that of Viswanathan's, so the droplets have less time to reach the velocity of gas at the end of the throat, and therefore the deviation of Calvert's model from the experimental data is greater for this venturi compared to Viswanathan's.

In spite of their simplifications, the accuracy of the prediction made by the models described by Yung and Leith is surprising. In these models, complete atomization of liquid was considered. Yung's model ignored the wall–gas stress, and the pressure drop due to the momentum change of the gas along the venturi, which compensates for the overestimation due to the assumption of complete atomization of liquid. Consideration of the pressure recovery due to the deceleration of droplets is the only correction made in the model described by Leith compared to Yung's model. Hence, in most of the cases, Leith's model predictions are lower than Yung's model. In the model described by Boll, the complete atomization of liquid was assumed, and wall–gas friction and pressure drop due to the momentum change of the gas were taken into account. As a result, Boll's model overestimates the pressure drop. This overestimation is considerably high in the case of Goncalves' venturi because pressure loss due to friction is quite important in small venturi scrubbers.

In Goncalves' venturi the liquid was introduced as a film and the fraction of atomized liquid was low, consequently the complete atomization of liquid that is assumed in the models described by Calvert, Yung, Leith and Boll predicts a greater pressure drop in this venturi in contrast to Viswanathan's venturi scrubber. But, as can be observed in Figs. 17–19, the deviation of these models decreases when the gas throat velocity increases, due to the increased fraction of atomized liquid.

Comparing Fig. 16 with Figs. 17–19 indicates that, except for $V_{gth}$ = 90 m/s, the modeling described here gives more accurate predictions for Goncalves' venturi scrubber. This can be explained by the fact that the flow of gas and liquid in this venturi scrubber, which is used film approach, is more similar to an annular two-phase flow pattern. In this pattern of flow, droplets are created only due to shear stress between the gas and the liquid film layer on the wall. Consequently, this modeling, which is based on annular two-phase flow pattern, gives more satisfactory predictions for Goncalves' venturi scrubber.

Fig. 20 shows a comparison between the results of ANN No. 1 and pressure drop calculated by the models described by Yung et al. [3], Calvert [2], Boll [5], Hesketh [25] and Azzopardi et al. [7] for the Allen and van Santen circular venturi scrubber [19]. This figure indicates that the artificial neural network predicts pressure drop more accurately than other models.

At the first use of ANNs, the optimum number of neurons in the hidden layer has to be found by trial and error. This method is extremely time-consuming and is not sufficiently accurate, so GA is used to optimize the number of neurons in the hidden layer. Many tests were performed for training the networks on the basis of two methods of updating the weights; momentum and Levenberg–Marquardt. For the momentum method, momentum rate and learning rate were optimized in addition to the number of neurons in a hidden layer. The results of these tests and those of the trial and error method are given in Table 5 based on the testing process. Table 5 shows that the GA method performs considerably better than the trial and error method. GA creates simpler networks with fewer neurons in the hidden layer, and for networks of equal size it has a better $R$-squared (close to unity). Also, the time taken

**Table 5**
The comparison of two methods of training of the networks and two methods of updating the weights.

| | | Momentum | | | Levenberg–Marquardt | | |
|---|---|---|---|---|---|---|---|
| | | $N$ | $R^2$ | MSE | $N$ | $R^2$ | MSE |
| Trial and error | Network 1 | 5 | 0.8536 | 4.6605 | 5 | 0.9826 | 3.1693 |
| | Network 2 | 4 | 0.7059 | 1.8146 | 6 | 0.9952 | 0.0364 |
| Genetic algorithm | Network 1 | 4 | 0.9240 | 0.9791 | 5 | 0.9912 | 0.1927 |
| | Network 2 | 5 | 0.9939 | 0.0748 | 5 | 0.9987 | 0.0255 |

$N$: the number of neurons in hidden layer.

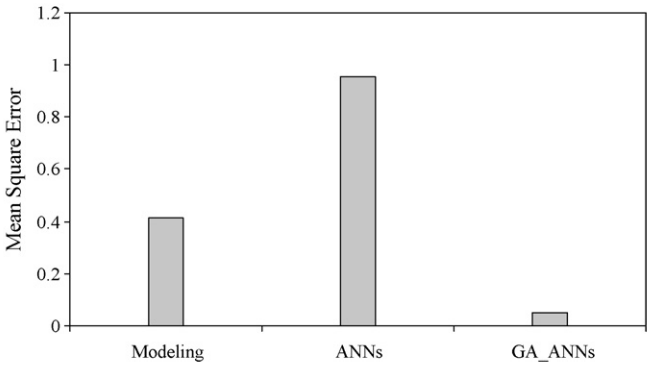


**Fig. 21.** The comparison of three models proposed in this work based on the experimental data reported by Viswanathan et al. [1].

to build the neural networks by using GA is less than trial and error method.

Comparing two methods of updating the weights indicates that the Levenberg–Marquardt method usually gives better results than the momentum method. This is not surprising, because the Levenberg–Marquardt is a quadratic method for updating the weights and performs better than linear methods. Also, using a quadratic method converges the outputs faster.

A comparison, based on mean square error, of the results obtained with the three models proposed in this work and the experimental data reported by Viswanathan et al. [1] is shown in Fig. 21. This figure shows that the artificial neural networks optimized by genetic algorithm (GA–ANNs) are in the closest agreement with the experimental data. In order to use the created neural networks for predicting pressure drop in a venturi scrubber, the range of inputs should be covered by the range of training data set.

## 7. Conclusions

Studying the available mathematical models indicates that each of them performs reasonably in a special range of conditions. So, in order to use these models, their limitations should be considered. In this work, the experimental data of venturi scrubbers with different types, shapes, sizes and operating conditions, with three liquid injection systems, were used for training two neural networks, and the results converged well. So neural networks have fewer restrictions. Finally, according to good predictions a neural network optimized by GA is a reliable tool for predicting pressure drop in venturi scrubbers.

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