MODELING THE COOLING PERFORMANCE OF VORTEX TUBE USING A GENETIC ALGORITHM-BASED ARTIFICIAL NEURAL NETWORK

by

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Original scientific paper
DOI: 10.2298/TSCI140126112P

In this study, artificial neural networks have been used to model the effects of four important parameters consist of the ratio of the length to diameter, the ratio of the cold outlet diameter to the tube diameter, inlet pressure, and cold mass fraction on the cooling performance of counter flow vortex tube. In this approach, experimental data have been used to train and validate the neural network model with MATLAB software. Also, genetic algorithm has been used to find the optimal network architecture. In this model, temperature drop at the cold outlet has been considered as the cooling performance of the vortex tube. Based on experimental data, cooling performance of the vortex tube has been predicted by four inlet parameters. The results of this study indicate that the genetic algorithm-based artificial neural network model is capable of predicting the cooling performance of vortex tube in a wide operating range and with satisfactory precision.

Key words: *vortex tube, modeling, neural network, genetic algorithm, cooling performance*

Introduction

The vortex tube is a simple device consists of a simple circular tube, one or more tangential nozzles, a cold-end orifice, and a hot-end control valve that is capable of producing cold and hot gas flows from compressed gas. High pressure gas enters the vortex tube via the inlet nozzles and achieves high angular velocity. Part of the gas swirls to the hot-end and exits but by adjusting a control valve downstream of the hot outlet, another part of the gas reverse and move from the hot-end to the cold -end orifice [1].

The streams of gas leaving through the hot and cold-ends are at higher and lower total temperatures, compared to the inlet temperature. Figure 1 shows a schematic diagram of vortex tube and the distribution of total temperature inside this device [2]. This phenomenon is referred to as the temperature separation effect. Vortex tube was first discovered by Ranque [3].

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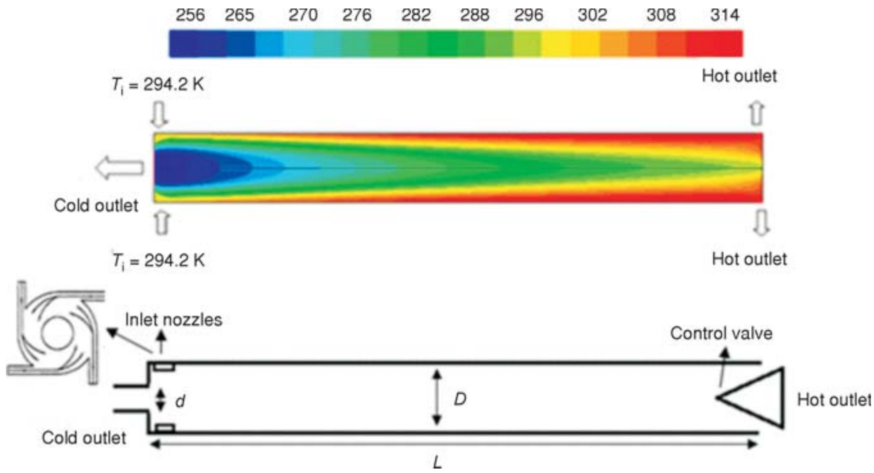

Figure 1. Schematic diagram of a vortex tube and the temperature separation effect

The vortex tube has many advantages compared to the normal commercial devices such as: simplicity, the absence of moving parts (except the hot-end control valve), the absence of need for electricity or chemicals, low cost, durability, smallness and lightness of weight, and adjustability of temperature [4, 5]. Hence, it becomes an appropriate device for heating and cooling gas, drying gas, separating particles in the waste gas industry, cooling for low temperature magic angle spinning, cooling equipment in laboratories, and other purposes [4, 6-8].

Although, vortex tube has a simple geometry, the temperature separation phenomenon is quite complex. Thus far various experimental, analytical, and numerical investigations have been carried out on the vortex tube. However, the fundamental mechanism of the process is still unknown and it is not easy to predict the outlet temperatures without experiments [1].

Artificial neural networks (ANN) are powerful tools for pattern classification and continuous function approximation. Owing to the great ability of ANN in discovering complex relationships among large number of variables with complex interdependencies, they can be used as an appropriate technique for developing predictive models in the short term. Many researchers have used ANN for studying diverse mechanical problems such as: loss efficiency modeling of compressors [9], performance study of solar-assisted air-conditioning system [10], performance and exhaust emissions of gasoline engines [11], evaluation of boiler behavior [12], modeling and control of evaporative condenser cooling load [13], and prediction of frost deposition [14].

