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Design of artificial neural networks using a genetic algorithm to predict collection efficiency in venturi scrubbers

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Abstract

In this study, a new approach for the auto-design of neural networks, based on a genetic algorithm (GA), has been used to predict collection efficiency in venturi scrubbers. The experimental input data, including particle diameter, throat gas velocity, liquid to gas flow rate ratio, throat hydraulic diameter, pressure drop across the venturi scrubber and collection efficiency as an output, have been used to create a GA–artificial neural network (ANN) model. The testing results from the model are in good agreement with the experimental data. Comparison of the results of the GA optimized ANN model with the results from the trial-and-error calibrated ANN model indicates that the GA–ANN model is more efficient. Finally, the effects of operating parameters such as liquid to gas flow rate ratio, throat gas velocity, and particle diameter on collection efficiency were determined.

Keywords: Venturi scrubber; Artificial neural networks; Genetic algorithms; Collection efficiency

1. Introduction

1.1. Literature review on venturi scrubbers

In recent decades, venturi scrubbers have been used to remove pollutants from effluent gasses. This device can remove very fine dissolved and adhesive particles present in pollutant gasses, and can resist corrosive acids and bases. In this device, the removal phenomenon is based on the inertial impaction. The other collision mechanisms such as interception and Brownian diffusion also exist, but they are very weak in comparison with the inertial impaction [1]. First, liquid is atomized into a high velocity gas stream. The high specific area formed by droplets of liquid in the scrubbing zone contributes to the effective elimination of fine particles. High efficiency for relatively small particles, low capital cost, and low maintenance costs are three major advantages of this device. Venturi scrubbers consist of a circular or rectangular section channel with three main parts: a convergent section, a throat and a divergent section (diffuser).

The performance of a gas cleaning equipment is evaluated by means of pressure drop and collection efficiency. The overall collection efficiency is defined by the mass ratio of the removed dust particles to the total inflow mass of dust particles. Particulate removal in a venturi scrubber has been studied by many researchers [1–3] and various mathematical models have been developed. Studies have shown that the collection efficiencies of laboratory-scale scrubbers are dependent on many variables, such as aerosol particle size, gas velocity, spray liquid rate and type of liquid injection [4]. Photographing of the throat of the scrubber has shown the non-uniform distribution of water droplets across the cross-section of the scrubber [5]. Comparative gas cleaning performance of a pilot-scale venturi scrubber was obtained for the three methods of water injection by Taheri and Hains [5]. For each method, the gas cleaning performance, as a function of the pressure drop was measured by absorption of SO_2 and collection efficiency for particles of methylene blue of controlled sized. A mathematical model developed by Calvert [6] to predict particulate removal efficiency. The collection efficiency was obtained from mass balance for dust where the amount of removed dust per droplet was determined from the correlation of target efficiency as suggested by Walton and Woolcock's experiment [7]. In Calvert's model, a correction factor was applied to take the effect of non-uniformity of water

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Nomenclature

D_p	particle diameter (μm)
D_{th}	throat hydraulic diameter of venturi scrubber (m)
E	collection efficiency
G	volume rate of gas flow (m^3/s)
L	liquid flow rate (m^3/s)
ΔP	pressure drop across venturi scrubber (Pa)
r	linear correlation coefficient between experimental data and neural network outputs
R^2	regression constant
V_{gth}	gas velocity in the throat (m/s)

droplets into consideration. Calvert et al. [2] studied the effects of particle size and wettability, venturi size and fluid flow rates on particle collection efficiency. Taheri and Sheih [8] developed a three-dimensional mathematical model to study the collection efficiency as a function of operating conditions. They made the assumption of a non-uniform distribution of water droplets. The roles of heat and mass transfer in determining the particle collection efficiency have been studied by Placek and Peters [3]. The mechanisms of inertial impaction, interception, and diffusiophoresis were analyzed simultaneously to account realistically for heat and mass transfer effects on particle collection. Azzopardi and Govan [9] presented a one-dimensional model of the gas, dust and liquid flows in a venturi scrubber to consider liquid flowing as a film to calculate pressure drop and dust removal. Fathikalajahi et al. [10,11] applied a diffusion model to obtain the droplet concentration distribution in a venturi scrubber. They studied the effect of non-uniformity of droplet dispersion on particulate removal efficiency [10,11]. This mathematical model has been used to investigate the effect of important parameters such as liquid to gas flow rate ratio, gas throat velocity, liquid nozzle diameter and the angle of the divergent section on efficiency of the scrubber. Ananthanarayanan and Viswanathan [12,13] used a simplified version of the model proposed earlier by Viswanathan [14]. It takes into account the jet penetration length, the non-uniform distribution of liquid droplets, the initial momentum of the liquid, and the non-uniformity in the droplet size distribution at the inlet. Goncalves et al. [15] considered jet dynamics, in particular, jet penetration, as an important design parameter affecting the collection efficiency and presented a mathematical description of the trajectory, penetration and break-up of a jet in a venturi scrubber. Their model was based on the superficial wave formation and growth mechanism described by Adelberg [16].

