Prediction of Controlling Parameters of a Gas Liquid Separator using Inverse Function of Stacked Neural Network

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***Abstract*— The work presented in this paper demonstrates a method to obtain an inverse function of a trained neural network by connecting it with a PID controller in a close loop. This scheme is implemented to predict a process parameter controlling the efficiency of a compact axial flow gas liquid separator (I-SEP). The data is taken from an experimental study of I-SEP (compact separator) with air-water two phase flow. It was found during these experiments that by manipulating the pressure difference between the two outlets of separator and the inlet, the performance parameter i.e. Gas Carry-Under (GCU) and Liquid Carry-Over (LCO) could be controlled but non-linearly. It requires a tedious job to set the differential pressure between tangential and axial outlet to control the GCU. A stacked neural network model consisting of several individual neural networks having different architecture is developed. The inverse function of the combined neural network was then determined by connecting this trained neural network with a PID controller in a closed loop, which is then used to predict the pressure at the two outlets of the I-SEP for a given GCU. The optimal weight determination techniques for stacked neural network is also studied and compared in this paper.**

***Index Terms*— Gas liquid cyclone; Separation Efficiency; Inverse Neural Network; Mutual Information; Stacked Neural Network.**

I. INTRODUCTION

ALTHOUGH the separation efficiency of the compact separators is inferior, compared to bulky separators, the former has found many applications where complete separation is not necessary. Other benefits of using such compact separators include the capability to design them to high pressure rating and the safety benefit of having very low fluid inventory. Researchers [1-7] have reported their usage for subsea separation and pumping facilities and multiphase measurement. Therefore it is one of the major requirements to be able to predict the efficiency of the I-SEP at different inlet operating conditions in order to size and design the system for a particular application. Although a few mechanistic models [7,8] have been proposed for design optimization and predicting the performance of reverse flow cyclonic separators. But these existing models of gas liquid separators are not applicable to this separator due to its special design. An empirical model was thus developed using neural network to map the non-linear relationship between the observed separation efficiency and the operating inlet conditions in this research study. This paper starts with the description of the compact separator and its working principle along with the description of the rig used in the experiments followed by a brief result of these experiments. Stacked neural network model development is discussed in the second section and method to determine the inverse function of this model is described in the third section followed by the conclusion in the end of the paper.

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A. The ISEP

The “I-SEP” shown in Fig. 1 is the name given to a novel axial-flow cyclonic separator patented by its inventors Caltec Ltd. UK [9] .

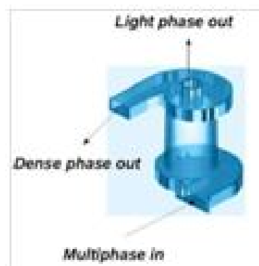

Figure 1 Compact Separator

It is suitable for a wide range of gas-liquid, liquid-liquid and solid-liquid separation applications, and presently it is mainly targeted to the offshore oil and gas industry. The fluids enter the I-SEP through an involute inlet path where it is made to spin, producing high ‘g’ forces, which makes it progress up to a compact separating chamber. In the separation chamber, the gas-liquid separation takes place and heavier fluid moves radially outwards through tangential outlet (also referred as the underflow), while the lighter fluid moves inwards and also axially upward towards another outlet, also known as the overflow.

B. The Multiphase Separator Rig

The compact separator rig used in this study, as shown in Fig. 2, was mainly consisted of a fixed geometry I-SEP connected serially on its axial and tangential ends with two gravity separators. The gravity separator at the axial outlet of I-SEP was used as a knock-out vessel to improve further efficiency, The water was pumped from water tank to the rig; the flow rate of the water was adjusted using a manual valve.