Thus far, few researchers used ANN in order to study the performance of vortex tube [15-18]. However, with the exception of one work [15], most of the studies were limited to the validation of the developed models with the experimental data and the developed models were not used for predicting the performance of the device in conditions where the experimental data were unavailable [16-18]. Also, the effect of the ratio of the cold outlet diameter to the internal diameter of the tube (*d/D*) has not been studied in previous works.

Furthermore, ANN models presented in the state of the art suffer from lack of generalization neglecting the importance of model selection. The main limitation of using neural network for solving a regression problem is lack of generalization [19, 20], also known as overfitting of the model. Therefore the model selection should be performed accurately to improve the generalization of the model.

In this study, a multi-layer feed forward neural network model has been developed to approximate the relationship among four important parameters (*P*, *d/D*, *L/D*, *Y*) and the cold outlet temperature drop of the vortex tube. In contrast to the previous works the developed model was used to predict the effects of these parameters in a wide operating range. Furthermore, we tried to enhance the generalization of the model employing two strategies: (1) genetic algorithm (GA) [20, 21] is used for model selection. The GA is used to find the optimized network architecture which results in better performance of the ANN model; (2) dividing data into three subsets, *i. e*. training dataset (60% of samples), validation dataset (20% of samples), and test dataset (20% of samples), and employing early stopping [19, 21] strategy in training phase. Training and validation datasets were used in model selection and training phase, and testing subset is used for evaluation of the performance of optimized network.

Theory

Artificial neural networks

The ANN are powerful tools for pattern classification and continuous function approximation [22]. A neural network is a computational model of the brain. Neural network models usually assume that computation is distributed over several simple units called neurons, which are interconnected and operate in parallel. The neurons are arranged in layers of network and connected through links which named as weights. By adjusting these weights the network can map input vectors to desired outputs. This process is done by learning algorithm and named as network training.

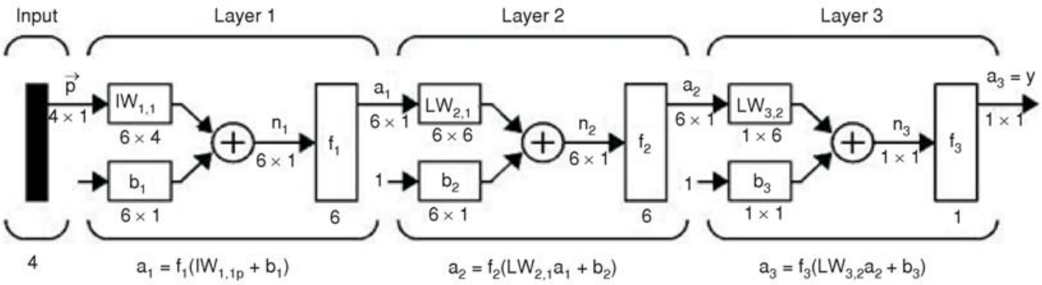

Figure 2. The ANN structure

In this work a multi-layer feed forward neural network (fig. 2) has been applied for predicting the cooling performance of vortex tube. Training is a step by step method for the calculation of the weight factors and biases. During the training, the network which is presented with training data learns to generate new outputs through an iterative method. Among the available methods to train a neural network, the back propagation method is most commonly used. This method has been applied for training of neural network in this work. At the beginning of the training process, initial weights are given to the connections randomly. Inputs are entered into the input layer and move forward through the hidden layer of neurons to the output layer. Generated outputs would be compared with real outputs (experimental data). In general, for function approximation problems regarding networks that contain up to few hundred weights, the Levenberg-Marquardt (LM) algorithm attains the fastest convergence and the highest accuracy [23]. Therefore LM was chosen as the network training method.

Genetic algorithm

Genetic algorithms (GA), to obtain a fast search and optimization technique, use the *survival of the fittest* principle of natural evolution with the genetic propagation of characteristics [24]. The most important aspect of a GA is that it determines many possible solutions simultaneously and explores different regions in desired space that choose by user [25]. Based on the Darwinian principle of *survival of the fittest*, GA can obtain the optimal solution after a series of iterative computations. The search process is composed of artificial mutation, crossover, and selection [26].The parameters and procedures used in GA for tuning the number of neurons in hidden layers of ANN are described [27]:

Initialization: Three main parameters should be initialized before applying GA: (1) number of genes, (2) population size, and (3) maximum number of generation. Our regression problem has four inputs and one output. Therefore, the neural network has 4-x-y-1 architecture. As mentioned previously, in this study we use GA to find optimal values for x and y, *i. e.*, number of neurons in first and second hidden layer, respectively. Hence, number of genes in the GA is equal to 2. The population size and the maximum number of generations are set to 100 and 50, respectively.

