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Predicting pressure drop in venturi scrubbers with artificial neural networks

S. Nasseh, A. Mohebbi*, Z. Jeirani, A. Sarrafi

Department of Chemical Engineering, Faculty of Engineering, Shahid Bahonar University of Kerman, Kerman, Iran

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Abstract

In this study a new approach based on artificial neural networks (ANNs) has been used to predict pressure drop in venturi scrubbers. The main parameters affecting the pressure drop are mainly the gas velocity in the throat of venturi scrubber ($V_{g_{th}}$), liquid to gas flow rate ratio (*L*/*G*), and axial distance of the venturi scrubber (*z*). Three sets of experimental data from five different venturi scrubbers have been applied to design three independent ANNs. Comparing the results of these ANNs and the calculated results from available models shows that the results of ANNs have a better agreement with experimental data.

Keywords: Venturi scrubber; Pressure drop; Back-propagation; ANNs

1. Introduction

Strict environmental regulations adopted in recent times and applied to pollutions especially air pollutions has forced factories to take steps to curb emission into the atmosphere. This means not only improving their existing equipments but also the use of new technologies. Venturi scrubbers are the most efficient wet devices for collecting fine particles and soluble gas pollutants.

The three main parts of a typical venturi scrubber is shown in Fig. 1, which are the convergence, throat, and diffuser whereby the velocity of the entering gas is increased so that the high kinetic energy generated atomizes the injected liquid to very small drops and liquid reaches the velocity of gas as it passes through the diffuser. In this way particles are transferred from the gas to the liquid, according to the inertial impaction, but the acceleration of the gas increases the pressure drop.

In this process the ratio of particle collection to pressure drop expresses the efficiency. Therefore, the study of pressure drop in venturi scrubbers due to its necessity have been the subject of many researches.

Calvert [6] who presented the first model for pressure drop in venturi scrubbers, neglected wall friction and momentum recovery in the divergent section, so other researchers tried to improve this model. Boll [5] solved simultaneous equations of drop motion and momentum exchange for variable cross section ducts with acceptable results except for very high and low liquid to gas ratios where it did not show agreement with the experimental data. Azzopardi and Govan [2] considered momentum losses due to accelerating droplets entrained from the film and the interfacial drag between the fast moving core and the slower moving liquid film. However, they had little successes with this procedure. Later on, Viswanathan et al. [17] developed an annular flow pressure drop model in which a constant core quality throughout the venturi were assumed. After that their model was improved by considering the growth and separation of the gas boundary layer [3,4]. Allen and van Santen [1] considered the importance of dry pressure drop in venturi scrubbers and compared the experimental pressure drop with the predicted values. Pulley [15] carried out various experiments and suggested more effective variables such as drop size, entrainment at liquid injection, entrainment and deposition along the venturi length and corrected the proposed model of Azzopardi et al. [3]. Viswanathan [18] investigated the effect of liquid to gas ratios, throat gas velocities, and throat areas and introduced a simple empirical correlation for the pressure drop in a variable throat

* Corresponding author.
E-mail address: amohebbi2002@yahoo.com (A. Mohebbi).

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Nomenclature

D_{th}	throat diameter of venture scrubber (m)
L	liquid flow rate (m^3/h)
L/G	the liquid to gas ratio (m^3/m^3)
ΔP	pressure drop (mm w g)
R^2	regression constant
$V_{g_{th}}$	overall gas velocity in the throat (m/s)
z	the axial distance of the venturi scrubbers (m)

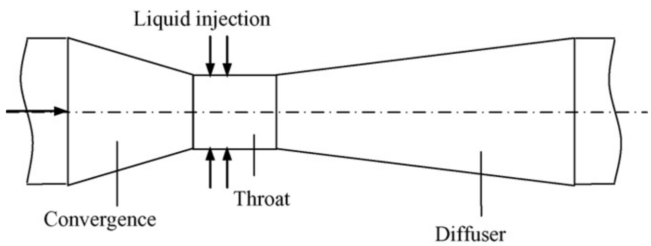

Fig. 1. The schematic of a venturi scrubber.

venturi scrubber. Gonçalves et al. [10] studied the previous models for the prediction of pressure drop in venturi scrubbers and stated that most of them must be used with caution. Gamisans et al. [9] studied the effect of throat diameter, length and spray angle on the performance of ejector venturi scrubbers.

