An application and modelling on the artificial neural network to the RHV Tube

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Abstract: Artificial neural networks represent highly advanced and adaptable tools for addressing challenges, attributed to their capacity for learning through examples and forming generalisations. The present investigation involved the development of an Artificial Neural Network (ANN) utilising a multilayer neural network model. An instance of the artificial neural network's application was demonstrated through the utilisation of the Ranque-Hilsch Vortex (RHV) tube. Through this study, the impact of transfer utilising function, data selection method, and data quantity on the artificial neural network's efficacy was examined. This approach is particularly favoured for resolving intricate non-linear issues that are challenging to model mathematically.

Keywords: Ranque-Hilsch Vortex (RHV), Artificial Neural Networks (ANN), Multi-layer Perceptron (MLP), Modelling.

1. Introduction

By the mid-last century, artificial intelligence and artificial neural networks (ANN) have provided the discovery of new techniques for the assessment, learning and decision-making processes for various events. The artificial neural networks technique nowadays is widely used in several fields. ANN has the capability of learning from data, making generalisation, and operation with an unlimited number of variables. ANN with these qualities provides important advantages and it is frequently used for foresight modelling as in the case other branches.

This technology, which is advancing day by day and providing several advantages, is utilised by several branches, particularly in areas which necessitate the description of data structure, such as foresight and forecast. Lenat & Feigenbaum (1987) define the intelligence as “the ability to collect the necessary information and combine them to solve a complex problem”. The intelligence is described by the Feigenbaum (Feigenbaum, 1989) as “the ability to solve a complex problem in the shortest route by narrowing the area of solution seeking”. Russel and Norvig (2003) defined artificial intelligence as “systems which think like a human, act like a human, think intelligently and act intelligently”. Many theoretical and applied studies have been carried on so far on artificial neural networks (Basheer & Hajmeer, 2000; Dastres & Soori, 2021; Goel et al., 2023; Hopfield, 1988; Luger & Stubblefield, 1989; Luger & Stubblefield, 1993; Mehrota et al., 1997; Qamar & Zardari, 2023; Xie, 2007).

The vortex tubes which were first discovered in 1932 by Ranque and then system performances studied in 1940 by Hilsch are composed of a simple mechanism that separates a compressed gas into hot and cold streams without any chemical reaction. The vortex tubes are generally divided into two groups: vortex tubes of counter flow type (VTCF) and vortex tubes of parallel flow type (VTPF).

There are outlets on both edges of VTCF. The high-velocity compressed gas inflows the tube from the nozzle and gains a rotational motion. The compressed gas, following a certain stagnation, is divided into two flows: hot stream peripheric rotating along the wall and cold stream rapidly rotating in the opposite direction along the axis. The hot air leaves the tube through the hot outlet and cold air through the cold outlet, there is no outlet around the nozzle in VTPF; both exits are on same side (Figure 1a). Unlike VTCF, two streams with different velocities and temperatures arising from energy separation flow in the same direction. The cold fluid leaves the tube from the hole at the centre of the valve, whereas hot fluid, as for the VTCF, leaves the tube peripherally. Since the mixing of hot and cold fluids in VTPF is highly probable, their efficiency is lower and therefore, they are not preferred (Figure 1b), (Korkmaz et al., 2012; Markal, 2009).

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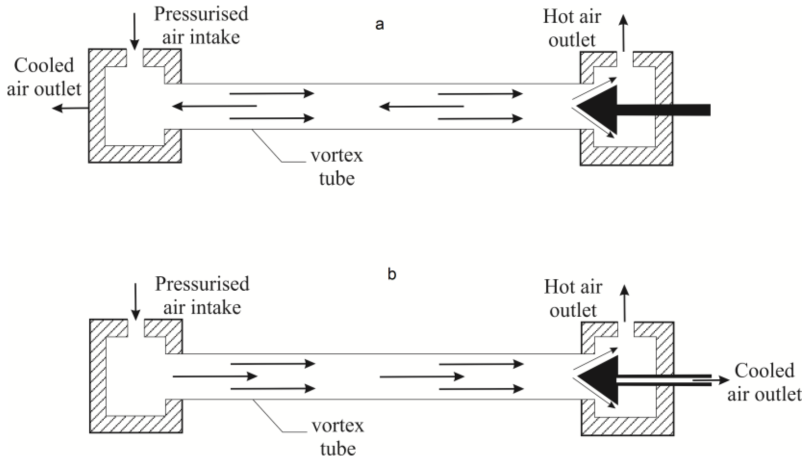