Evaluating fitness: to prevent ANN from over fitting, root mean squared error, eq. (1), of validation set is used as fitness function. This value is computed for each ANN set-up defined by gene values of GA:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{Target} - \mathrm{Predicted})^2} \tag{1}$$

Selection: The roulette wheel selection method is applied here to decide whether a chromosome can survive to the next generation. The chromosomes that survive to the next generation are placed in a matting pool for cross-over and mutation operations.

Cross-over: The cross-over is performed between the parents to form a new offspring. The probability of creating new chromosomes in each pair was set to 0.6. The newly created chromosomes constitute a new generation of population.

Mutation: The mutation operation follows the cross-over operation, and determines whether a chromosome should be mutated in the next generation. Here, we employed adaptive feasible method for mutating selected chromosomes.

Stop condition: The process was repeated until the number of generations was equal to 50 (stopping criteria).

After convergence of GA, a 4-6-6-1 neural network is selected by GA as the best architecture to simulate vortex tube behaviors.

Preparation of training dataset

Many parameters affect the performance of vortex tube such as: the number of nozzles, shape of nozzles, inlet pressure (P), type of working fluid, L/D, d/D, cold mass fraction (Y), angle of the control valve, the divergence angle of the tube, *etc*. [28-32]. Among the several parameters mentioned previously, the effects of four important parameters namely the inlet pressure P, L/D, d/D, and Y have been studied in the present work.

The cold mass fraction is defined as the ratio of the cold outlet mass flow rate to the inlet mass flow rate, eq. (2):

$$Y = \frac{\dot{m}_c}{\dot{m}_i} \tag{2}$$

Cold mass fraction can be controlled by the control valve that is placed at the hot outlet. The cold outlet temperature drop (ΔT_c) is defined as the difference between the cold outlet temperature and the inlet temperature and reflects cooling performance of the vortex tube eq. (3).

$$\Delta T_c = T_c - T_i \tag{3}$$

In this work, we used two hundred and ninety six experimental data that were presented by Hamoudi [33] to model the effects of d/D, L/D, Y, and P on the cooling performance of vortex tube. The internal diameter of the vortex tube was 2 mm, the cold outlet diameter was 0.25D, 0.4D, and 0.55D, respectively, and the length of the vortex tube (L) was 10D, 30D, and 50D, respectively. The vortex tube consisted of four inlet nozzles and the angle of the control valve was fixed at 60°. Furthermore, the working fluid was compressed air. The experiments were conducted for three inlet pressures (200, 300, and 400 kPa) and the cold mass fraction was gradually varied from 0.05 to 0.95 [33]. The geometry and operating condition of the experiment is shown in tab. 1.

Table 1. The description of the geometry of vortex tube and operating condition

Diameter of tube	2 mm
Diameter of cold outlet	(0.5, 0.8, 1.1) mm
Length of vortex tube	(20, 60, 100) mm
Angle of conical control valve	60°
Number of nozzles	4
Dimension of nozzles	Width = 0.382 mm, height = 0.164 mm
Inlet pressure	(200, 300, 400) kPa
Inlet temperature	296 K
Cold mass fraction	(0.05-0.95)

In fact, the appropriate ranges of variation of these parameters were the main reason for using these data. In order to improve the performance of the training process, the training and validation data sets were normalized.

Optimization of ANN based on GA

As mentioned previously, GA has been applied for optimization of the structure of ANN. In this study total available data were randomly divided into three parts: training subset (60% of data), validation subset (20% data), and testing subset (20% data) and RMSE of testing data was calculated by eq. (1). Also learning rate of network, training goal, and epoch have been selected 0.05, 0.01, and 1000, respectively.

Results and discussion

In this study ANN have been used to investigate the effects of four important parameters (Y, P, L/D, and d/D) on the cooling performance of the vortex tube. Figure 3 shows a linear regression between the network outputs and the corresponding targets among three subsets. The R values about three subsets and total data prove appropriate match between network outputs and desired targets. Also the final network parameters (weights and biases) are shown in tabs. 2-5.