There are several data infilling techniques which have been used commonly, e.g. artificial neural networks (ANNs), regression methods, etc. Despite the criticisms formulated against ANNs techniques, these techniques were found to be powerful tools when compared to multivariate regression based models for infilling the missing data [13]. ANNs techniques can be used to express a non-linear mapping between variables with no prior assumptions on the variables (linear or non-linear as in regression methods) and these techniques can cope with missing data [8]. In the past decade, ANNs have been used intensively in various fields. However, their applications for infilling pressure drop data in venturi scrubbers have not been considered so much before.

2. Artificial neural networks

In general neural networks are simply mathematical techniques designed to accomplish a variety of tasks. Neural networks can be configured in various arrangements to perform a range of tasks including pattern recognition, data mining, classification, and process modeling. ANNs are networks of interconnected simple units (nodes) that are based on a greatly simplified model of the human brain.

The advantage of the ANNs, even if the "exact" relationship between sets of inputs and outputs data is unknown but is acknowledged to exist, is that the network can be trained to learn that relationship, requiring no prior underlying assumptions (non-linear versus linear) as in conventional methods, and they are regarded as ultimate black-box models.

The architecture of an ANN consists of input, hidden, and output layers. The number of neurons (nodes) in the input and output layers is the same as the number of the known independent parameters. The number of hidden neurons has been determined during the training process by trial and error method.

There are two main types of ANNs, i.e. feed-forward networks (where the signal is propagated only from the input nodes to the output nodes) and recurrent networks where the signal is propagated in both directions. A neural network is trained in order to establish a fit to a set of examples, i.e. the network should output values close to the target values assigned by an expert-teacher to the training set of objects. Well trained networks generalize in the sense that their outputs are correct for objects not available in the training set.

The back-propagation method is a technique used in training multilayer neural networks in a supervised manner. The back-propagation method, also known as the error back propagation algorithm, is based on the error-correction learning rule [14]. It consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an activity pattern is applied to the input nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network.

Although ANNs are utilized in various fields of science, however, the application of ANNs in infilling data of pressure drop in venturi scrubbers remains sparse. In this study ANN techniques by feed-forward back-propagation algorithms are employed using Matlab's toolbox [12].

3. Methodology

Azzopardi and Govan [2] identified five mechanisms causing pressure drop in venturi scrubbers and showed that three main parameters in this phenomenon are gas velocity in the throat part of the venturi scrubber ($V_{g_{th}}$), liquid to gas flow rate ratio (L/G), and axial distance of the venturi scrubber (z) which indicated venturi geometry. In previous investigations empirical or semi-empirical pressure drop correlations for numerous and varied venturi scrubbers has been produced as a function of these parameters.

In this study, ANNs are devoted to the estimation of pressure drop in venturi scrubbers. Three separate neural networks are designed. The experimental data are extracted from five different venturi scrubbers, a rectangular venturi scrubber of the Pease Anthony type [17], a circular and an adjustable prismatic venturi scrubber that are both used wetted wall irrigation [1] and two ejector venturi scrubbers with different throat diameter [9]. All the five venturi scrubbers are used for training the first network. The input vectors for this network are $V_{g_{th}}$, L/G and z. The second network that evaluates dry pressure drop, is based on the experimental data of circular venturi scrubber. The main parameters of this network are $V_{g_{th}}$ and z. In the third network we have shown that throat diameter, liquid flow rate, throat gas velocity and axial distance of the venturi scrubber, can be equally considered as the main parameters in pressure drop of a venturi scrubber. So, the third network has four inputs and is trained based on the experimental data of both ejector venturi

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)	ΔP (mm w g)	Reference
Rectangular	45.7, 61.0, 76.0	0.40, 1.23, 1.87	0–2	0–818.6	[17]
Circular	88.7	0.61, 0.76, 0.88, 1.01	0–1.415	453.3–834.5	[1]
	79.1, 99.5, 110	0.2–1.0	1.415	178.3–670.0	
Prismatic	47, 66, 84, 114	0.2–1.3	0.74	70–827	[1]
Ejector	8–24	0–12.75	0.75	−9.4–67.1	[9]
	11, 27	3.573, 7.145, 10.432	0–0.75	−18.0–62.2	
Ejector	39	2.267, 4.534, 6.620	0–0.75	0.1–166.3	[9]

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

Venturi type	Circular
V_{gth} (m/s)	80.3, 94.5, 99.5
z (m)	1–1.415
ΔP (mm w g)	0–668.7
Reference	[1]

scrubbers and the circular one. Tables 1–3 show the domain of input and output parameters for three networks.