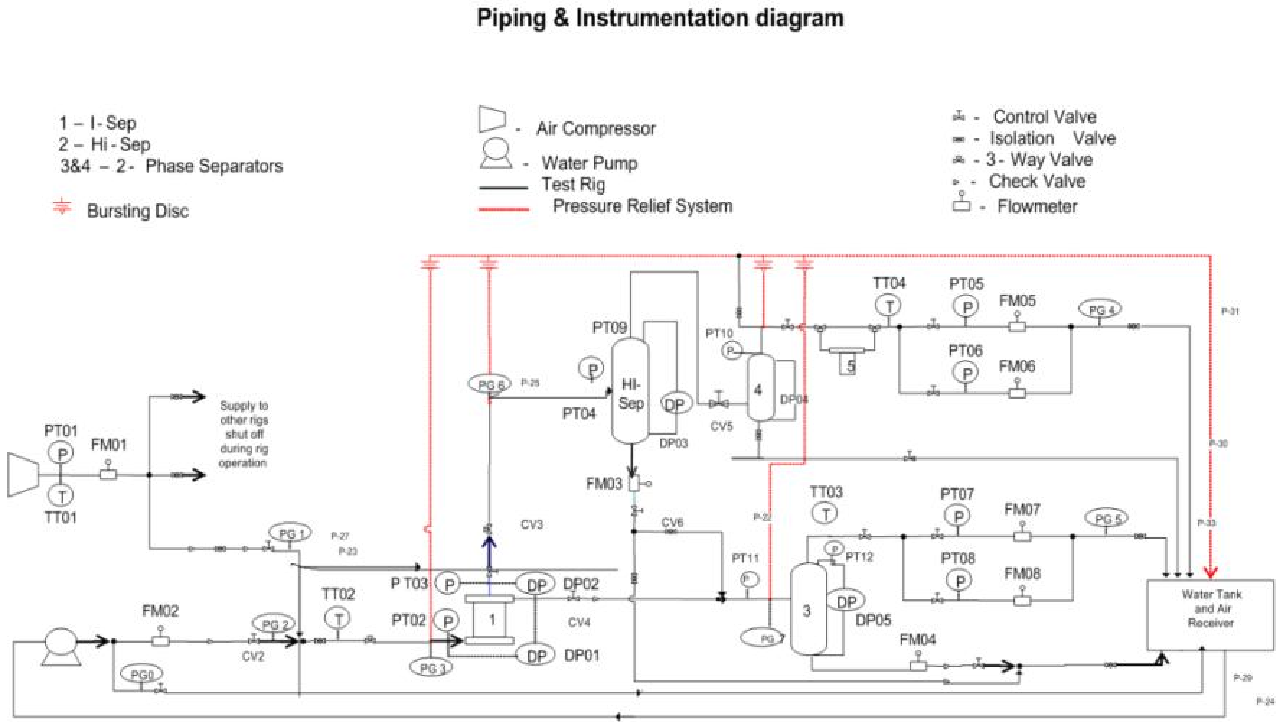

Figure 2 Simplified Process & Instrumentation Diagram of Compact Separator Ri

Single phase V-cone flow meters were used to measure the volumetric flow rate of the gas at the inlet of the rig, while the volumetric flow rate of the liquid was measured by magnetic flow meters. After metering the gas and liquid inlet streams separately by these V-cone gas flow meters and liquid flow meters, they were then commingled to form a gas-liquid (G-L) mixture. The G-L inlet mixture, before entering into the I-SEP, was passed through a straight 50.8mm pipe about 15 meters long to ensure flow regimes are fully developed (L/D=297). After passing through the I-SEP, this mixture is separated into a liquid-rich stream and a gas- rich stream at the tangential and axial outlets of I-SEP respectively. The experiments, covering mainly slug flow conditions, were performed at room temperature in two sets of constant gas volume fractions and constant mixture velocities, with gas volume fraction (GVF) between 80 to 95% ,and the mixture velocity between 5m/s to 60 m/s. A data acquisition system (DAS) using LABVIEW was developed to acquire the data from the two-phase multiphase rig. The acquired data consisted of pressure measurements at different locations of the rig, gas and liquid flow rates at the inlets and outlets of the I-SEP and the two gravity separators.