By choosing appropriate data and optimizing the network architecture, the developed ANN model is capable of predicting the effects of these parameters in a common operating range ($10 < L/D < 70$, 100 kPa $< P <$ 600 kPa, $0.2 < d/D < 0.7$ and $0.05 < Y < 0.9$). In 3-D diagrams (fig. 4) surfaces show the prediction of cooling performance by the ANN model, while the points indicate the experimental data. In fact, these figures confirm the ability of the ANN model in predicting the cooling performance of the vortex tube.

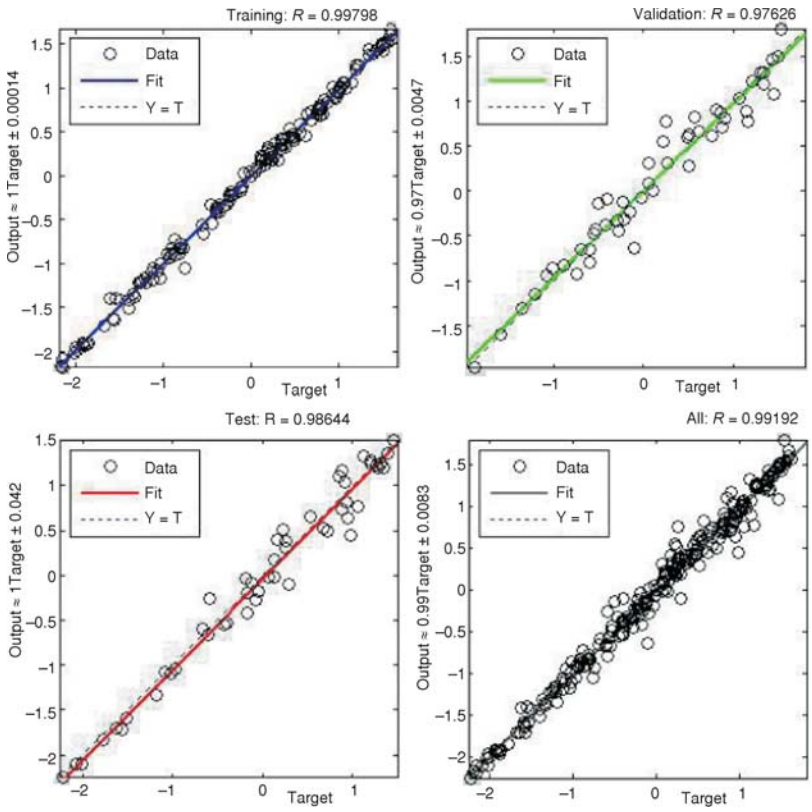

Figure 3. Linear regression between the network outputs and the corresponding targets among three subsets

Table 2. Input weights of network

Input number/ Neuron number	I_1	I_2	I_3	I_4
N_1	0.279859	0.159818	1.011067	2.251781
N_2	0.24495	0.241257	0.693288	1.333692
N_3	0.351066	0.493433	0.338091	0.292423
N_4	0.189232	0.140633	0.294957	0.528894
N_5	0.06757	0.250924	0.391577	0.905895
N_6	0.086276	0.197375	1.11096	0.406038

Table 3. Weights that connect first layer to second layer

Input number/ Neuron number	I_1	I_2	I_3	I_4	I_5	I_6
$N1$	0.567416	0.049173	0.399667	1.758988	0.013056	1.794992
N_2	0.089218	0.548828	0.463642	0.722959	1.427054	0.592396
N_3	0.216026	0.738732	0.669523	0.230278	1.531354	0.962624
N_4	0.572936	0.914109	1.643914	0.620357	0.233510	0.052885
N_5	0.489648	1.488486	0.830648	2.124615	1.599990	0.566895
N_6	2.376985	2.037587	0.674295	0.326412	1.808234	1.141541

Table 4. Weights that connect second layer to third layer

Input number/ Neuron number	I_1	I_2	I_3	I_4	I_5	I_6
N_1	0.644029	2.197503	1.025351	0.720903	0.923351	0.875025

Table 5. Network biases

Layer number/ Neuron number	L_1	L_2	L_3
N_1	0.081958	1.438152	0.22036
N_2	1.742789	1.729585	–
N_3	0.535839	0.385201	–
N_4	0.017371	0.146709	–
N_5	0.951375	0.55413	–
N_6	1.633537	2.080385	–

Each of these figures shows the cooling performance of the vortex tube with constant *d/D* and *L/D* but the pressure varies from 100 to 600 kPa and *Y* increases gradually from 0.05 to 0.95. According to these figures, an increase in the inlet pressure improves the cooling performance of the vortex tube. Previous studies confirm this statement [34, 35].