Figure 1. a) Vortex tubes of counter and b) parallel flow types (Markal, 2009)

Although vortex tubes are of lower efficiency, their lightweight, suitableness for instant cooling and environmentally friendly nature make them used in several engineering applications, particularly for cooling purposes. Unlike other cooling machines, no other cooling fluid is needed except for compressed air. In systems where compressed air is used, cooling and heating may be provided without any additional cost using vortex tubes. Low efficiency and loud running are the major disadvantages (Markal, 2009). Several studies were carried out on the performance of Vortex tubes (Aydin et al., 2010; Dezfouli, 2022; Dincer et al., 2011; Eiamsa-ard & Promvonge, 2008; Korkmaz, 2011; Korkmaz et al., 2012; Markal, 2009; Nezhad, 2017; Nezhad, 2023; Valipour & Niazi, 2011; Wu et al., 2012).

2. Method

Invented by Ranque and further developed by Hilsch, the Rangue-Hilsch Vortex (RHVT) tube is a device that effectively divides the compressed gas flow into separate hot and cold streams simultaneously, with no involvement of chemical reactions. This piping structure is characterized by its simplicity, housing solely a control valve as the solitary moving component. The RHVT system facilitates both cooling and heating functions concurrently by utilizing pressurized fluid. Within the scope of this investigation, an experimental arrangement was established by interconnecting counter-flow Ranque-Hilsch Vortex Tubes (RHVT) in a parallel configuration, featuring inner diameters of 10 mm and lengths varying from 100-400 mm. The experimental setup primarily encompasses a compressor, dehumidifier, testing zone, various measuring instruments, as well as valves and connectors. Experimental measurements and results are described in the next sections.

In this study, data obtained from experimental measurements were evaluated utilizing artificial neural networks (ANN). Numerous artificial neural networks have been devised for a variety of objectives. Despite disparities in their configuration, functionality, and operational principles, they have some common features. The primary role of ANN is to facilitate computers in acquiring knowledge and making analogous decisions when confronted with comparable situations through the process of learning. During the execution of these tasks, all computational units within the ANN can generate outcomes rapidly due to their concurrent operation, i.e., in parallel. The cell, which serves as the fundamental computational unit of ANN, is characterised by non-linearity. Consequently, the ANN constructed from these cells is also non-linear, with this attribute permeating the entire network. This non-linear property enables ANN to address intricate non-linear issues, a capability not shared by conventional programming techniques and artificial intelligence methodologies. Artificial Neural Networks have the capacity to execute a wide range of functions, including data analysis, optimisation, regulation, categorisation, and visual data processing. They are also instrumental in resolving diverse engineering challenges and finding applications in domains such as finance, transportation, healthcare, and telecommunications. The present study involved the deployment of the Multilayer Sensor model for the Ranque-Hilsch vortex tube. The subsequent sections delineate the structure of the artificial neural network devised to tackle this specific problem.

3. Applied studies

3.1. RHVT modelling using artificial neural network

In this investigation, utilising the applied data, the impacts of conical point angle and tube length of VTCF on efficacy were simulated through artificial neural networks. The data utilised in the simulation were acquired from experimental studies conducted in a laboratory setting. The artificial neural network was established using the NeuroSolutions 6.0 software developed by NeuroDimension Company. Within this scholarly inquiry, the network simulation was executed utilising this software, and network parameters were defined within the software. The software operation was conducted on a computing system equipped with Microsoft Windows 7 Professional 32-bit operating system, featuring a Pentium Dual Core processor clocked at 2.00 GHz, 3 GB of RAM and a 150 GB Disk space. The schematic diagram of the experimental setup is shown in Figure 2. It consists of two main parts as an air supply system (a rotary screw compressor, an air tank, a dehumidifier unit, a pressure regulator) and a test section (a vortex tube, joining components, rotameters and thermometers). The compressed working fluid supplied by a rotary screw compressor passes through the air tank and the dehumidifier unit. Then, it passes through a pressure regulator, which is used to adjust pressure to the to desired level. After the regulator, flow tangentially enters the tube. By a conical valve at the far end of the tube, the flow rate of the working fluid at two exits is adjusted. Temperatures are measured before inlet and after outlets by three K-type thermocouples. The volumetric flow rate is gauged by rotameters located outside of both exits. Also, out of the cold exit, there is digital manometer in order to measure the pressure of cold air leaving from the vortex tube (Korkmaz et al., 2012).