The ANNs contain three layers and follow feed-forward back-propagation algorithm to train the input data. The number of neurons in the first layer may be varied from two to four neurons. Despite this fact, the target vectors for all networks include only one parameter which is the pressure drop value (ΔP) in the venturi scrubbers. In this work we have just one hidden layer with different number of neurons for three networks. The design of ANNs is shown in Fig. 2. The input and target vectors are entered in the network in the normalized way and the networks are trained by these vectors. After the end of training in the best manner with the least error compared with the input data, the network is capable of simulating a set of data not seen before.

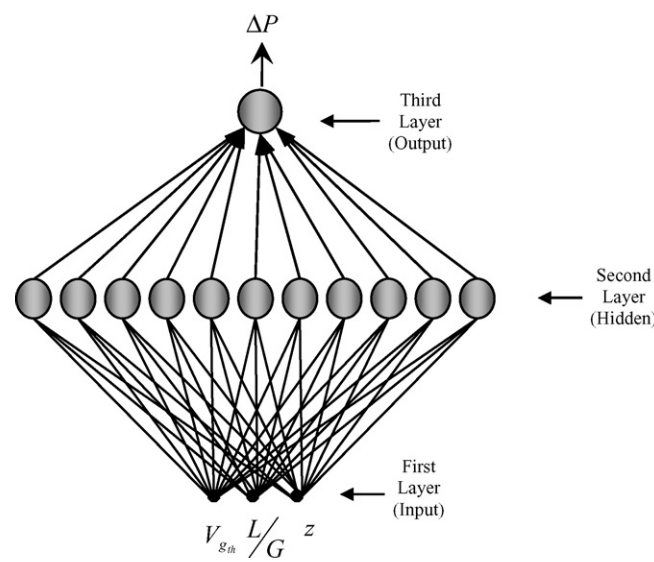

Fig. 2. The design of ANNs.

4. Results and discussions

In this study, three different experimental data sets have been used to design the ANNs. In order to increase the number of data, we have interpolated between every two close data. The number of patterns (i.e. number of data sets) for training and simulating networks 1, 2 and 3 are 661, 87 and 368, respectively. One half of three different data sets for various venturi scrubbers are used here to train three independent ANNs and the other half are entered to the networks as the input necessary for simulating process. Networks are containing 11, 5 and 6 neurons, respectively for their hidden layers. The number of neurons for this layer was ascertained by trial and error, and the most suitable number of neurons was chosen in such a way that the training results were converge out to the experimental data. Fig. 3 shows that the best number of neurons for ANN No. 1, is a network with 11 neurons in hidden layer which gives results in good agreement with the experimental data. Figs. 4–6 show the training results and the agreement between these data. On the basis of such good trainings, the resulting ANNs are capable enough to simulate the other half of data by their application to the relevant networks gave such simulated data as depicted in Figs. 7–9. In these figures, simulated and experimental data are compared. An excellent agreement can be seen in between them. The equation in the form of $y = ax + b$ appearing in Figs. 4–9 is the equation of the adapted least regression line with best state

Table 3
The range of experimental data used for training network No. 3

Venturi type	D_{th} (m)	V_{gth} (m/s)	L (m^3/h)	z (m)	ΔP (mm w g)	Reference
Circular	0.16	88.7	1.088, 1.355, 1.569, 1.964	0–1.415	453.3–834.5	[1]
		79.1, 99.5, 110	0.442–1.871	1.415	178.3–670.0	
Ejector	0.15	8–24	0, 2.5, 5, 7.3	0.75	−9.4–67.1	[9]
		11, 27	0, 2.5, 5.0, 7.3	0–0.75	−18.0–62.2	
Ejector	0.10	39	2.5, 5.0, 7.3	0–0.75	0.1–166.3	[9]

