Artificial Neural Network modelling for pressure drop estimation of oil-water flow for various pipe diameters

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Abstract – *The flow of two immiscible liquids in pipeline occurs many times in chemical industries. Oil-water mixture is dispersion and estimation of pressure gradient for flow through pipeline using empirical equation is tedious and less accurate. The present work is aimed at development of artificial neural network models for estimation of pressure gradient as a function of pipe diameter, flow rate, composition of oil-water mixture and angle of elevation of the pipe. 175 experimental runs have been conducted by varying process parameter combinations. Three ANN models have been developed using elite-ANN© based on the experimental data generated. Comparison among actual values with predicted values using ANN models is carried out. Based on the results and discussion, it can be said that all the ANN models developed have excellent accuracy level of prediction for both the training as well as test data sets. The relative error of prediction is in the range of 5 to 20%, highlighting the success of the present work. The work is demonstrative and it is felt that many such models can be developed for various combinations of input and output parameters that is readily available in process industry.*

Key Words: Artificial Neural Network modelling, two phase flow, oil-water dispersion, pressure gradient and angle of elevation of pipe.

1. INTRODUCTION

1.1 liquid-liquid two phase flow

The flow of two immiscible liquids occurs in a pipeline many times in chemical industries, mostly in the petrochemical industry where oil and water are pumped from the wells and transported together [1]. The interactions between the two liquids, with respect to interfacial tension and the wetting properties of the pipe material, means that phenomena are more complex compared to gas-liquid systems [2]. There are large differences in the test fluids used in liquid-liquid experimental studies so that it is difficult to draw any definitive rules for flow pattern boundaries and properties [3].

The flow patterns of liquid-liquid flow are divided into three main categories that are separated flow, dual continuous and dispersed flow. In separated flow both liquids retain their continuity at the top and bottom of the pipe. It consists of stratified flow, where the oil flows above the water and the interface between the two liquids is smooth; and stratified wavy flow where the flow is still stratified but the interface has large waves. Dual continuous flow is flow pattern where both phases remain continuous, but there is a degree of dispersion of one phase into the other. There are limited experimental studies for pressure gradient of liquid-liquid two phase flow in pipelines.

There are mainly two types of pressure measuring devices manometers and mechanical gauges. Mechanical gauges are the most used pressure gauges for industrial purposes. Types of mechanical gauges are Bourdon tube gauge, Bellow gauge, Diaphragm gauge and dead weight gauge.

1.2 Artificial Neural Network

Artificial Neural network is derived from biological neural network. It can be compared with a black box having multiple inputs and multiple outputs which operates using large number of data which have non-linear relationship with each other. Artificial neurons behave like biological neurons. It accepts signals from adjoining neurons and process to give output signals [4]. There are various types of ANN & Error Back-propagation is one amongst them. It requires at least two layers of nodes. One is the hidden layer and second is output layer. The nodes of two layers are interconnected by the constants called weights. In error back-propagation learning the weights in output layer are corrected first and after having these weights corrected together, the errors have been evenly distributed to the last hidden layer. Then the weights of last hidden layer are corrected and so on [5]. Learning of error back-propagation is in cycles called epochs. The period in which all inputs are presented once to the network is one epoch. After each epoch, RMS (root mean square) error is reported. RMS value decides the accuracy of the model [6]. The aim of all the researchers is to reach as small RMS value as possible. Various applications of ANN in modeling, simulation and optimization of chemical processes have been reported in literature, these include, Estimation of Pressure Drop of Packed Column Using Artificial Neural Network [7], Modeling of Artificial Neural Network for Leak Detection in Pipe Line [8], Artificial Neural Network Modeling of Equilibrium Relationship for Partially Miscible Liquid-Liquid Ternary System [9], Modeling of Packed Bed Using Artificial Neural Network [10], Developing Optimum ANN Model for

Mass Transfer with Chemical Reaction in Packed Column for Air-Carbon Dioxide and Aqueous Sodium Hydroxide System [11], Artificial Neural Network Modeling for Estimation of Composition of a Ternary Liquid Mixture with its Physical Properties such as Refractive Index, pH and Conductivity [12] and similarly others are also reported.

Researchers have reported, 'A Study of Pressure Gradient Characteristics of Oil-Water Dispersed Flow in Horizontal Pipe' [13], 'Experimental investigation on flow patterns and pressure gradient through two pipe diameters in horizontal oil–water flows' [14], 'Investigation of pressure drop in horizontal pipes with different diameters'[15], 'Flow structure and pressure gradient of extra heavy crude oil-water two-phase flow' [16], 'Modeling of Two-Phase Flows in Horizontal Tubes' [17], 'Experimental investigation of oil–water two phase flow regime in an inclined pipe' [18], and so on which are associated with two phase liquid systems.

2. PRESENT WORK

The objective of the present work is to develop ANN models for prediction of pressure gradient for flow of oil-water mixture in a pipeline.

2.1 Methodology

Present work [19] is divided in two parts, experimental and model development.

The first part of the present work deals with the experimental studies of pressure drop. Data based on experimental studies for oil-water mixture in pipeline generated by varying pipe diameter, oil-water composition and angle of elevation of pipe.