Some investigators including Kuznetsov and Oratovskii [17], Boyadzhiev [18], Volgin et al. [19], Beg and Taheri [20] have attempted to simulate the operation of the venturi scrubber for gas absorption. Johnstone et al. [4] reported a venturi scrubber study in which SO_2 was absorbed in 0.6N-NaOH solutions and measured the amount of sulfur dioxide absorbed in the liquid at various distances from the point of liquid injection. They found that the mass transfer increased substantially as the liquid injection rate increased. Kuznetsov and Oratovskii [17] developed a mathematical model for predicting chemisorption of CO_2 by NaOH solution in cylindrical venturi type scrubber. The degree of absorption was determined by the equation of

$$\eta = 1 - \exp(-m) \quad (1)$$

where the number of transfer units is given by

$$m = \frac{KF}{V} \quad (2)$$

In which K is the overall coefficient of absorption, m/h; F the phase contact surface, m^2; and V is the volumetric flow rate of the gas mixture, m^3/h. Volgin et al. [19] have studied absorption of SO_2 in ammonium sulfite–bisulfate solution scrubbing system experimentally. The throat was rectangular with a 10 mm × 15 mm cross-section and a length of 13 mm. The extent of absorption (in %) has been calculated from the following equation:

$$\eta = \frac{P_i - P_f}{P_i - P_e} \times 100 \quad (3)$$

where P_i, P_f, and P_e are the initial, final, and equilibrium partial pressure of SO_2, in mmHg, respectively. The main results of this experiment indicate that throat length is not important for increasing the extent of absorption. Uchida and Wen [21] applied a complete mathematical model to gas absorption in a venturi scrubber. They performed mass, heat and momentum balances and obtained a set of differential equations relating the droplet velocity and the gaseous pollutant concentration in both the gas and liquid phase along the axial coordinate of the venturi tube. They assumed a uniform droplet concentration distribution in the scrubber. SO_2 removal efficiency of a scrubber has been investigated by Talaie et al. [22] using a three-dimensional mathematical model. The model is based on a non-uniform droplets concentration distribution which is predicted from a dispersion model in the gas flow. Gas-phase mass transfer coefficient was calculated by empirical equations. Gamisans et al. [23] studied the absorption of SO_2 and NH_3 from the flue gas into NaOH and H_2SO_4 by using an industrial scale ejector-venturi scrubber to determine the performance of the scrubber under different conditions. Their results showed a strong influence of the liquid scrubbing flow rate on pollutant removal efficiency, but initial pollutant concentration and the gas flow rate had slight effect. Ravi et al. [24] used a non-dominated sorting genetic algorithm (GA) for optimization of a venturi scrubber. In their model, two objective functions were used, namely, maximization of the overall collection efficiency and minimization of the pressure drop together with three decision variables, the liquid–gas flow ratio, the gas velocity in the throat and the aspect ratio. Hills et al. [25] proposed a gas–liquid reactor, in which the two phases flow in annular flow through a number of units consisting of a venturi followed by a twisted tape inserted in the pipe. Their experiments in a 38 mm pipe, with a 19 mm venturi throat, showed that up to 35% of the liquid can be atomized, at the cost of a pressure drop of 0.2–0.3 bar. Nasseh et al. [26] have predicted pressure drop in venturi scrubbers with artificial neural networks (ANNs). Their results were in good agreement with experimental data.

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

Venturi type	D_p (μm)	V_{gth} (m/s)	L/G ($\times 10^3$ m^3/m^3)	E	Reference
Rectangular (6 in. × 34 in.)	0.47–1.5	66.5, 55.169, 60.959, 66.446, 137.16	1.118–1.738	0.16–0.99	[28]
Rectangular (4 in. × 12 in.)	0.75, 0.8, 1	228.6, 137.16, 91.44, 182.8	0.134–1.069	0.04–0.79	[2]

In the past decade, ANNs have been used intensively in various fields. The major reason for the rapid growth and diverse applications of neural networks is their ability to approximate virtually any function in a stable and efficient way. In spite of the wide range of applications, neural networks are still designed through a time consuming iterative trial-and-error approach. Hence, the time and effort required for network design are totally dependent on the nature of the task and the designer's experience. This leads to a significant amount of time and effort being expended to find the optimum or near optimum structure of a neural network for the desired task.

In this study, a GA is used for the first time in the design of neural networks for predicting collection efficiency in venturi scrubbers. A GA–ANN model has been created using the experimental data.

1.2. Artificial neural network

Neural networks generally consist of a number of interconnected processing elements or neurons. How the inter-neuron connections are arranged and the nature of the connections determines the structure of a network. How the strengths of the connections are adjusted or trained to achieve the desired overall behavior of the network is governed by its learning algorithm. Neural networks can be classified according to their structures and learning algorithms. In terms of their structures, neural networks can be divided into two types: feed forward networks and recurrent networks. In a feed forward network, the neurons are generally grouped into layers. Signals flow from the input layer through the output layer via unidirectional connections, the neurons being connected from one layer to the next, but not within the same layer. Multi-layer perceptrons (MLPs) are perhaps the best known type of feed forward network. The MLP has three layers: an input layer, an output layer and an intermediate or hidden layer. Neural networks are trained by two main types of learning algorithm: supervised and unsupervised learning algorithms. A supervised learning algorithm adjusts the strengths or weights of the inter-neuron connections according to the difference between the desired and actual network outputs corresponding to a given input. An example of supervised learning algorithms is the back-propagation algorithm. One of the learning algorithms suitable for training MLPs is the GA [27].