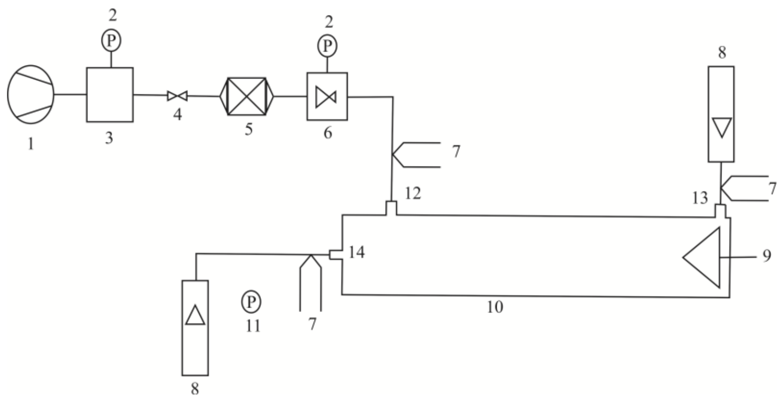

Figure 2. A schematic diagram of the experimental setup (Korkmaz et al., 2012)

(1. Compressor; 2. Pressure gauge; 3. Air tank; 4. Valve; 5. Dehumidifier; 6. Pressure regulator; 7. Thermocouple; 8. Rotameter; 9. Conical valve; 10. Tube; 11. Digital manometer; 12. Inlet nozzle; 13. Hot end nozzle (hot exit); 14. Cold exit)

In the research, the effects of various geometric planes and thermophysical properties on the performance of a cylindrical counter-flow type vortex tube and the occurrence of energy separation within the tube were empirically examined. Independent trials were executed for each set of geometric parameters. These individual sets were specifically created for Pi=3,4,5 bar pressures. A total of four distinct tube lengths (L), six varied conical point angles (Ø), and five different lengths of the vortex generator (helix step) were utilised. Temperature measurements were conducted at the inlets and outlets of the vortex tube, where cold and hot air were expelled. In the experiment involving the utilisation of air as the primary fluid, discharge values were obtained at the hot and cold outlet locations, alongside the recording of static pressure at the cold outlet point (1). Throughout the experimental procedure, temperature measurements were predominantly carried out under varying pressure conditions and discharge values. Under constant pressure settings, changes in discharge values at the outlets were implemented to ascertain the temperature readings at both hot and cold outlet points. The fluid discharge at the outlets could be manipulated through the use of a conical point, specifically an adjusting valve within the system. By comparing the mass flow rate from the cold outlet to the inlet discharge, the cold mass ratio (Yc) was determined. This particular ratio is derived from the following equation:

$$Yc = \dot{m}c/\dot{m}i \quad (1)$$

For each mass flow ratio, the temperature difference between cold and hot points. A temperature difference of cold air is estimated from the equation:

$$\Delta Tc=Ti-Tc \quad (2)$$

Temperature difference of hot air is found from the following equation:

$$\Delta Th=Th-Ti \quad (3)$$

The total Temperature difference is computed as in the following:

$$\Delta T=Th-Tc \quad (4)$$

Eq. (4) can be expressed as the performance of the vortex tube (Korkmaz et al., 2012).

3.2. Determination of parameters used in the ANN model

In the construction of an artificial neural network model, data obtained from experiments were used. In the ANN model developed, as the input parameters, gauge pressure (Pi), cold mass ratio (Yc), conical point angle and the ratio of vortex pipe length to pipe inner diameter (L/D) were used. The difference (T) between the temperature of fluid outgoing from the hot point and the temperature of fluid outgoing from the cold point is used as the output parameter. The parameters used for the construction of the ANN model are summarised in Table 1.

Table 1. Parameters used for artificial neural network

Pipe dimension of the vortex tube			Conical point angle (Ø)	Gauge pressure (Pi) (bar)	Helix length (h) (mm)
Length (L) (mm)	Inner diameter (D) (mm)	L/D			
100	10	10	30	2	30
200	10	20	45	3	-
300	10	30	60	4	-
400	10	40	75	-	-
-	-	-	90	-	-
-	-	-	120	-	-

The parameters given in Table 1 are constant parameters. When preparing the data set to be used for training of ANN model, in addition to these parameters, other parameters measured during the experiment (as mentioned above) were also taken into account. Since the length of the helix (h) shown in the table is taken constant during all the experiments, it is not considered during the construction of the ANN model. In the experimental study, measurements were taken using helix step of five different lengths. However, when forming a network model with ANN the network was established, trained and run for only one helix step.