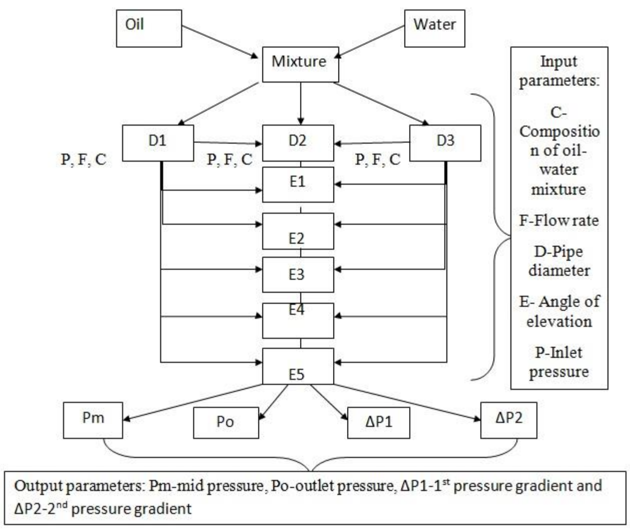

Fig.1: Details of methodology adapted for present work part1

In second part; data generated in part1 are used in developing ANN models to correlate the mid pressure, outlet pressure and pressure gradient along the pipe as a function of flow rate, oil-water composition, angle of elevation and pipe diameter. In this study, elite-ANN© is used in developing all ANN models.

2.2 Present work part1: Experimental studies

Used machine oil-water mixture coming under the category of liquid –liquid two phase mixture is used for flow of this mixture in the present work. It aims at estimation of pressure drop as a function of pipe diameter, mass flow rate, composition of oil-water mixture, angle of elevation of pipe and inlet pressure. The experimental data generated is used for prediction of pressure drop in development of ANN models.

2.2.1 Experimental setup

Figure 2 shows the schematic of the experimental setup. It consists of a reservoir tank having 60 liters' capacity, 1HP centrifugal pump, valve to control flow rate, inlet pressure gauge, mid pressure gauge, outlet pressure gauge and 1.6 m long acrylic pipes having 1.27cm, 2.54cm and 3.81cm diameter respectively. Experiments are performed by pumping oil-water mixture into the pipe and noting pressure by varying flow conditions.

175 Experimental runs are conducted separately for different pipe diameters. The various concentrations of oil in water solutions used for experimental runs are 2%, 4%, 6%, 8%, and 10% by volume. Similarly angle of elevation varied are 5, 10, 15, 20 to 25. Pressure is measured by employing pressure gauges. Flow rate is measured by weighing the oil-water mixture leaving the pipe for known time interval.

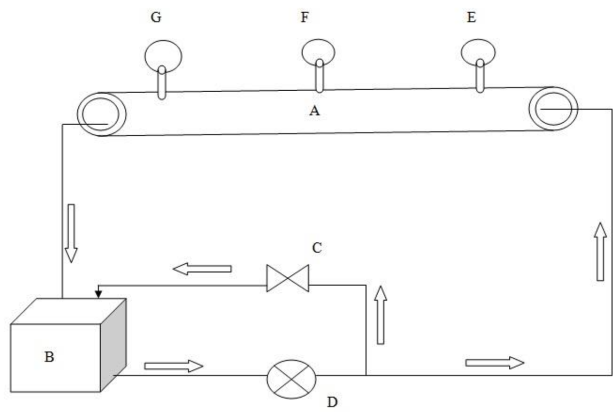

Fig.2: Schematic of the experimental setup

A→ acrylic pipe, B→ storage tank, C→ valve to control flow rate, D→ centrifugal pump, E→ Inlet pressure gauge, F→ Mid pressure gauge, G→ Outlet pressure gauge
The actual photographs of experimental setup in run mode are shown in fig 3, 4, 5 and 6

Fig.3: Actual photograph of experimental setup in run mode for 1.27cm pipe diameter

Fig.4: Actual photograph of experimental setup in run mode for 2.54cm pipe diameter

Fig.5: Actual photograph of experimental setup in run mode for 3.81cm pipe diameter

Fig.6: Photograph of two phase flow oil-water mixture

2.2.2 Experimental procedure

The oil-water mixture is pumped from the tank to the test section using a centrifugal pump. Flow rate of mixture is adjusted by outlet valve and bypass valve. Pressure gauges' readings are recorded. The flow rate is varied for given oil-water mixture. The procedure is repeated for various flow rates for different compositions of oil-water mixture. The entire procedure is repeated for same pipe diameter but for various angle of elevation. Similarly, the entire procedure is repeated for second and third pipe diameters. The oil-water mixture is pumped around through pipe for some time to have better distribution of oil in water.

2.3 Present work part 2

The experimental data generated in part 1 is used for development of models using artificial neural network software elite ANN© [20]. Three ANN models have been developed in present work.

- ANN Model Development

The procedure of developing an ANN model is as follows:

- Specifying the number of inputs and outputs for the network. Creating a database of specified input-output variables.
- Selection of network type, number of layer, number of neurons.
- Training of the network.
- Checking the performance and precision of trained neural network, changing and retraining of network as per accuracy level.
- Validation on a set of test data.