Figure 4 also shows the effect of *Y* on the cooling performance of the vortex tube when other parameters change. According to these figures, the optimum *Y* is almost independent of *L/D* and *P*. However, it is dependent on *d/D*. Figures 5 and 7 shows these facts with more clarity. According to fig. 5, the optimum value of *Y* is dependent on *d/D* and when *d/D* increases, the maximum temperature drop occurs at higher *Y*. However, from fig. 7 it can be seen that under constant *d/D* and *P*, when we change *L/D*, there is no significant change in the optimum *Y*. The next important parameter studied in this work was the ratio of the cold outlet diameter to the internal diameter of the vortex tube (*d/D*).

The cold outlet diameter considerably affects the shape of streamlines and the temperature separation phenomenon. In vortex tubes with small ratio of the cold outlet diameter to the internal diameter of the tube, part of the cold inner flow cannot exit through the cold outlet and reverses which results in the formation of a secondary circulation flow. Secondary circulation flow degrades the cooling performance of the vortex tube due to the transfer of colder fluid elements near the cold outlet through the swirling secondary loop to the warmer flow region. However, in a vortex tube with a high value of *d/D*, instead of secondary circulation flow, another performance degrading mechanism occurs and degradation could be due to the transfer of warmer flow in the peripheral region to the cold inner region. Furthermore, cold outlet diameter has an important effect on back pressure and back flow at cold outlet that can reduce the performance of vortex tube [28, 35, 36]. According to fig. 4, *d/D* has an important effect on the cooling performance of the vortex tube. However, fig. 5 shows this dependency with more clarity. From these figures it is obvious that *L/D* does not have a significant effect on the optimum value of *d/D* and the best cooling performance of the vortex tube always occurs at *d/D* = 0.5. The present result agrees well with the past experimental and numerical studies [34-38]. Nevertheless, numerical simulation was carried out to predict the cooling performance of vortex tubes with different cold outlet diameters.