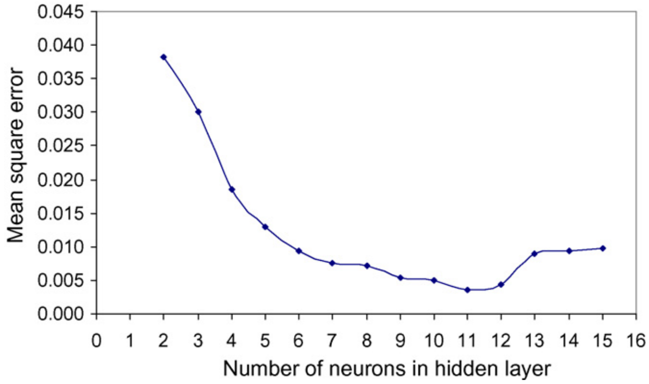

Fig. 3. Mean square error for training data with various numbers of neurons in hidden layer for ANN No. 1.

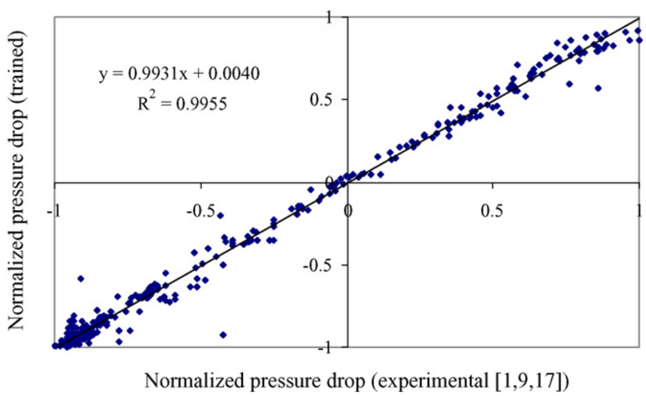

Fig. 4. The ANN No. 1 training results.

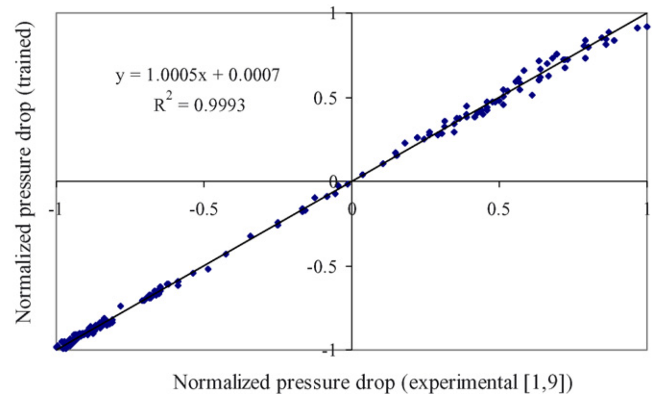

Fig. 6. The ANN No. 3 training results.

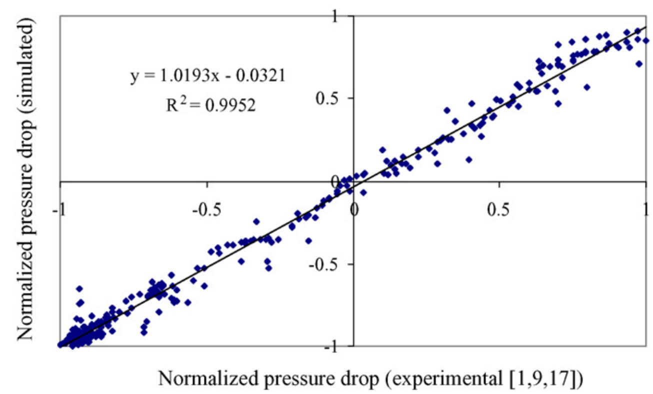

Fig. 7. The ANN No. 1 simulating results.

as $y = x$ happening when all the points fall exactly on a line at 45°, i.e. the network predicts results exactly the same as the experimental ones. Constants of the equation however, show the deviation of the state from the ideal one. In addition to the equation, the regression constants (R^2-value) which are also appeared in these figures show the agreement of trained and simulated data with experimental data to be better than the regression line. In an ideal situation, when these parameters are exactly similar, $R^2 = 1$.