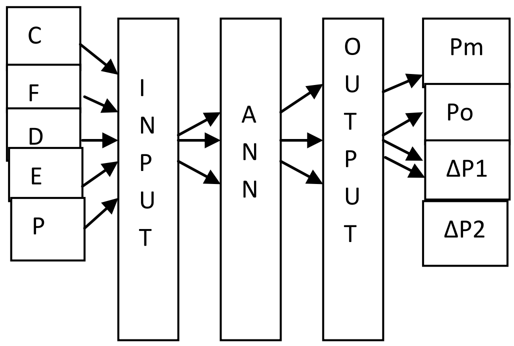

Fig.7: General architecture of artificial neural network model

2.3.1 Model CFDP development

Pressure drop estimation for horizontal pipe with different diameters:

This model correlates percentage of oil, mass flow rate, pipe diameters and inlet pressure to pressure gradients. This Model have two hidden layers with five neurons each and

four output parameters as mid pressure, outlet pressure, 1st pressure gradient and 2nd pressure gradient.
The topology and ANN architecture of CFDP model are given in table no.1 and fig.8 respectively.

No. of neurons				Data points		Learning rate
Input parameters	2nd hidden layer	3rd hidden layer	Output parameters	Training	Test	
4	05	05	4	59	16	0.3
Iteration termination = 1000		First momentum factor = 0.75 First momentum factor = 0.01		RMSE for training data = 0.05695 RMSE for test data = 0.01094		
Input parameters: Percentage of oil, Mass flow rate, Pipe diameter and Inlet pressure.			Output parameters: Mid pressure, Outlet pressure, 1st pressure gradient and 2nd pressure gradient.			

Table no.1: Neural network topology for ANN model CFDP using elite-ANN©

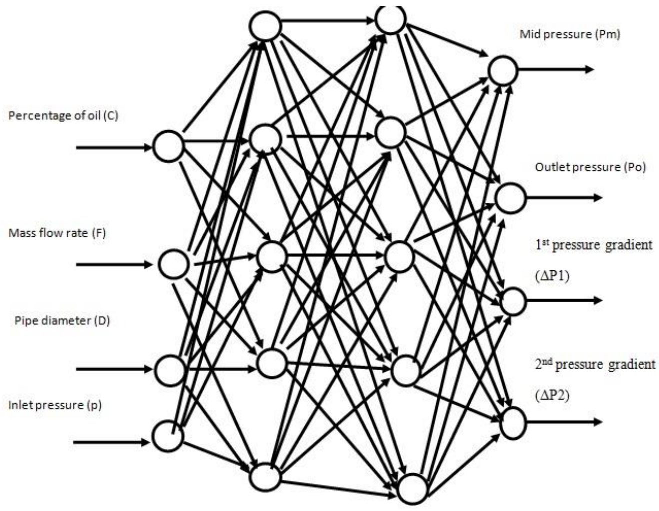

Fig.8: Typical architecture of artificial neural network model used for Model CFDP

2.3.2 Model CFEP development

Pressure drop estimation for same diameter with different angle of elevations:

This model correlates percentage of oil, mass flow rate, angle of elevation and inlet pressure. This model has two hidden layers with five neurons each and four outputs as mid pressure, outlet pressure, 1st pressure gradient and 2nd pressure gradient. It is felt necessary to optimize the ANN topology with respect to iterations, number of hidden layers and number of neurons in each layer.

The topology and ANN architecture of CFDP model are given in table no.2 and fig.9 respectively.

No. of neurons				Data points	Learning rate
Input parameters	2nd hidden layer	3rd hidden layer	Output parameters	Training	
4	05	05	4	25	0.3
Iteration termination = 1000		First momentum factor = 0.75 First momentum factor = 0.01		RMSE for training data = 0.069	
Input parameters: Percentage of oil, Mass flow rate, Angle of elevation and Inlet pressure.			Output parameters: Mid pressure, Outlet pressure, 1st pressure gradient and 2nd pressure gradient.		

Table no.2: Neural network topology for ANN model CFEP using elite-ANN©

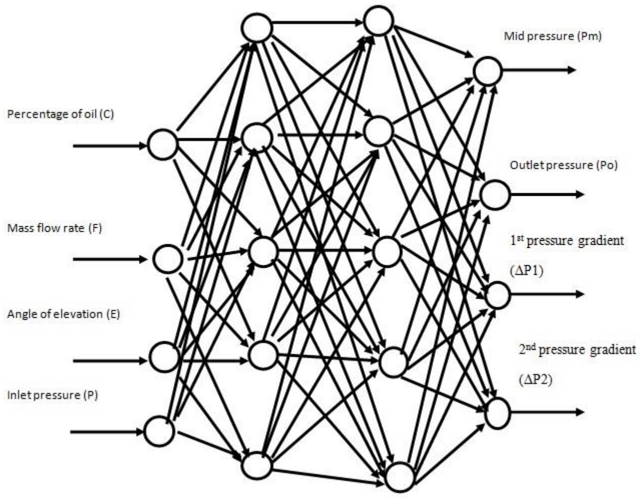

Fig.9: Typical architecture of artificial neural network model used for Model CFEP

2.3.3 Model CFDEP development

Pressure drop estimation for different diameters with different angle of elevations:

This model correlates pipe diameter, percentage of oil, mass flow rate, angle of elevation and inlet pressure. This model has two hidden layers with five neurons each and four outputs as Mid pressure, Outlet pressure, 1st pressure gradient and 2nd pressure gradient.