3.3. Preparation of training, test and application sets for ANN

As a result of experiments, a number of 1515 data were obtained. These values to be used in ANN were arranged with respect to input and output parameters. 70% of 1515 data (1060 data) were selected as training and test sets, and the remaining 30% (455 data) were selected as the application set. During the training, the application set was not introduced to the system. Following the completion of training and testing of the network, network performance was tested in practice. 1060 data selected for the training and test sets were internally separated into training sets and test sets. Among these data, 80% (848 data) were arranged for training set, and the remaining 20% (212 data) were selected for testing purposes.

3.4. Selection of network model for ANN

The problems to be solved with ANN are generally represented by non-linear relations between inputs and outputs. In this study, a multilayer feedforward neural network model was used, which is widely preferred for forecasting in engineering applications (Sencan & Kalogirou, 2005). This model uses a supervised learning method. Inputs and outputs are introduced to the network during the training. The multilayer network is mostly composed of three layers: input, output, and hidden layers (Figure 3). For this study, various network models were tested, and as a result, a multilayer neural model was preferred by means of performance and usability.

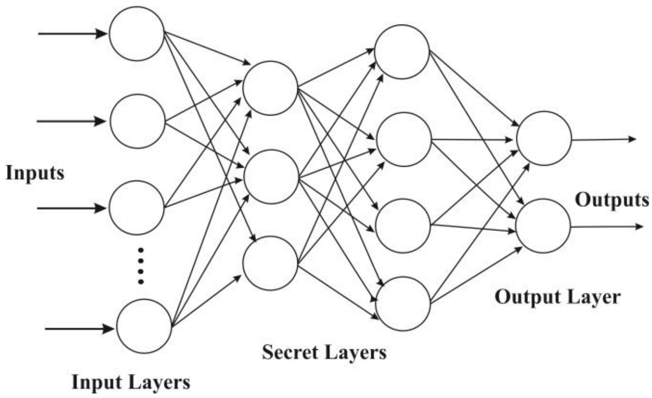

Figure 3. A multilayer sensor model

3.5. Selection of learning model for ANN and determination of other parameters

In the established artificial neural network, the Levenberg-Marquardt Training Algorithm (LMTA) was selected as the learning model. The LMTA is the most popular algorithm used recently and has been extended as an alternative to other algorithms. The learning algorithms used can be divided into two parts: the trial-and-error technique and standard numerical optimisation. In the established network, a multilayer neural model and Levenberg-Marquardt Training Algorithm were used. As a result of tests, the network was modelled to have a single hidden layer providing the best performance and six process elements in this layer. In the hidden layer, the Hyperbolic Tangent Function was selected as the transfer function. In the output layer, the Hyperbolic Tangent Function was selected as the transfer function, and the Levenberg-Marquardt Training Algorithm was used as the learning algorithm. Each example was introduced to the network 1000 times, and the error rate coefficient for stooping of training is designed as 0.01.

4. Results and discussions

In this investigation, the impact of the conical point angle of RHVT on its cooling and heating capacities was analyzed utilizing the Artificial Neural Network (ANN) method.

4.1. Error curve, training result and network model examples

In the network established by the NeuroSolutions program, input parameters are taken as gauge pressure (Pi), cold mass ratio (Yc), conical point angle and the ratio of vortex pipe length to pipe inner diameter (L/D). The difference (T) between the temperature of fluid outgoing from the hot point and the temperature of fluid outgoing from the cold point is used as the output parameter. The network was modelled to use a multilayer feedforward neural network and the Levenberg-Marquardt Training Algorithm. The architecture of the network was intentionally structured with thredesigned to have three layers: and the input layer, the hidden layer and the output layer, each containing 4, 20 and processing elements respectively. The hyperbolic tangent transfer function was used in the hidden and output layers. The learning algorithms in both layers are composed of the Levenberg-Marquardt Training Algorithm. The symbolic illustration of the established artificial neural network is given in Figure 4, and the graphics for the results of network training is shown in Figure 5. The solid line indicates outputs introduced (required) to the network during the training, while the dashed line stands for outputs generated by the network training. Both lines are required to coincide as much as possible, the more the results are close, the less the error rate.