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

Venturi type	Rectangular (6 in. × 34 in.)
L (m^3/s)	0.00934–0.01325
ΔP (Pa)	4791.987–8994.19
D_p (μm)	0.67–1.15
E	0.923–0.986
Reference	[28]

1.3. Genetic algorithm

GAs were invented by John Holland in the 1960s and were developed by Holland and his students in the 1960s and 1970s. GA is one of the stochastic optimization methods which simulates the process of neural evolution. This learning algorithm is based on principles from genetics and evolution. The algorithm starts with a randomly generated population of chromosomes and the applied genetic operators are the selection, crossover and mutation operators. The selection operator chooses chromosomes from the current population for reproduction. The crossover operator creates two new chromosomes from two existing chromosomes by cutting them at a random position and exchanging the parts following the cut. The mutation operator produces new chromosomes by randomly changing the genes of existing chromosomes. Together, these operators simulate a guided random search method which can eventually yield the optimum set of weights to minimize the differences between the actual and target outputs of the neural network.

2. Methodology

The previous investigators [9–15,28], showed the most important parameters on the collection efficiency of the venturi scrubber were liquid to gas flow rate ratio, pressure drop across the venturi scrubber, gas throat velocity, liquid nozzle diameter and the angle of the divergent section. In present work, these parameters were used as inputs to the ANN–GA network and collection efficiency as an output.

The purpose of this study was to apply GAs to determine the number of neurons in the hidden layers, the momentum and the learning rates for minimizing the time and effort required to find the optimal architecture. Four separate networks were designed. The first three investigated the particle collection effi-

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

Venturi type	D_p (μm)	V_g (m/s)	L/G ($\times 10^3$ m^3/m^3)	f	Reference
Circular (2 in.)	0.55, 1, 2, 4.6	60.96, 121.92, 154.838	0.16042–4.545	0.22–1.2	[2]
Rectangular (4 in. × 12 in.)	0.75, 0.8, 1	228.6, 137.16, 91.44, 182.8	0.134–1.069	0.31–0.78	[2]

Table 4
The range of experimental data used for training network no. 4

Venturi type	Rectangular
G (m^3/s)	0.295–0.521
V_{gth} (m/s)	41.45–73.152
L/G (m^3/m^3)	0.0949–0.728
E	0.391–0.886
Reference	[29]

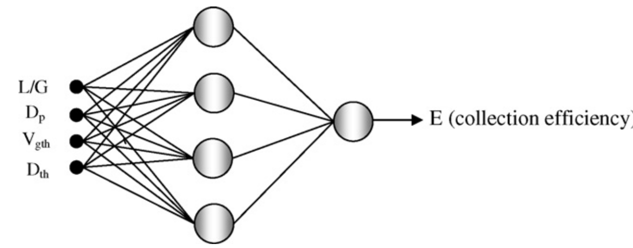

Fig. 1. The design of ANNs.

ciency in the venturi scrubber and the fourth network studied the collection efficiency of sulfur dioxide by alkaline solution. The experimental data were extracted from three rectangular venturi scrubbers with different sizes and one circular venturi scrubber. Two rectangular venturi – 4 in. × 12 in. [2] and 6 in. × 34 in. [28] in cross-section at the throat – were used for training the first network. The input vectors for this network were particle diameter (D_p), throat gas velocity (V_{gth}), liquid to gas flow rate ratio (L/G) and throat hydraulic diameter of the venturi scrubber (D_{th}). The second network was based on experimental data from the rectangular venturi scrubber of Pease Anthony type [28] which is 6 in. × 34 in. in cross-section. The main parameters of this network were liquid flow rate (L), D_p and pressure drop across the venturi scrubber (ΔP). The main parameters in the third network were D_p, V_{gth}, L/G and D_{th}, based on Calvert's experimental data for rectangular and circular venturi scrubbers [2]. In the fourth network, we considered volume rate of gas flow (G), L/G and V_{gth} as the input parameters for calculating the removal efficiency of the venturi scrubber. So, the fourth network had three inputs and was trained based on experimental data from a rectangular venturi which was 1.5 in. × 8 in. [29] in cross-section at the throat. Tables 1–4 show the domain of input and output parameters for the four networks. The ANNs contained three layers and feed forward back-propagation was used for training the input data. The number of neurons in the first layer was 3 or 4. There was just one neuron in the output layer which for networks 1, 2 and 4 is collection (removal) efficiency and for network 3 is f which is proportional to the collection efficiency [2] and defined as velocity ratio (i.e. V_r/V_g). V_r is droplet velocity relative to gas and V_g is gas velocity relative to duct. We also used one hidden layer for training networks and the number of neurons in this layer was obtained by GA. The design of the ANNs is shown in Fig. 1.

In this study, the process of designing the networks was managed by NeuroSolution for Excel Release 4.2 software which incorporates ANN and GA, and this was used to obtain the optimal network size and parameters in the ANN collection efficiency estimation model. Typically, 75% of the data were used for training and cross-validation purposes. The remainders were categorized as testing data.