The topology and ANN architecture of CFDP model are given in table no.3 and fig.10 respectively.

No. of neurons				Data points	Learning rate
Input parameters	2nd hidden layer	3rd hidden layer	Output parameters	Training	
5	05	05	4	75	0.3
Iteration termination = 1000		First momentum factor = 0.75 First momentum factor = 0.01		RMSE for training data = 0.06490	
Input parameters: Pipe diameter, Percentage of oil, Mass flow rate, Angle of elevation and Inlet pressure.			Output parameters: Mid pressure, Outlet pressure, 1st pressure gradient and 2nd pressure gradient.		

Table no.3: Neural network topology for ANN model CFDEP using elite-ANN©

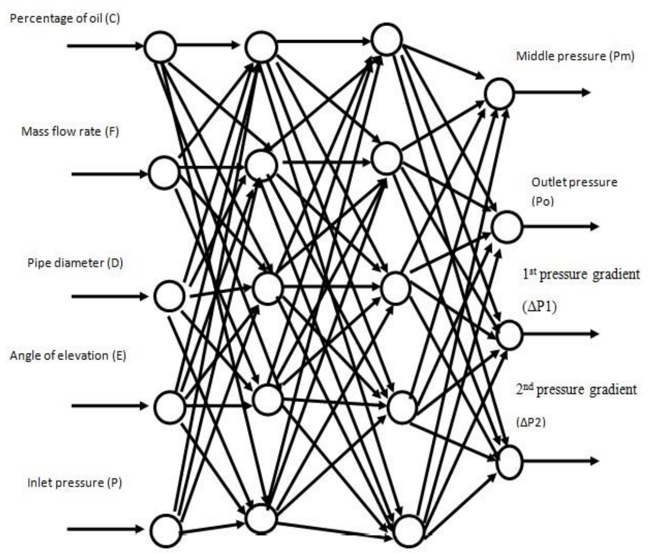

Fig.10: Typical architecture of artificial neural network used for Model CFDEP

3. Results and discussion

3.1 Model CFDP output interpretation

The model CFDP developed has been used for prediction of output parameters for given set of input parameters for both the training & test data sets. Comparison of actual and predicted values has also been carried out to find the most suited model CFDP.

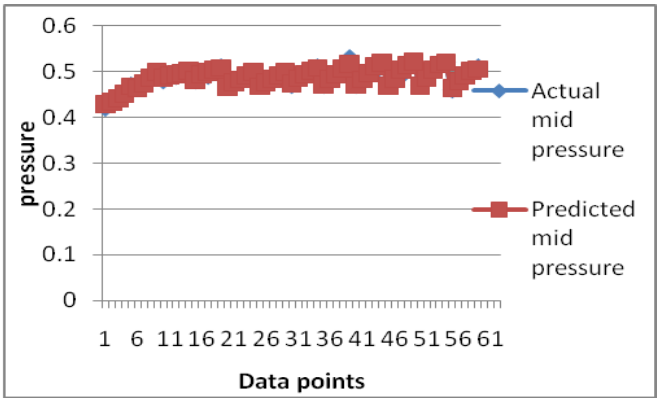

Fig.11: Comparison of actual and predicted output values of mid pressure for training data points obtained by model CFDP

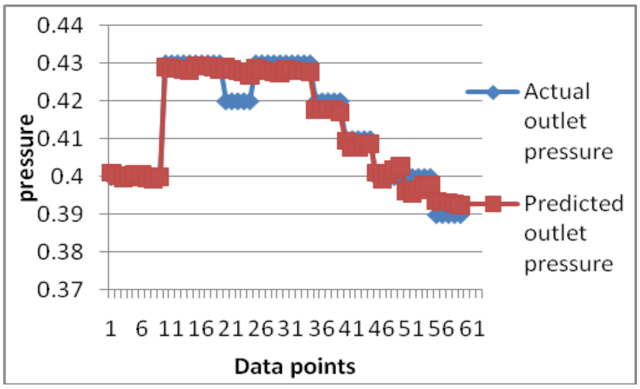

Fig.12: Comparison of actual and predicted output values of outlet pressure for training data points obtained by model CFDP

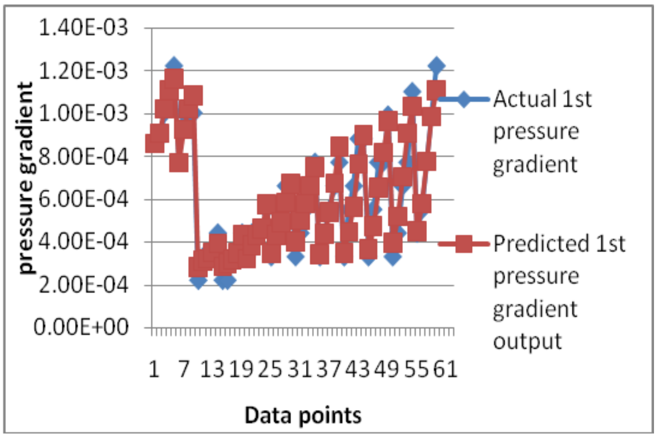

Fig.13: Comparison of actual and predicted output values of 1st pressure gradient for training data points obtained by model CFDP