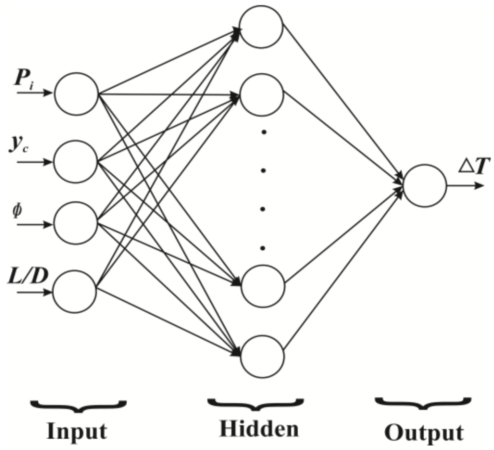

Figure 4. Neural network model (Korkmaz et al., 2012)

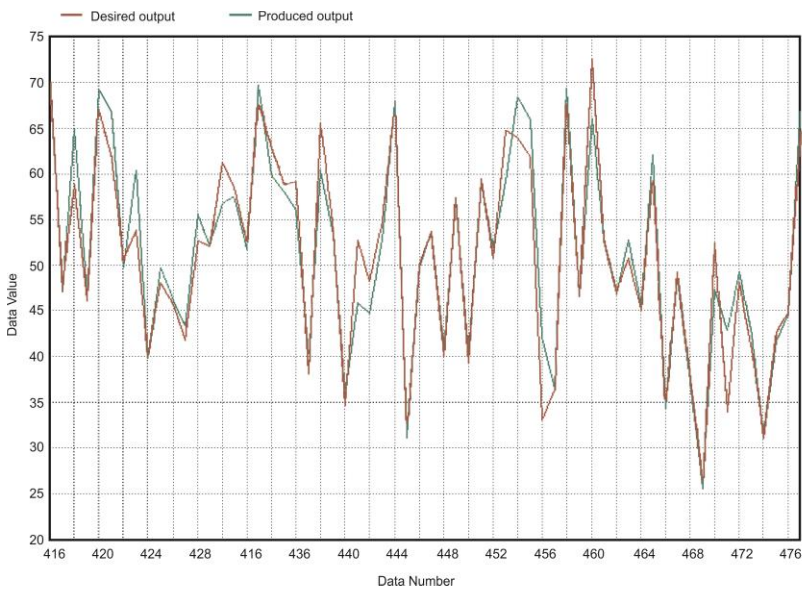

Figure 5. An example diagram of expected and produced outputs

4.2. The effects of transfer function selection on education

In the application performed to show the effect of the selection of the Transfer Function (TF) on network performance, the network was trained and tested assuming that the following parameters are constant and only the transfer function is varied. The results of the training are given in Figure 6 a and Figure 6 b.

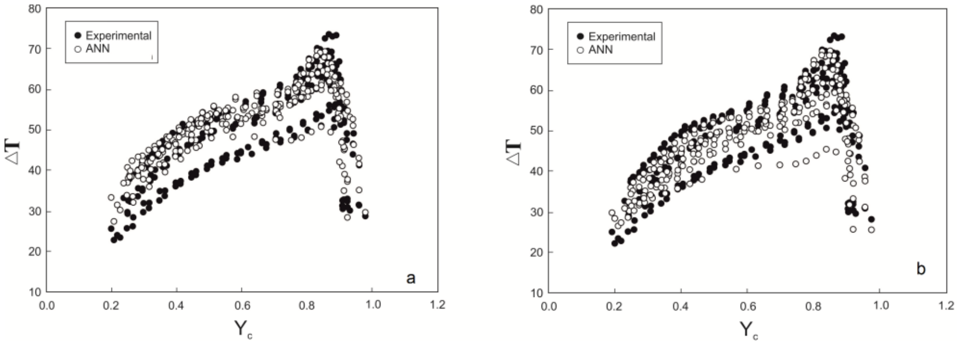

Figure 6. a) Networks trained by tangent and b) sigmoid transfer functions

The investigation utilised a three-layer network (comprising input, output, and hidden layers) by employing the multilayer feedforward neural network and the Levenberg-Marquardt Training Algorithm. The input layer incorporated four process elements: gauge pressure (Pi), cold mass ratio (Yc), conical point angle (Ø), and the ratio of vortex pipe length to pipe inner diameter (L/D). In the output layer, the sole process element present was the disparity (T) between the temperatures of fluid exiting from the hot and cold points. The hyperbolic tangent transfer function was adopted in the hidden and output layers as the designated transfer function. To show the effect of various parameters on the network training and application performance, the network was modelled in different ways.

Figure 5 shows the result of a training example generated by the NeuroSolutions program. The success of training is related to the closeness of the required output and generated output curves. As the training is repeated, the curves are converged to some extent. After a certain point, it is shown that the curves diverge and training performance is lowered, which can be attributed to the fact that the network memorises rather than learning. A network which showed very successful performance during the training but generated disappointing results during the application is thought to have memorised the training data and be designated as unsuccessful in the application.