After confirming the networks (i.e. training and simulating), the effect of various parameters such as throat gas velocity, liquid to gas ratio and distance along venturi on the pressure drop of the venturi scrubber were obtained. The effects of the three parameters L/G, $V_{g_{th}}$ and z on the pressure drop in venturi scrubbers have been investigated in different works previously [6,5,2,3,10]. The simulated results for ANN No. 1, confirm the trend proposed by their works. Figs. 10–12 indicate their effects on the pressure drop in this network. As one can see, there is good agreement between the experimental data and the results of ANNs. The dependence of pressure drop in venturi scrubber No. 1 on liquid to gas ratio (L/G) is due to droplet acceleration and friction of gas with wall or film. As a result, the pressure drop increases linearly

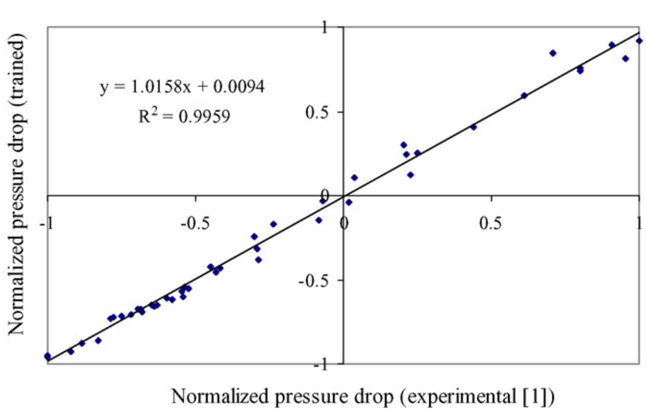

Fig. 5. The ANN No. 2 training results.

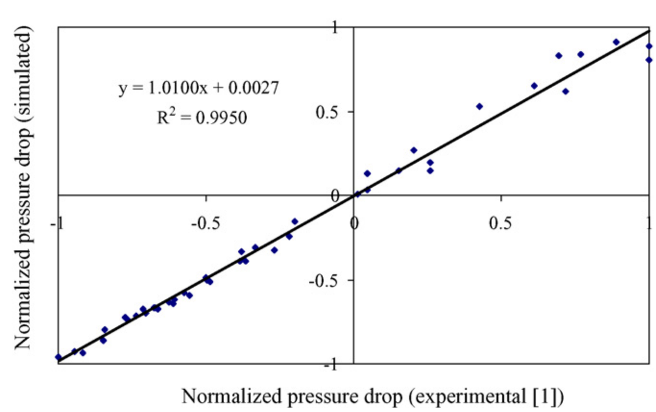

Fig. 8. The ANN No. 2 simulating results.

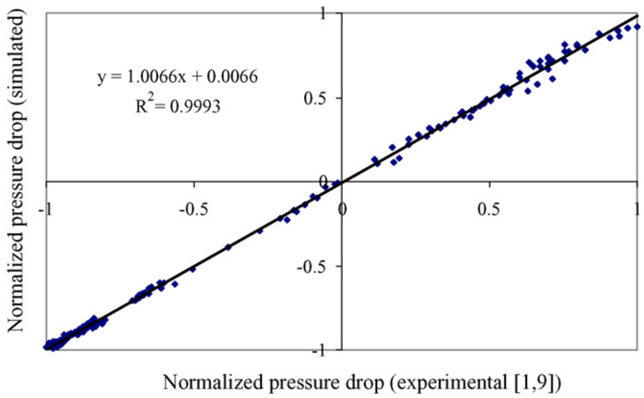

Fig. 9. The ANN No. 3 simulating results.

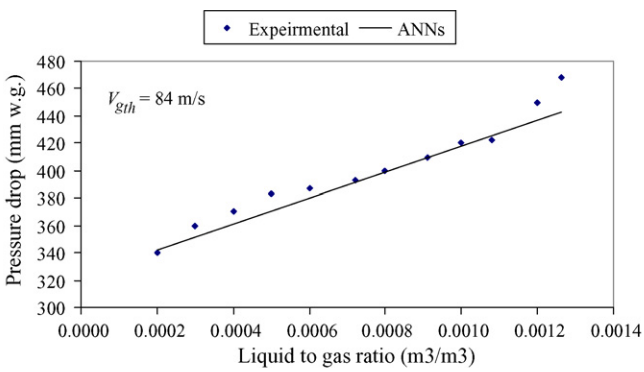

Fig. 10. The effect of liquid to gas ratio on the total pressure drop in prismatic venturi scrubber (ANN No. 1).