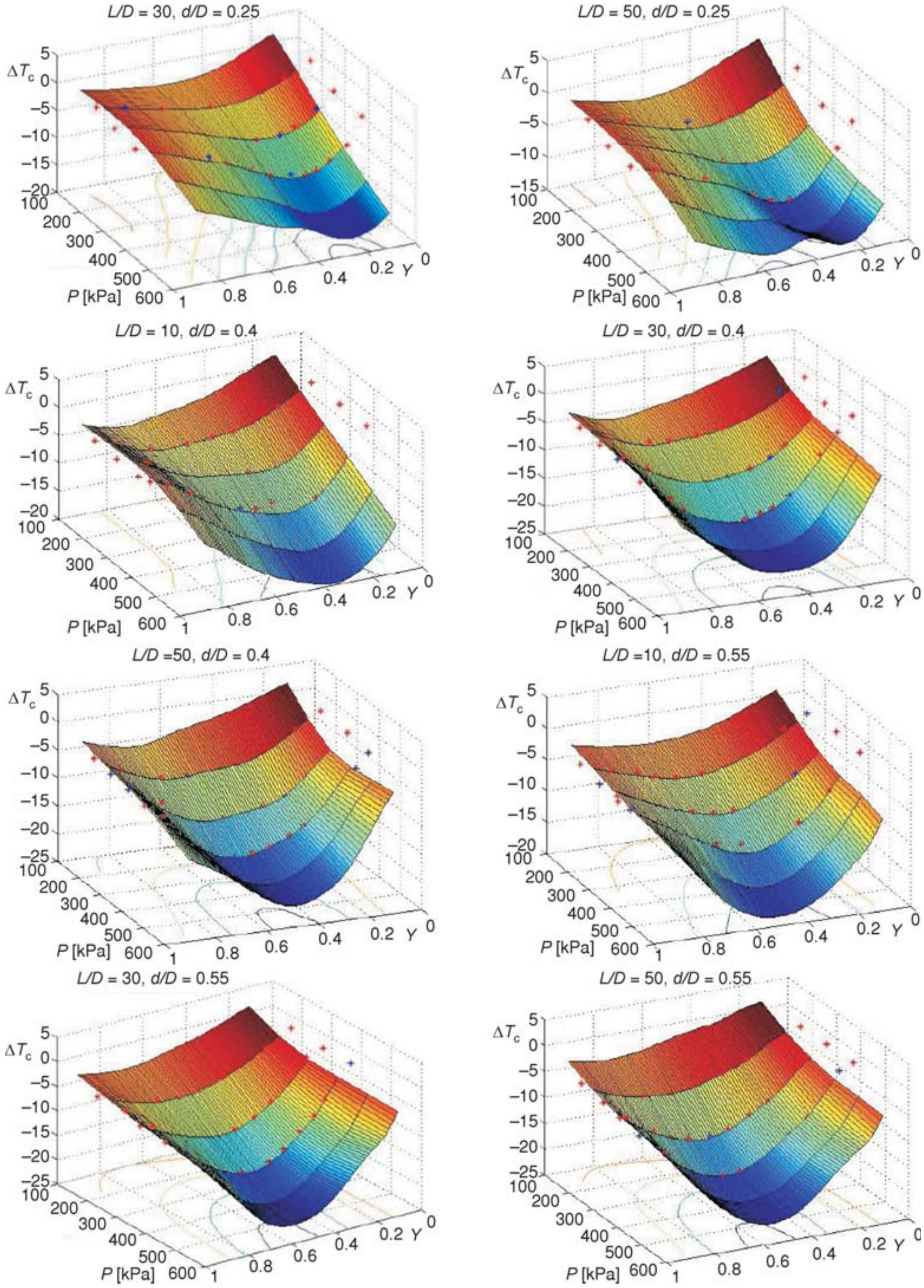

Figure 4. Experimental data and ANN prediction

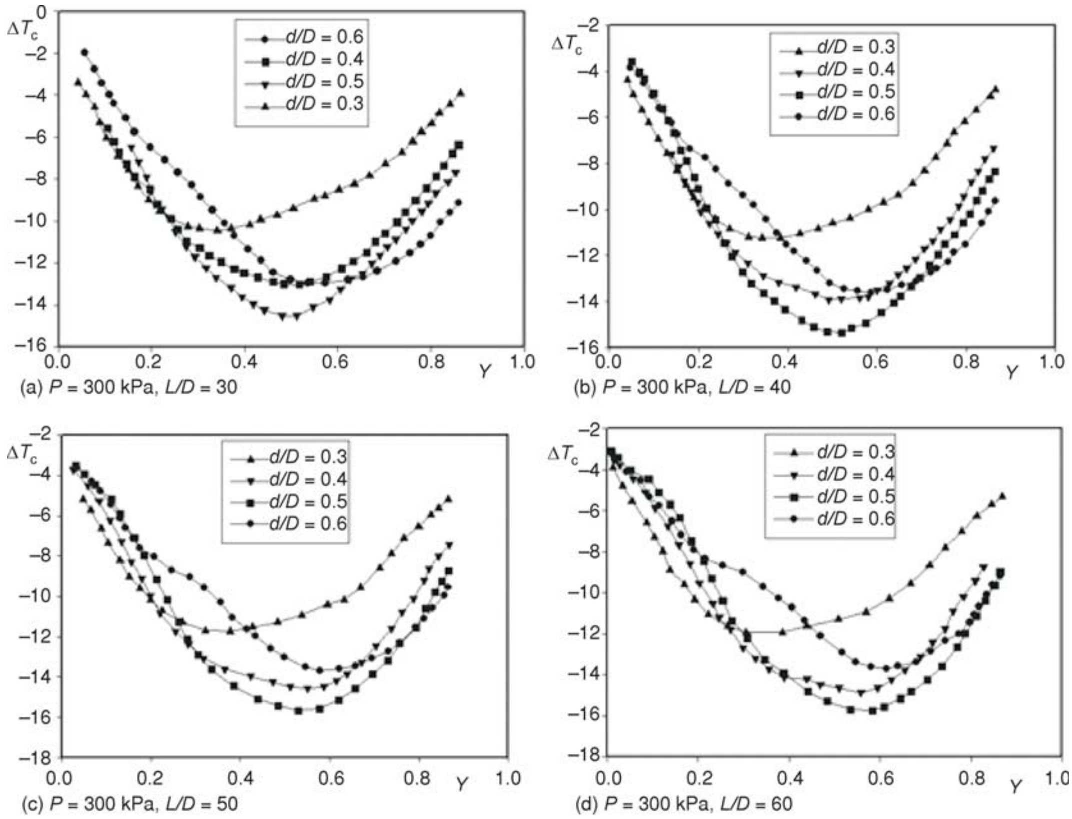

Figure 5. Predicting the effect of *d/D* on the cooling performance of the vortex tube