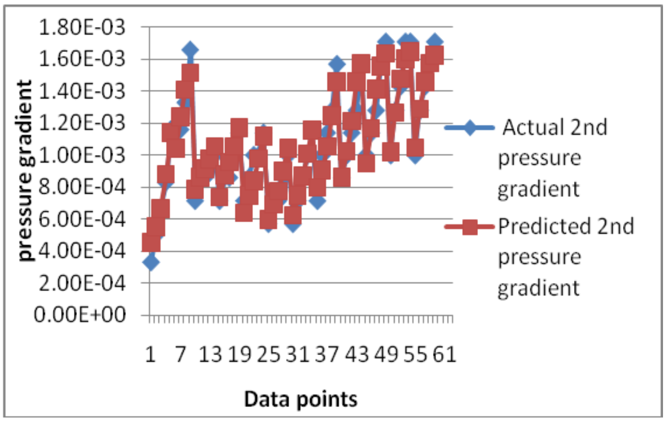

Fig.14: Comparison of actual and predicted output values of 2nd pressure gradient for training data points obtained by model CFDP

Test data sets

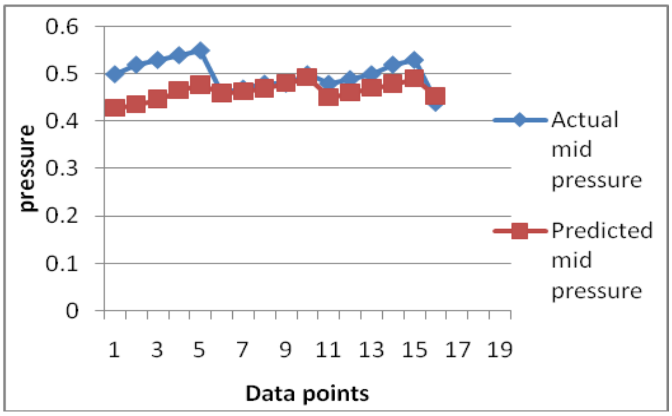

Fig.15: Comparison of actual and predicted output values of mid pressure for test data points obtained by model CFDP

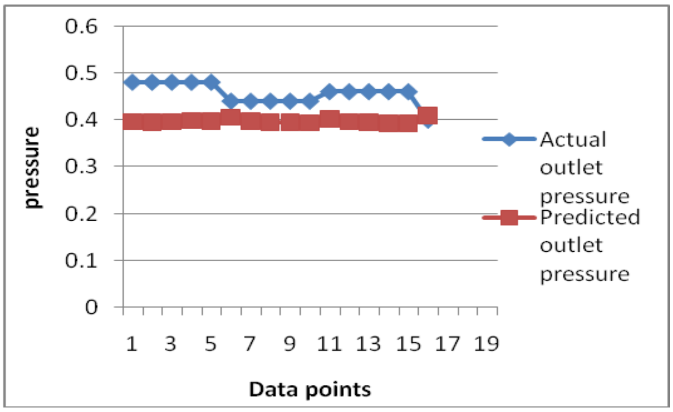

Fig.16: Comparison of actual and predicted output values of outlet pressure for test data points obtained by model CFDP

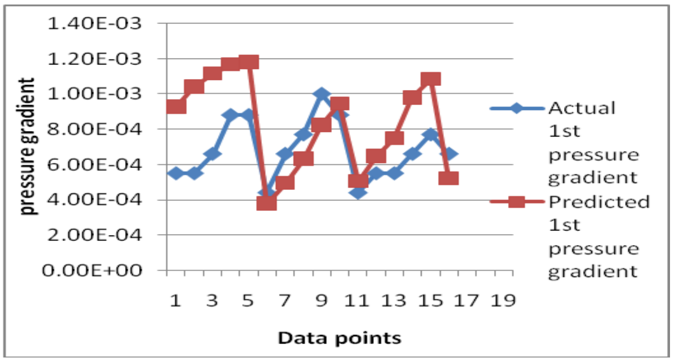

Fig.17: Comparison of actual and predicted output values of 1st pressure gradient for test data points obtained by model CFDP

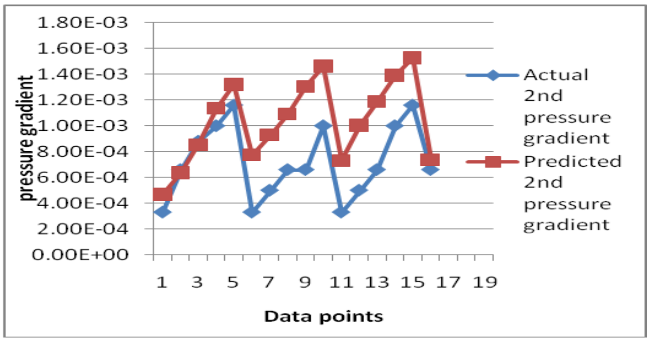

Fig.18: Comparison of actual and predicted output values of 2nd pressure gradient for test data points obtained by model CFDP

Figures 11, 12, 13 & 14 and 15, 16, 17 & 18 show the comparison for actual and predicted values of mid pressure, outlet pressure, 1st pressure gradient and 2npressure gradient for training & test data sets respectively as obtained by ANN model CFDP. As can be seen from these graphs there are very small deviation from actual values of mid pressure, outlet pressure, 1st pressure gradient and 2nd pressure gradient for both training & test data set respectively using model CFDP.