C. Experimental Result

The performance of I-SEP was measured by calculating the separation efficiency of I-SEP which is defined as the percentage fractions of the inlet mass of liquid and gas recovered at the tangential and axial outlets of the I-SEP respectively. The performance of I-SEP i.e. GCU and LCO at the varying GVF and mixture velocity was found to be very complex and nonlinear. Additionally, it was also revealed that during experiments, the backpressure due to throttling of the valve at the tangential outlet improved the GCU but non-linearly. For this reason, controlling of the valve to improve the performance for a required GCU or LCO is a difficult task for the operator. However, prediction of these parameters with great accuracy is quite difficult and complicated due to their observed complex and nonlinear relationship with the inlet operating parameters. This led to developing a model for the I-SEP that may be used in predicting the required pressure at the tangential outlet or axial outlet in order to adjust the control valve for a desired value of GCU or LCO. This complex mapping of the input inlet conditions to the target output can be achieved by different techniques such as fuzzy logic, artificial neural network (ANN) and support vector machines. ANN cover research in multiphase flow metering [3] aerospace[8],banking [1] etc. Up to the best knowledge of authors, artificial neural network has not been used in modelling the separation performance of the separators, and it is the first attempt to develop an empirical model using ANN for the compact separator, I-SEP.

II. Neural Network Model Development

Neural networks have been increasingly used in the chemical process field, especially for dealing with some complex nonlinear processes where understanding is limited [5]. This work has also used a variant of MLP neural network due to its ability of approximating any nonlinear relationship between inputs and outputs [9]. The multiple layer neural networks are composed of several layers of neurons. The first layer in the network is called as input layer and the last layer of the network is named as output layer, all the other layers between the input and output layers are hidden layers of the network and play a vital role in learning process of a neural network. The neural network development model process is shown in the Fig. 3.

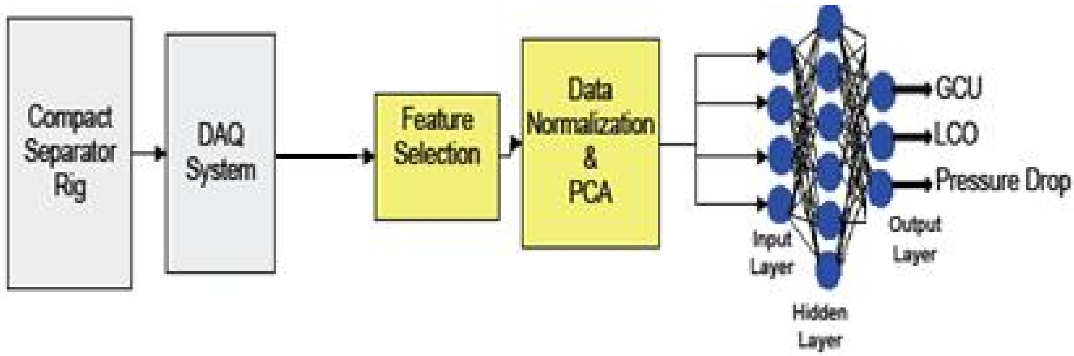

Figure 3 ANN Model Development for I-SEP

A. Input Feature Space

The first step in modeling the separation efficiency of the I-SEP is the selection of appropriate input and output variables. GCU, LCO and pressure at the inlet was selected as output and gas and liquid superficial velocities along with pressure at tangential and axial outlet were selected of the neural network model. This selection of the input parameters was based on the high value mutual information between these parameters with the required output parameters.

B. Data Pre-Processing

The experimental data was then pre-processed before passing it to the neural network to remove any noise from the data. The input training data was normalized using the statistical or z-score normalization. In this technique the mean (μ) and standard deviation (σ) are computed for the given input training data set then the transformation is made according to the following equation xi=(xi-μ)/σ. This produces training data set having a zero mean and a unit variance. The principle component analysis was then applied to remove multi-co linearity and redundancy of the data.