Table 5
Summary of the networks architecture in hidden layer by GA method

Network	Number of neurons	Momentum rate	Learning rate
1	4	0.113	0.836
2	2	0.921	0.720
3	2	0.862	0.872
4	3	0.112	0.679

First we trained four networks in GA–ANN with the momentum algorithm. In this study, the roulette wheel and tournament for the reproduction, one point and uniform for crossover and uniform for mutation operators were applied to train the networks. Some tests were performed to represent the combination of different options for crossover, reproduction operators, population size and generation number.

After adjusting the parameters mentioned above in the training phase, it was found that the optimum number of neurons in the hidden layer for networks 1–4 was 4, 2, 2 and 3, respectively.

3. Results and discussions

In this study, four different experimental data sets have been used to design the networks. The number of data sets for training, cross-validation and simulating networks 1, 2, 3 and 4 were 90, 56, 80 and 25, respectively.

Networks 1–4 contained 4, 2, 2 and 3 neurons in their hidden layer, respectively. These numbers of neurons for the hidden layers have been achieved by GA–ANNs. Table 5 gives the optimal momentum rate, learning rate and number of neurons in the hidden layer by the GA method.

Table 6
Results of two trial and error methods and their comparison to the GA method

Networks	GA–ANN model		Trial and error methods			
			Method 1		Method 2	
	r	Number of neurons	r	Number of neurons	r	Number of neurons
1	0.993	4	0.992	9	0.982	11
2	0.988	2	0.984	7	0.986	4
3	0.951	2	0.950	7	0.95	5
4	0.988	3	0.985	6	0.980	2

Table 7
GA–ANN performance for network no. 1

Performance	Collection efficiency (E)
MSE	0.00162
NMSE	0.01570
MAE	0.02643
Min abs. error	0.00017
Max abs. error	0.11299
r	0.99334

Table 8
Summary report for network no. 1

Optimization summary	Best fitness	Average fitness
Generation number	13	18
Minimum MSE	0.004546	0.004546
Final MSE	0.004546	0.005017

Networks 1–4 have also been trained by two different methods of trial-and-error by changing the number of neurons in the hidden layer from 2 to 20. In the first method, momentum has been selected as the learning algorithm and the default values of NeuroSolution software have been adjusted for momentum rate and learning rate. In the second method, the Levenberg–Marquardt learning algorithm has been used. Table 6 shows the results of the methods mentioned above and their comparison to the GA method. So, it is concluded that the GA method is better than the trial-and-error method.

Table 7 reports the performance of network no. 1 in terms of mean squared error (MSE), normalized mean squared error (NMSE), mean absolute error (MAE), minimum absolute error and maximum absolute error and the linear correlation coefficient (r) between experimental data and neural network outputs. The ANN predictions are optimal if r, MAE, NMSE and MSE are found to be close to 1, 0, 0, 0, respectively [30]. In the present study, MSE is only used for the estimation of network training performance, whereas r, MSE, and NMSE are used to measure the prediction performance of GA–ANN on the validation data set.

The fitness function is an important factor for the convergence and stability of the genetic algorithm. Table 8 shows a summary of the best fitness and the average fitness values for network no. 1. In this table, the minimum MSE (across all generations), the generation of this minimum and the final MSE are displayed. Also, corresponding plots which resulted from Table 8 are shown in Figs. 2 and 3. Fig. 2 demonstrates the best fitness value versus the number of generations.

In Fig. 3, the average fitness achieved during each generation of the optimization is illustrated. The average fitness is the average of the minimum MSE taken across all of the networks within the corresponding generation.

In Fig. 4, the outputs of network 1 are compared to the experimental data for collection efficiency [28,2].

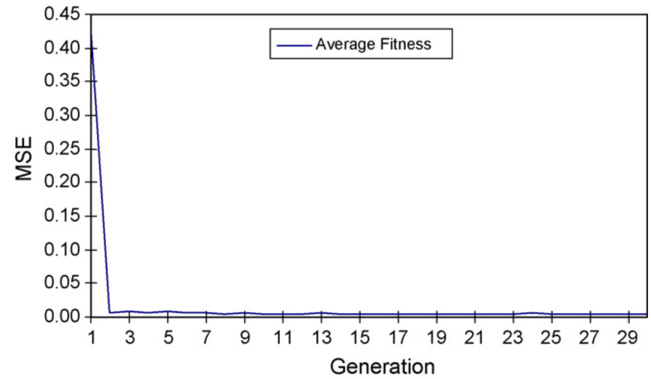

Fig. 3. Average fitness (MSE) vs. generation for network no. 1.

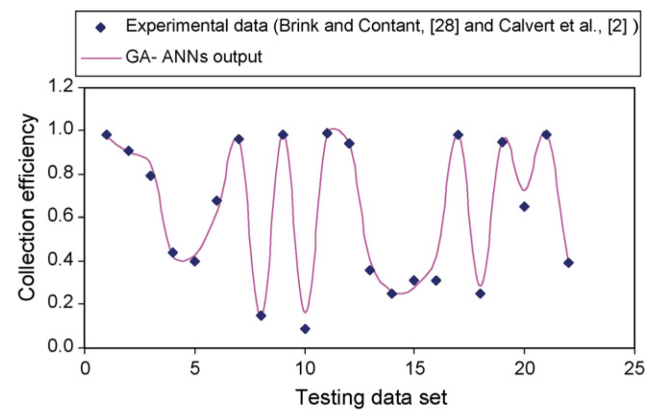

Fig. 4. Comparison of the output of GA–ANN network no. 1 with experimental data.