An axis-symmetric model was developed to model a vortex tube with the length of 60 mm and three different cold outlet diameters. The detail of the geometry of vortex tube and operating condition can be found in tab. 1. At the inlet, a circumferential slot was assumed instead of the actual four nozzles. Previous studies show that for a numerical modeling of vortex tubes with more than four nozzles, an axis-symmetric swirl model can be as efficient as 3-D model in predicting the cooling performance of the device. However, when the nozzle number is less than or equal to four the numerical solution cannot predict the performance of the device with high accuracy [39]. Nevertheless, it can still be an efficient tool for qualitative studies. The details of numerical modeling have not been reported here for the sake of brevity. However, the procedure can be found in literatures [37, 40, 41]

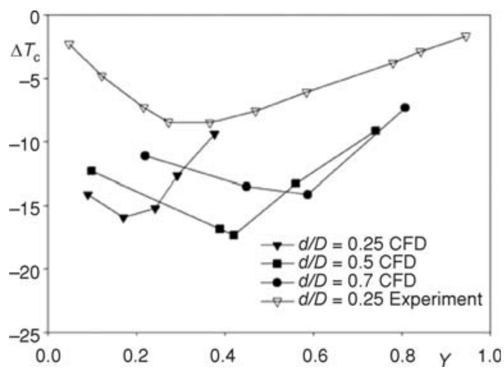

Figure 6. Predicting the effect of *d/D* on the cooling performance of the vortex tube as obtained by CFD mode

Figure 6 shows the cooling performance of vortex tube with three different *d/D* values as

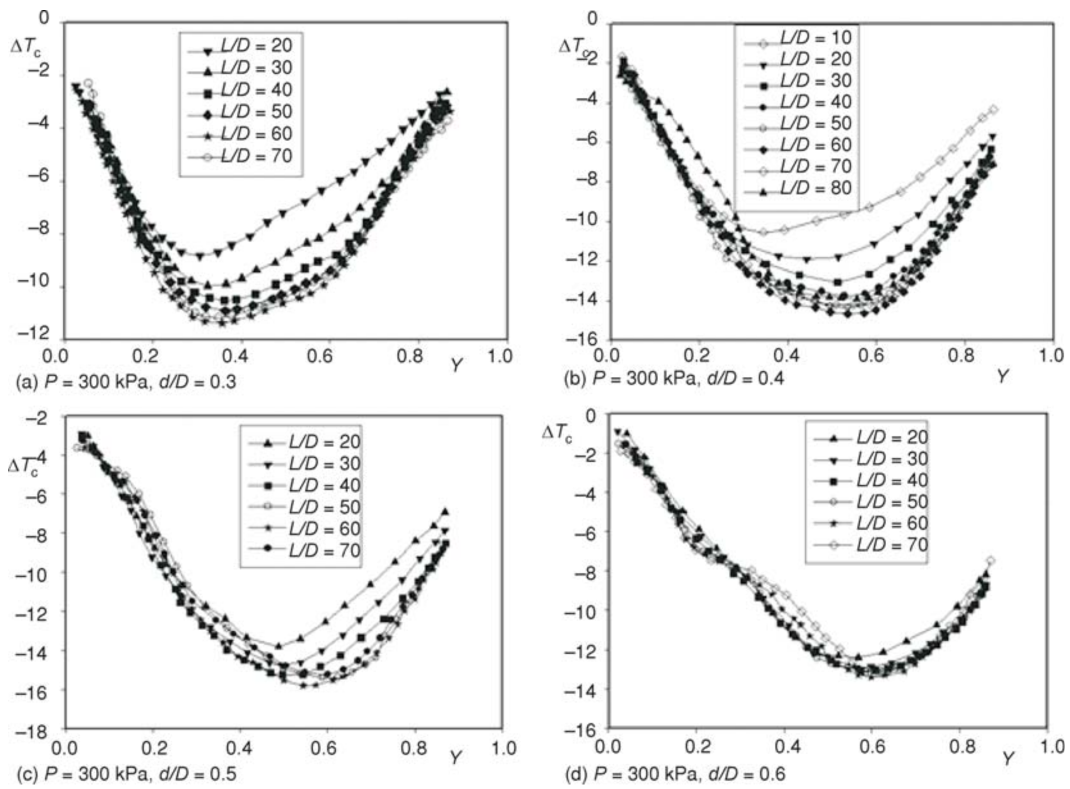

Figure 7. Predicting the effect of *L/D* on the cooling performance of the vortex tube