4.3. The effects of data selection method and data number on network performance

In the second study, only the application set was changed, and other network model parameters were held constant. In both network models, a hyperbolic tangent transfer function was used. In the experimental work, results were obtained by making measurements for conical point angles 30-45-60-75-90-180 degrees. In the first study, data obtained at a conical point angle of 75 degrees were removed from the data set and introduced to the network following the training. In the second study, which was carried out to show the effect of data selection, data obtained at a conical point angle of 180 degrees was removed from the data set and the network was asked to generate results for 180 degrees following the training (Figure 7 a). Network outcomes generated at a conical point angle of 75 degrees are shown in Figure 7 b.

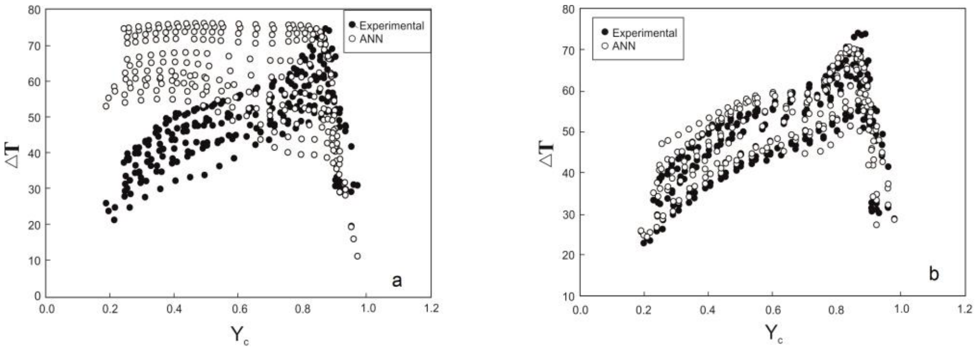

Figure 7. a) Application results of conical point angles for 180 and b) 75 degrees

Furthermore, in this study the effect of data number on the network performance was examined. The study was implemented for a network model for which data with conical point angle of 75 degree are separated as application set and the remaining 1263 data are used as training set. The training sets are divided into 9 different series (Table 2).

Table 2. Average error rates of trained and applied data vary with respect to number of data

Training sets	Training average error rate (%)	Application average error rate (%)
Training 20% -Test 80%	10.2	12.02
Training 30% -Test 70%	7.43	6.83
Training 40% -Test 60%	7.42	10.14
Training 50% - Test 50%	7.30	7.30
Training 60% -Test 40%	8.13	8.50
Training 70% -Test 30%	9.27	8.15
Training 80% -Test 20%	7.55	6.78
Training 90% -Test 10%	11.28	11.33
Training 100 %	-	9.68

The results of measurements in Table 2 indicate that the most successful results were obtained from the network model with 80% training and 20% test sets which were used during studies of the present investigation. Low data number of training test results in error rate to increase. Generaly, average training error rates are very close but become quite variable during the application, and there is no linear increase or decrease. Considering the data shown in this table, increasing the number of trainings does not necessarily improve the network performance. To find a suitable a network structure, different alternative methods must be tested, and a network model with the most consistent results should be applied.

5. Conclusions

In the present investigation, the utilisation of the artificial neural networks approach was implemented in the analysis of the Ranque-Hilsch Vortex Tube. The construction of the Artificial Neural Network (ANN) model involved a preference for the multilayer feedforward neural network model due to its extensive utilisation in various engineering domains. The adoption of the Levenberg-Marquardt Training Algorithm, commonly employed in predictive applications, was chosen as the learning algorithm, with a three-layer configuration (comprising input, output, and hidden layers) being favoured for the network model.

In the prediction phase, a conical point angle of 75 degrees was specifically chosen, with an intermediary value selected among six distinct conical point angles being deemed as appropriate. To illustrate the impact of parameter selection on network performance, a limit parameter of 180 degrees was imposed, revealing inferior performance at the limit values. In the hidden and output layers, the Hyperbolic Tangent Transfer Function was selected as the preferred transfer function and was subsequently compared with the Sigmoid Transfer Function. Experimental results indicated that the Hyperbolic Tangent Transfer Function yielded more favourable outcomes for the specific problem. The training, test, and application data were introduced to the network in various ways (e.g., regular, ordered, and mixed), showing very similar results for this specific problem.

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