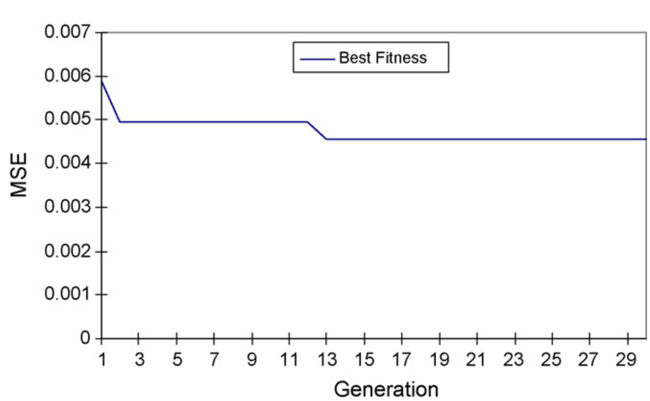

Fig. 2. Best fitness (MSE) vs. generation for network no. 1.

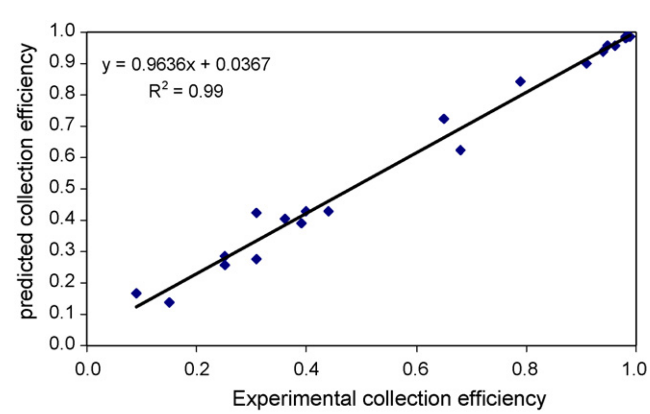

Fig. 5. Simulating results for the GA–ANN no. 1.

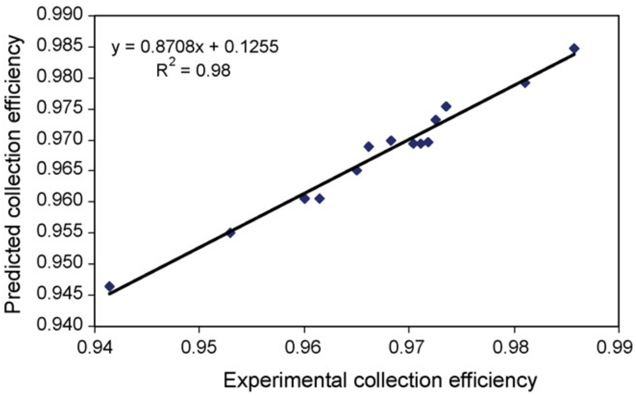

Fig. 6. Simulating results for the GA–ANN no. 2.

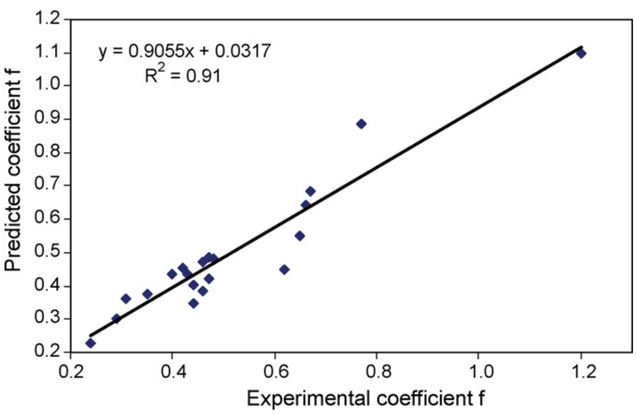

Fig. 7. Simulating results for the GA–ANN no. 3.

Figs. 5–8 show good agreement between the predicted and experimental data for networks 1–4.

Figs. 9 and 10 indicate the effects of particle diameter on the collection efficiency for network 1, for two different L/G and V_{gth} values. Fig. 11 shows the effect of V_{gth} on the collection efficiency. It is apparent that increasing gas throat velocity will increase the collection efficiency. As can be seen, there is a good agreement between the experimental data and the results of GA–ANNs.

Figs. 12–15 indicate the effect of L/G, D_p and V_{gth} on the coefficient of f for network no. 3. As can be seen, there is a good agreement between experimental data and the GA–ANN model. As liquid to gas ratio increases, the collection efficiency increases and the coefficient of f decreases. Increasing particle diameter results in a decrease in f. This is in close agreement with the fact that the collection of larger particles is more efficient. In addition, increasing V_{gth} results in increasing f.