with increasing liquid to gas ratio. Similarly, the pressure drop in venturi scrubbers varies with throat gas velocity ($V_{g_{th}}$) in a linear form. On the other hand, by increasing the distance along venturi (z) the pressure drop first increases and then decreases. In the throat section as a result of energy transferred in accelerating the liquid film, the pressure drop increases. However, the pressure drop rise in the throat is linear. The maximum pressure drop happens at the end of the throat part. In the diffuser, pressure is recovered from both the expansion of the gas and energy transfer from the decelerating droplets. Figs. 13 and 14 show the effects of throat gas velocity and distance along venturi on dry pressure drop in ANN No. 2. Pressure drop increases with

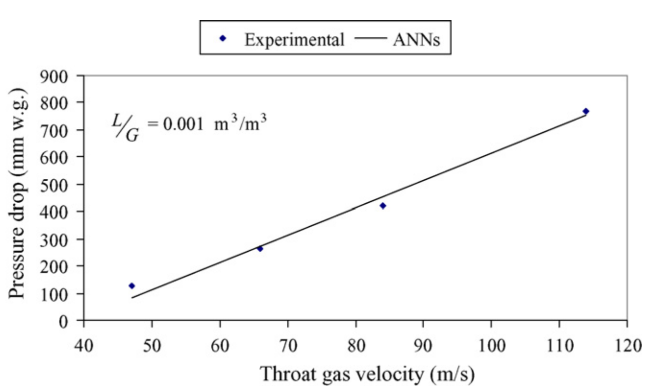

Fig. 11. The effect of throat gas velocity on the total pressure drop in prismatic venturi scrubber (ANN No. 1).

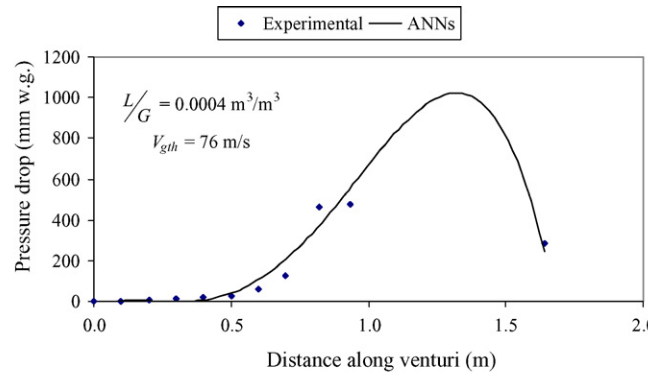

Fig. 12. The effect of distance along venturi on the pressure drop in rectangular venturi scrubber (ANN No. 1).

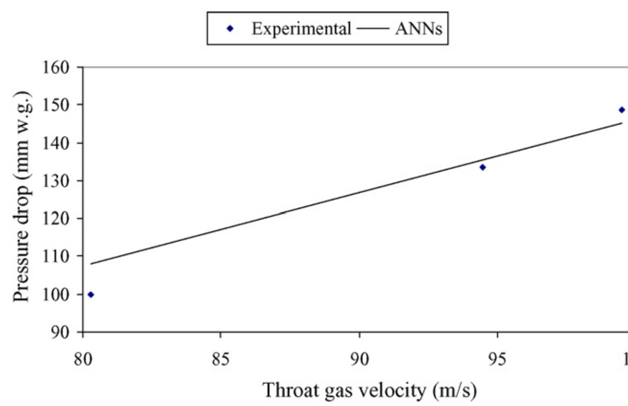

Fig. 13. The effect of throat gas velocity on the total pressure drop in circular venturi scrubber (ANN No. 2).

throat gas velocity because of friction of the gas against the wall (see Fig. 13) and it increases with axial distance in convergence section, being nearly constant in throat section and decreases in diffuser because of the variations of velocity in different parts of venturi scrubber (see Fig. 14).