The nature of graphs depicted in these figures shows high level of accuracy for predicted values of output parameters for the both training & test data sets.

The RMSE for the output parameters of training and test data sets are 0.05695 and 0.1094 respectively.

The accuracy of CFDP is further tested by calculation of % relative error for each data point and is depicted in table no. 4.

Based on the % relative error values, it can be said that the accuracy of prediction is high and ranged between 80 to 95 %. So, the CFDP model is acceptable.

Data points	% Relative error = (Actual value –Predicted value)/ Actual value × 100				
	Output parameters	<±5	± 5 to ±20	±20 to ±40	>±40
Training data points 59	Mid pressure	59	0	0	0
	Outlet pressure	59	0	0	0
	1st pressure gradient	29	26	4	0
	2nd pressure gradient	32	26	1	0
Test Data points 16	Mid pressure	6	10	0	0
	Outlet pressure	1	15	0	0
	1st pressure gradient	0	6	5	5
	2nd pressure gradient	2	2	3	9

Table no.4: Distribution of % relative error for data points for ANN model CFDP

3.2 Model CFEP output interpretation

The model CFEP developed has been used for prediction of output parameters for given set of input parameters for the training data sets. Comparison of actual and predicted values has also been carried out to find the most suited model CFEP.

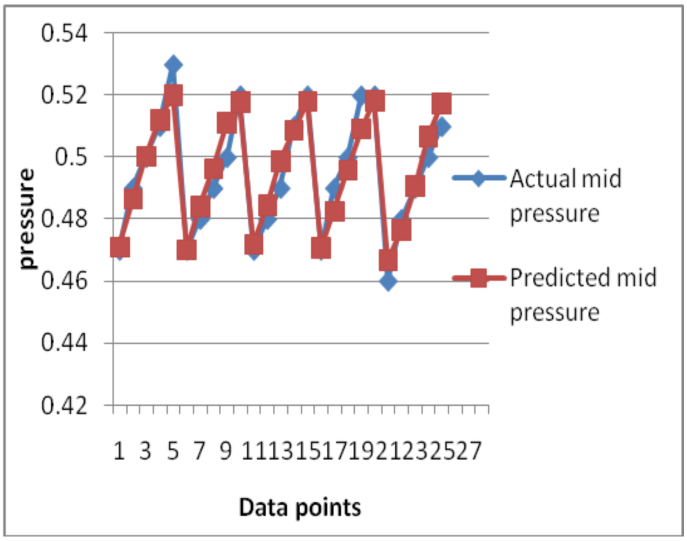

Fig.19: Comparison of actual and predicted output values of mid pressure for training data points obtained by model CFEP

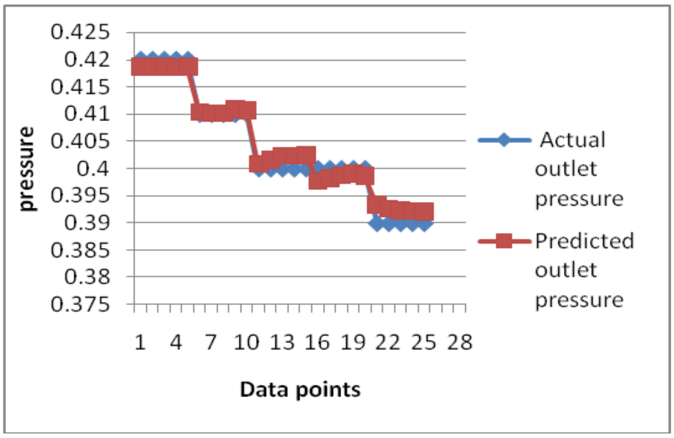

Fig.20: Comparison of actual and predicted output values of outlet pressure for training data points obtained by model CFEP

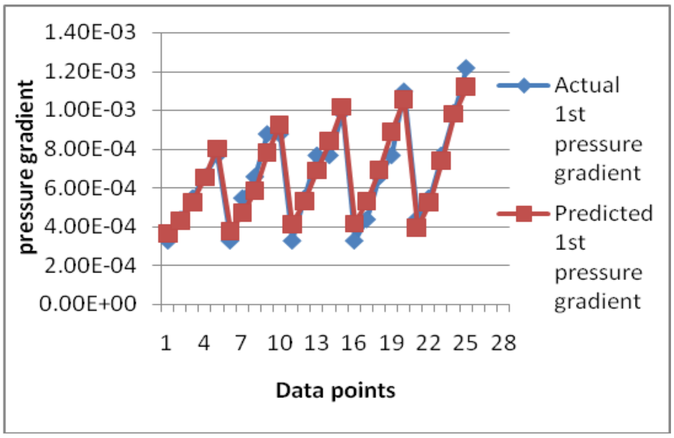

Fig.21: Comparison of actual and predicted output values of 1st pressure gradient for training data points obtained by model CFEP