In the next step, the calculated results of the GA–ANN no. 1 as presented in this work and the calculated results from the model of Ananthanrayanan and Viswanathan [13] were compared with the experimental data. These results are represented

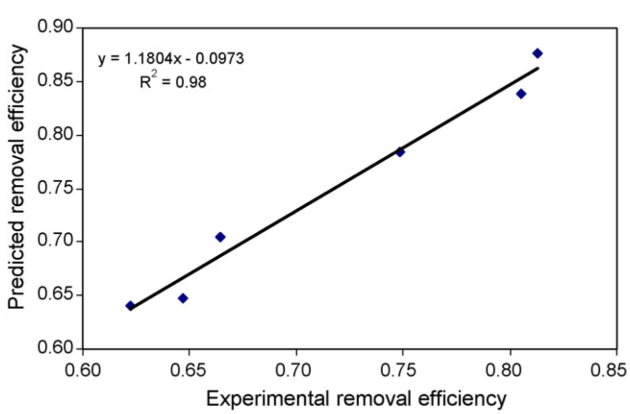

Fig. 8. Simulating results for the GA–ANN no. 4.

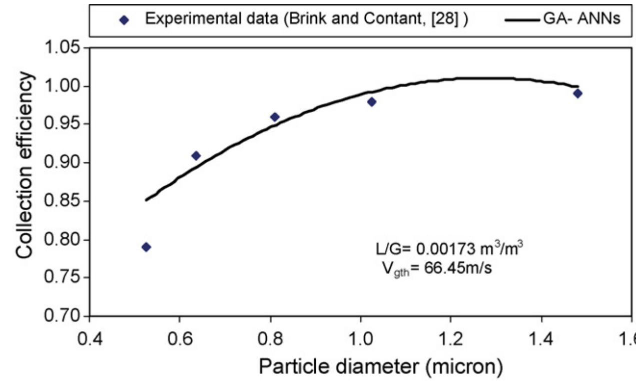

Fig. 9. The effect of particle diameter on the collection efficiency in venturi scrubber (GA–ANN no. 1) at $L/G = 0.00173\ m^3/m^3$ and $V_{gth} = 66.45$ m/s.

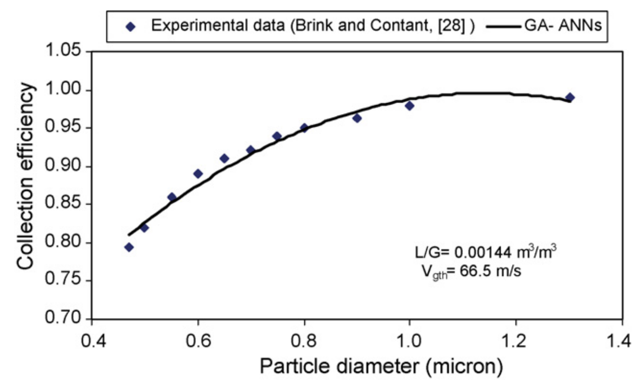

Fig. 10. The effect of particle diameter on the collection efficiency in venturi scrubber (GA–ANN no. 1) at $L/G = 0.00144\ m^3/m^3$ and $V_{gth} = 66.5$ m/s.

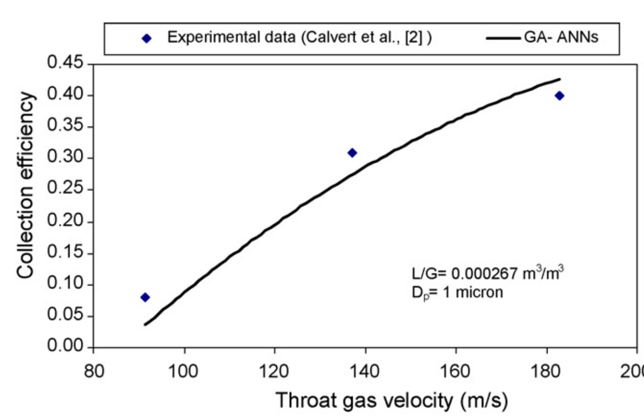

Fig. 11. The effect of throat gas velocity on the collection efficiency in venturi scrubber (GA–ANN no. 1).

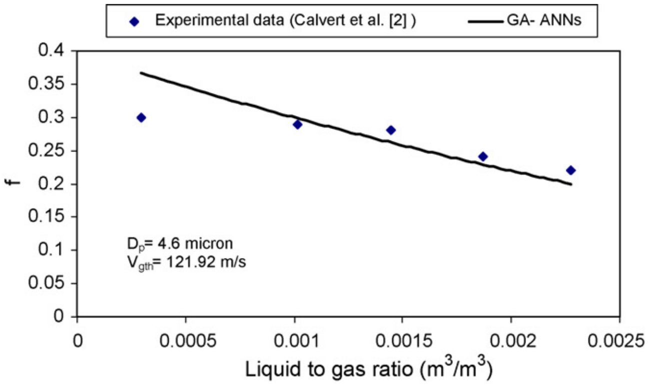

Fig. 12. The effect of liquid to gas ratio on the coefficient of *f* in venturi scrubber (GA–ANN no. 3).