predicted by CFD model. This figure also shows the experimental data for a vortex tube with cold outlet diameter of 0.5 mm (d/D = 0.25). Comparison between the CFD results and the experimental data for vortex tube with d/D = 0.25 indicates that the numerical model over predicted the cooling performance. However, both the numerical and experimental data show the same trend so that the optimum cold mass fraction is almost identical.

According to the present numerical results, for a vortex tube with d/D = 0.5, the cooling performance reaches its maximum value. This prediction agrees well with ANN model. Moreover, it is seen that as we increase the cold outlet diameter the optimum cold mass fraction increases. This prediction is consistent with the ANN predictions.

The last parameter examined in this study was the ratio of length to the diameter (L/D) of vortex tube. Figure 7 shows the effect of L/D on the cooling performance of the vortex tube for different d/D values. According to fig .7(b), for a vortex tube with L/D = 10, we have the lowest cooling performance and from L/D = 10 to L/D = 40, there is a significant upward trend in the cooling performance of the vortex tube. Beyond L/D = 40, we can see a slight increase but after L/D = 60, there is a slight downward trend in the cooling performance of the vortex tube. Therefore, it can be concluded that the best cooling performance of the vortex tube occurs at around L/D = 60. This trend is seen in all the figures irrespective of the d/D ratio.

Conclusions

In this study artificial neural network model has been used to investigate the effects of four important parameters (*L/D*, *d/D*, *P*, and *Y*) on the cooling performance of a vortex tube. Comparison between ANN predictions and experimental data has confirmed the acceptable precision of this model. It was observed that Genetic algorithm can play an important role in order to choose appropriate ANN architecture so that the optimized ANN model can predict the cooling performance in a wide operating condition.

According to this study, the maximum temperature drop occurs at a specific cold mass fraction (*Y*) and the optimum value of *Y* is almost independent of pressure (*P*) and length to diameter ratio (*L/D*) but dependent on the ratio of cold outlet diameter to the diameter of tube (*d/D*). Also, the effect of pressure on cooling performance was investigated. The present results indicate that an increase in the inlet pressure improves the cooling performance of the vortex tube.

The effect of *d/D* has been studied in a wide operating range ($0.2 < d/D < 0.7$) and it was observed that the optimum value of *d/D* is independent of other parameters. The present results indicate that the maximum temperature drop always occurs at $d/D = 0.5$. Furthermore, the CFD simulations were carried out to study the effect of cold outlet diameter on cooling performance of the device. Comparison among the experimental data, ANN predictions and 2-D CFD results shows that the ANN model can predict the cooling performance of vortex tube with higher accuracy. However, the predicted results with both the models agree well in qualitative manner.

The effect of the length to the diameter ratio (*L/D*) on cooling performance of vortex tube was studied at different *d/D* and *Y*. The present results show that an increase in length to the diameter ratio results in an increase in the cooling performance of the vortex tube. However, there is a critical value, so that further increase will lead to the reduction in the cooling performance. Furthermore, it was observed that the optimum *L/D* ratio is almost independent of the *d/D*.

Nomenclature

a – output
b – bias
d/D – ratio of the cold outlet diameter to the diameter of the tube
f – transfer function
L/D – ratio of the length to the diameter
LWi,j – layer weights from layer *j* to layer *i*
$\dot{m}_c$ – cold outlet mass flow rate, [kgs^{-1}]
$\dot{m}_i$ – inlet mass flow rate, [kgs^{-1}]
P – inlet pressure, [kPa]
$\vec{p}$ – input vector
R – regression
T_c – temperature at cold outlet, [K]
ΔT_c – temperature drop at cold outlet, [K]
T_i – inlet temperature, [K]
Y – cold mass fraction
W – weight matrix

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Paper submitted: January 26, 2014
Paper revised: September 9, 2014
Paper accepted: September 11, 2014