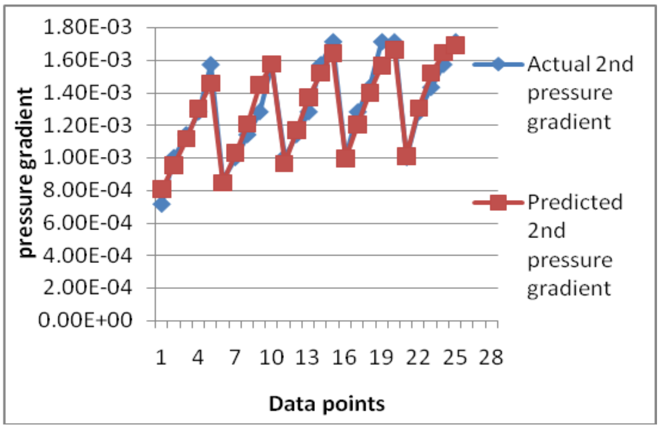

Fig.22: Comparison of actual and predicted output values of 2nd pressure gradient for training data points obtained by model CFEP

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Data points	% Relative error = (Actual value –Predicted value)/ Actual value × 100				
	Output parameters	<±5	± 5 to ±20	±20 to ±40	>±40
Training data points 25	Mid pressure	25	0	0	0
	Outlet pressure	25	0	0	0
	1st pressure gradient	11	11	3	0
	2nd pressure gradient	17	8	0	0

Table no.5: Distribution of % relative error for data points for ANN model CFEP

Figures 19, 20, 21 & 22 show the comparison for actual and predicted values of mid pressure, outlet pressure, 1st pressure gradient and 2nd pressure gradient for training data sets as obtained by ANN model CFEP. As can be seen from these graphs there are very small deviation for prediction of mid pressure, outlet pressure, 1st pressure gradient and 2nd pressure gradient for training data set using model CFEP.

The nature of graphs depicted in these figures shows high level of accuracy for predicted values of output parameters.

The RMSE for the output parameters of training data set is 0.069. Table no. 5 gives the details by percent relative error distribution for various output parameters predicted using model CFEP.

Based on the % relative error values, it can be said that the accuracy of prediction is high and ranged between 80 to 95 %. So, the CFEP model is acceptable.

3.3 Model CFDEP output interpretation

The model CFDEP developed has been used for prediction of output parameters for given set of input parameters for the training data sets. Comparison of actual and predicted values has also been carried out.

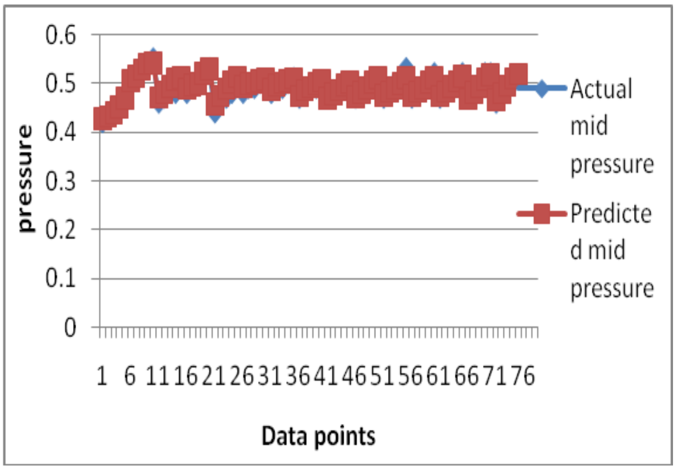

Fig.23: Comparison of actual and predicted output values of mid pressure for training data points obtained by model CFDEP

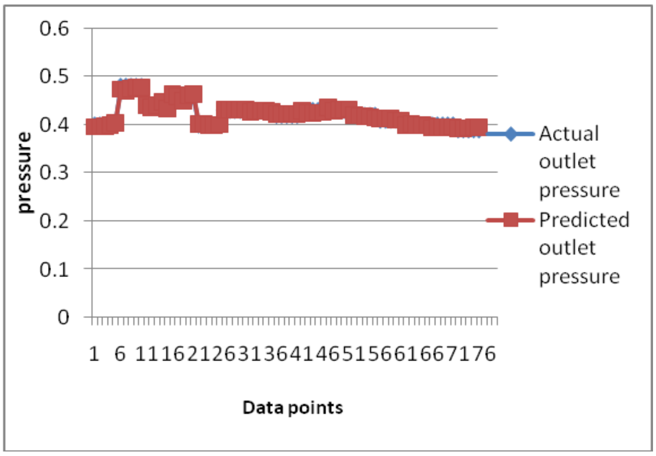

Fig.24: Comparison of actual and predicted output values of outlet pressure for training data points obtained by model CFDEP