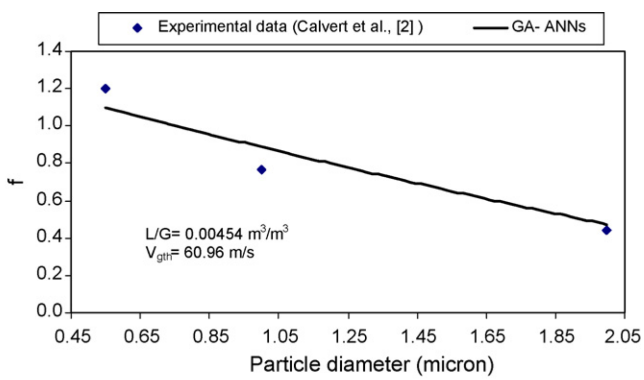

Fig. 13. The effect of particle diameter on the coefficient of *f* in venturi scrubber (GA–ANN no. 3) at $L/G = 0.00454\ m^3/m^3$ and $V_{gth} = 60.96$ m/s.

in Fig. 16. As one can see, a better agreement exists between the results of GA–ANNs and the experimental data. AAPD shows it statistically.

$$\mathrm{AAPD} = \frac{100}{N}\sum_{i=1}^{N}\frac{\eta_{\mathrm{exp}}^{i} - \eta_{\mathrm{cal}}^{i}}{\eta_{\mathrm{exp}}^{i}} \quad (4)$$

AAPD for GA–ANN model = 2.04%; AAPD for Ananthanrayanan and Viswanathan's model = 3.63%.

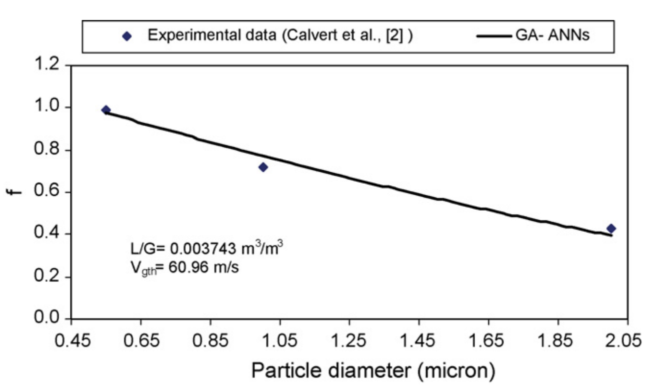

Fig. 14. The effect of particle diameter on the coefficient of *f* in venturi scrubber (GA–ANN no. 3) at $L/G = 0.003743\ m^3/m^3$ and $V_{gth} = 60.96$ m/s.

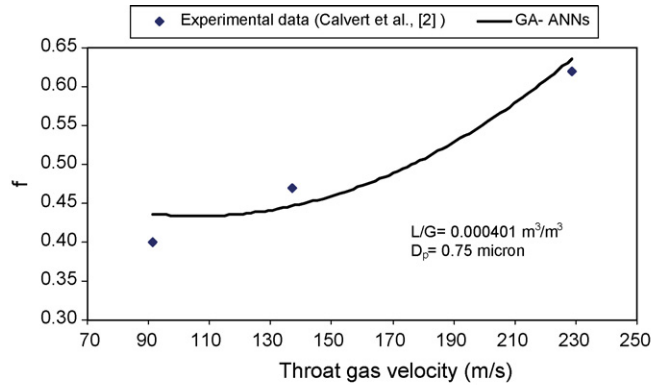

Fig. 15. The effect of throat gas velocity on the coefficient of *f* in venturi scrubber (GA–ANN no. 3).

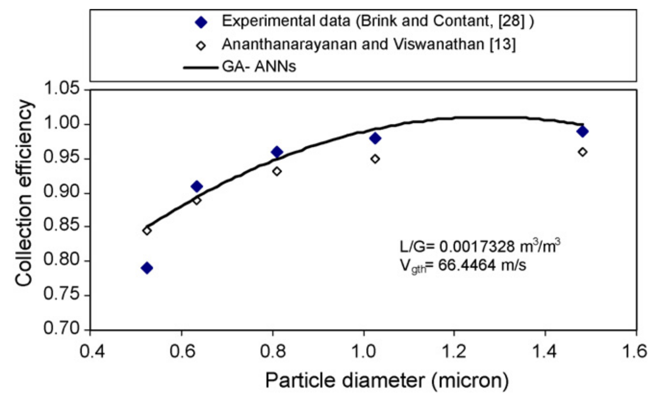

Fig. 16. The comparison of experimental data of Brink and Contant [28] with GA–ANN and Ananthanarayananm and Viswanathan model.

4. Conclusions

In this work, for the first time, an attempt has been made to design a neural network architecture using a genetic algorithm to predict collection efficiency in venturi scrubbers. The number of neurons in the hidden layer, the momentum and learning rates have been determined using the GA algorithm to minimize the time and effort required to find the optimal architecture and parameters of the back-propagation based on ANN.

Comparison of the results of GA–ANNs with the trial-and-error method indicates that the GA approach is more efficient. In other words, GA is found to be a good alternative over the trial-and-error approach to determine the optimal ANN architecture and internal parameters quickly and efficiently.

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References

[1] R.H. Boll, Particle collection and pressure drop in venturi scrubber, Ind. Eng. Chem. Fundam. 12 (1973) 40–50.