In the next step, the calculated (simulated) results of the ANN No. 1 as presented in this work and the calculated results from models proposed by Azzopardi and Govan [2], Boll [5], Calvert [7], Hesketh [11], and Yung et al. [19] are compared with the experimental data. These results are represented in Fig. 15. In

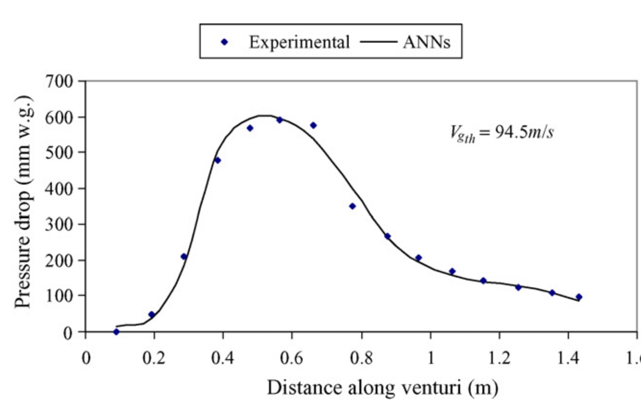

Fig. 14. The effect of distance along venturi on the pressure drop in venturi scrubber No. 2.

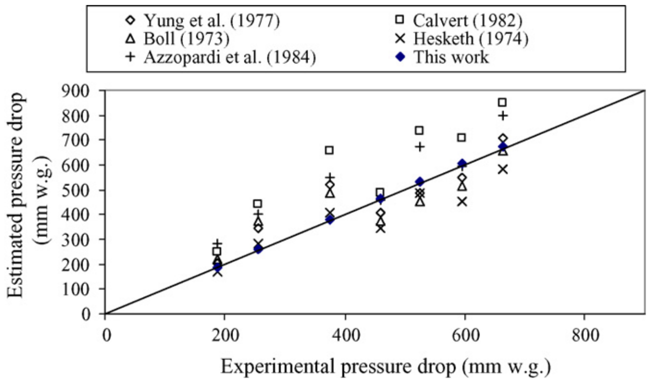

Fig. 15. The comparison of different models with the simulated results of ANN No. 1.

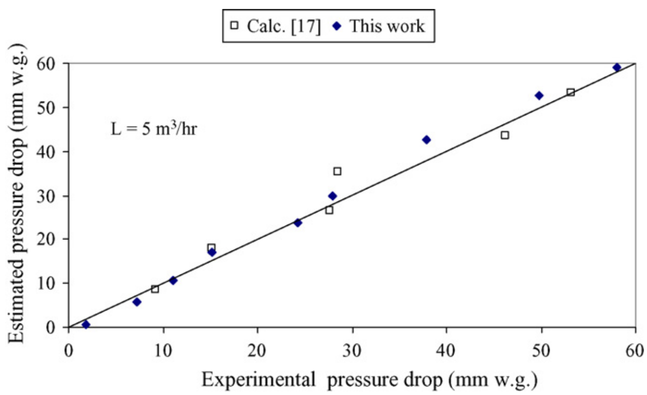

Fig. 16. The comparison between the simulated results of ANN No. 3 with the calculated results from modified model of Ripperger and Dau [16], for the ejector venturi scrubber with 150 mm throat diameter.

Fig. 16, a comparison between the simulated results of ANN No. 3 with the calculated results from modified model of Ripperger and Dau [16], for an ejector venturi, is shown. In these figures, simulated data are compared with the experimental and correlated data. As can be seen, an excellent agreement exists between simulated (ANNs results) and experimental data. Therefore, ANNs can predict the pressure drop in venturi scrubbers more precisely than the other models. The agreement between the simulated results of this work with experimental data approves ANNs as a new useful tool for calculating the pressure drop in venturi scrubbers compared to other models.

5. Conclusions

In this work, for the first time ANN approach was used for predicting pressure drop in venturi scrubbers and the results indicated that the methodology described using back-propagation Artificial Neural Network (ANN) is a powerful tool not only for accurately predicting pressure drop in venturi scrubbers, but also to identify the most important independent parameters.

The recommended ANNs approach has these advantages:

- It is possible to train large systems with many inputs on the basis of relatively small data sets. The resulting systems usually have a moderately non-linear structure. They are of significant scientific interest as they contradict the earlier state of knowledge.
- For an available ANN that is trained well, the prediction of data not seen before is not only precise but also speedy.
- The modern technique, ANNs performs the prediction of the outputs more accurately than the empirical and semi-empirical correlations announced by previous researchers.
- Cost reduction of the tests for measuring the pressure drop in venturi scrubbers is the ultimate benefit gained by this approach. Performing these tests and getting a large number of data, need vast expense which can be decreased by using this method. When a system is trained, it can simulate similar other data and give acceptable results to them without requesting experimental results. Therefore, we can obtain results by less experiment and less cost.

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