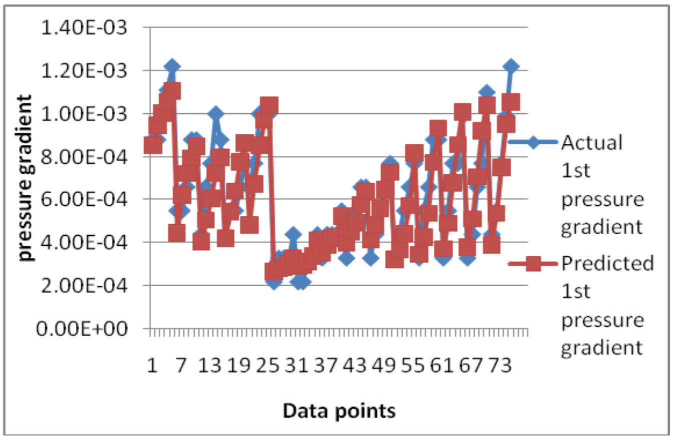

Fig.25: Comparison of actual and predicted output values of 1st pressure gradient for training data points obtained by model CFDEP

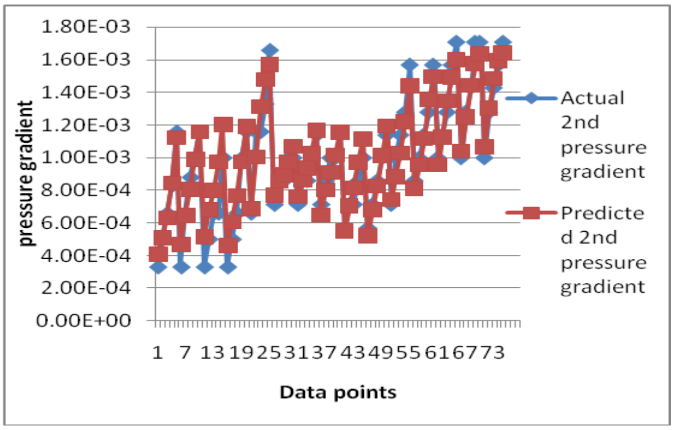

Fig.26: Comparison of actual and predicted output values of 2nd pressure gradient for training data points obtained by model CFDEP

Data points	% Relative error = (Actual value –Predicted value)/ Actual value × 100				
	Output parameters	<±5	± 5 to ±20	±20 to ±40	>±40
Training data points 75	Mid pressure	74	1	0	0
	Outlet pressure	75	0	0	0
	1st pressure gradient	21	45	9	0
	2nd pressure gradient	41	25	5	4

Table no.6: Distribution of % relative error for data points for ANN model CFDEP

Figures 23, 24, 25 & 26 show the comparison for actual and predicted values of mid pressure, outlet pressure, 1st pressure gradient and 2nd pressure gradient for training data sets as obtained by ANN model CFDEP. As can be seen from these graphs there are very small deviation for prediction of mid pressure, outlet pressure, 1st pressure gradient and 2nd pressure gradient for training data set using model CFDEP.

The nature of graphs depicted in these figures shows high level of accuracy for predicted values of output parameters.

The RMSE for the output parameters of training data set is 0.06490.

The accuracy of CFDEP is further substantiated by calculation of % relative error for each data point and is depicted in table no.6.

Based on the % relative error values, it can be said that the accuracy of prediction is high and ranged between 80 to 95 %. So, the CFDEP model is acceptable.

3. CONCLUSIONS

Oil and water mixture is dispersion and estimation of pressure drop using empirical method is tedious and with low accuracy rate. The present work is aimed at the development of artificial neural network models in estimation of pressure drop for flow of used machine oil and water mixture through pipeline. Experimental setup has been used for conducting experimental runs. 175 experimental runs have been conducted. Effect of various input parameters have been studied that includes oil-water volume ratio, flow rates, pipe diameter and angle of elevations on pressure drop at two locations mid pressure and outlet pressure.

Three ANN models CFDP, CFEP and CFDEP have been developed using elite-ANN©. Model CFDP correlates oil-water volume ratios, flow rates, diameter of pipes and inlet pressure with mid pressure and outlet pressure. The comparisons of actual and predicted values are indicative of high accuracy level of prediction. Hence, it is successful development of model. Most of the points for both training and test data set are observed within % relative error of 5 to 20 which is acceptable. Model CFEP correlates oil-water volume ratios, flow rates, angle of elevations and inlet pressure with mid pressure and outlet pressure. The comparisons of actual and predicted values are indicative of high accuracy level of prediction. Hence, it is successful development of model. Most of the points for training data set are observed within % relative error of 5 to 20 which is acceptable. Model CFDEP correlates oil-water volume ratios, flow rates, diameter of pipes, angle of elevations and inlet pressure with mid pressure and outlet pressure. The comparisons of actual and predicted values are indicative of high accuracy level of prediction. Hence, it is successful development of model. Most of the points for training data set are observed within % relative error of 5 to 20 which is acceptable.

Based on results and discussion it can be concluded that the present work successfully addressed the development of ANN models for prediction of pressure at two locations for two liquid-liquid phase flow in a pipeline. The novel feature of the present work is incorporation of input parameters such as diameter of pipe and angle of elevation of pipe. The data usually available in any process plant pertaining to these parameters can be utilized in development of these models. This will help in decision making, fault detection diagnostics and designing purposes. The work is demonstrative and many other similar input output parameters can be incorporated.

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