[2] S. Calvert, D. Lundgren, D.S. Mehta, Venturi scrubber performance, J. Air Pollut. Control Assoc. 22 (1972) 529–532.

[3] T.D. Placek, L.K. Peters, Analysis of particulate removal in venturi scrubbers—role of heat and mass transfer, AIChE J. 28 (1982) 31–39.

[4] H.F. Johnstone, R.B. Field, M.C. Tassler, Gas absorption and aerosol collection in a venturi atomizer, Ind. Eng. Chem. 46 (1954) 1601–1608.

[5] M. Taheri, G.F. Hains, Optimization of factors affecting scrubber performance, J. Air Pollut. Control Assoc. 19 (1969) 427–431.

[6] S. Calvert, Venturi and other atomizing scrubbers efficiency and pressure drop, AIChE J. 16 (3) (1970) 392–396.

[7] W.H. Walton, A. Woolcock, Aerodynamic Capture of Particles, Pergamon Press, New York, 1960.

[8] M. Taheri, C. Sheih, Mathematical modeling of atomizing scrubbers, AIChE J. 21 (1975) 153–157.

[9] B.J. Azzopardi, A.H. Govan, Modeling of venturi scrubbers, Filtr. Sep. 21 (3) (1984) 196–200.

[10] J. Fathikalajahi, M.R. Talaie, M. Taheri, Theoretical study of liquid droplet dispersion in a venturi scrubber, J. Air Waste Manage. Assoc. 45 (1995) 181–185.

[11] J. Fathikalajahi, M. Taheri, M.R. Talaie, Theoretical study of non-uniform droplets concentration distribution on venturi scrubber performance, Part. Sci. Technol. 14 (1996) 153–164.

[12] N.V. Ananthanarayanan, S. Viswanathan, Estimating maximum removal efficiency in venturi scrubbers, AIChE J. 44 (1998) 2549.

[13] N.V. Ananthanarayanan, S. Viswanathan, Predicting liquid flux distribution and collection efficiency in cylindrical venturi scrubbers, Ind. Eng. Chem. Res. 38 (1999) 223–232.

[14] S. Viswanathan, Modeling of venturi scrubber performance, Ind. Eng. Chem. 36 (1997) 4308–4317.

[15] J.A.S. Goncalves, M.A.M. Costa, P.R. Henrique, J.R. Coury, Atomization of liquids in a Pease-Anthony venturi scrubber. Part I. Jet dynamics, J. Hazard. Mater. 97 (2003) 267–279.

[16] M. Adelberg, Breakup rate and penetration of a liquid jet in a gas stream, AIAA J. 5 (1967) 1408–1415.

[17] M.D. Kuznetsov, V.I. Oratovskii, Rate of chemisorption in a venturi-type apparatus, Int. Chem. Eng. 2 (1962) 185–188.

[18] Kh. Boyadzhiev, On the optimal flow rate of liquids during chemisorption in a venturi tube, Int. Chem. Eng. 4 (1964) 22–26.

[19] B.P. Volgin, T.F. Efimova, M.S. Gofman, Absorption of sulfur dioxide by ammonium sulphite–bisulphite solution in a venturi scrubber, Int. Chem. Eng. 8 (1968) 113–118.

[20] S.A. Beg, M. Taheri, Gas absorption studies in butterfly valve scrubber, Atmos. Environ. 8 (1974) 947–955.

[21] S. Uchida, C.Y. Wen, Gas absorption by alkaline solutions in a venturi scrubber, Ind. Eng. Chem. Process Dev. 12 (1973) 437–443.

[22] M.R. Talaie, J. Fathikalajahi, M. Taheri, Mathematical modeling of SO_2 absorption in a venturi scrubber, J. Air Waste Manage. Assoc. 47 (1997) 1211–1215.

[23] X. Gamisans, M. Sarra, F. Lafuente, Gas pollutants removal in a single- and two-stage ejector-venturi scrubber, J. Hazard. Mater. B 90 (2002) 251–266.

[24] G. Ravi, K. Santosh, S. Viswanathan, M.B. Ray, Optimization of venturi scrubbers using genetic algorithm, Ind. Eng. Chem. 41 (2002) 2988–3002.

[25] J.H. Hills, B.J. Azzopardi, A.S. Barhey, Spatial unsteadiness—a way towards intensive gas–liquid reactors, Trans. IChemE 74 (5) (1996) 567–574.

[26] S. Nasseh, A. Mohebbi, Z. Jeirani, A. Sarrafi, Predicting pressure drop in venturi scrubbers with artificial neural networks, J. Hazard. Mater. 143 (2007) 144–149.

[27] A.B. Bulsari, Neural Networks for Chemical Engineering, Elsevier Science, 1995, pp. 1–19.

[28] J.A. Brink, C.E. Contant, Experiments on an industrial venturi scrubber, Ind. Eng. Chem. 50 (1958) 1157–1160.

[29] H.F. Johnstone, M.H. Roberts, Deposition of aerosol particles from moving gas streams, Ind. Eng. Chem. 41 (1949) 2417–2423.

[30] G.B. Sahoo, C. Ray, Flow forecasting for a Hawaiian stream using rating curves and neural networks, J. Hydrol. 317 (2006) 63–80.