C. Network Architecture and Optimization

The developed neural network model consisted of one input layer, one hidden layer and one output layer. Such a network with log sigmoid and linear activation functions in the hidden and the output layers respectively can be used to approximate any function with arbitrary accuracy [9] Consequently, these two activation functions were used to construct the networks used in this work. The critical problem of optimizing the number of neurons in the hidden layer was tackled by following the constructive algorithms approach. The smallest possible network with one hidden neuron in the hidden layer was used at the start of the training and then the number of neurons was increased in the hidden layer to improve the performance. The validation error and effective parameters did not change much after 25 neurons so that the total number of the neurons in the hidden layer was then determined to 25. A number of training algorithms such as Levenberg-Marquardt, conjugate gradient back propagation, and gradient descent momentum with an adaptive learning rate were investigated to train the neural networks. MATLAB neural tool box routines were used for these training algorithms. The early stopping technique was used to solve generalization or over-fitting problem which occurs during the training of a neural network. This technique continuously monitors the validation error and stops the training if validation error begins to rise. The total experiment of 170 data points was divided into three sets of training, testing and validation data sets. After testing different portioning ratios (2:1:1, 3:1:1 and 4:1:1) finally the ratio of (2:1:1) was selected as it gave the best result. One half of the data was set for the training and the remaining half was divided into validation and testing data set. The testing data set was then use to evaluated the performance of the trained network. The network simulated data was then un-normalized to convert them back to their physical meaning.

A number of neural networks were trained using the above methodology. The performances of all these trained networks were then evaluated using absolute average relative percent error (AARPE) and correlation coefficient on the tested data set. The performance comparison of individual neural network based on AARPE% revealed that a single candidate neural network was not enough to extract all the relevant information from the data for all of the neural network outputs. While any of these best selected network can be used, but it could affect the overall robustness of the model. Stacked neural network on the other hand are more accurate than individual trained neural network [13]. Therefore all the trained neural network were combined using the linear optimal weights techniques.

D. Optimal weight Determination for Combination of trained neural network

The overall output of the combined neural network model is determined as a weighted combination of the output of the individual neural network joined in the group. Mathematically this combination can be shown in the following equation.

$$F(x) = \sum_{i=1}^{n} w_i f_i(X)$$

Where

X is the input vector to the individual neural network

$F(x)$ is combined neural network predictor

$F_i(x)$ is the i^{th} neural network output used in the combination process

w_i is the weight of the i^{th} neural network.

This procedure however requires the determination of the optimal weight for every included individual neural network.

Equal weight, linear regression and process component regression techniques were used to calculate the weight of the individual neural network. The mathematical equations for these methods are given by $w_i = \frac{1}{N}$, $w = (Y_c^T Y_c)^{-1} Y_c^T y$ and $w = P_k(P_k^T Y_c^T Y_c P_k)^{-1} Y_c^T y$ respectively.
N is the total number of the participant neural network in the combined model.
Y_c is the output vector of the combined model, y is the measured output, P_k is the principle component vector of the combined output vector.
The stacked neural work obtained after the combination of all three trained neural network using the above mentioned techniques were tested on unseen data and the result was found more accurate as compare to individual trained network. The absolute relative percentage error AARPE% resulted after this combination of network is presented in Table 1. It can be seen that the individual neural network was found to improve their accuracy through PCR as compared to other weight determination techniques. The correlation coefficient was also found to lie near 98% for all outputs.

Table 1 Stacked Neural Network Accuracy

List Candidate	AAPE%			Correlation Coefficient
	GCU	LCO	P_{in}	
Equal weight	6.33	6.94	2.76	0.95
PCR	5.43	3.29	2.12	0.98
Linear Regression	9.96	8.10	3.41	0.88

III. INVERSE FUNCTION THROUGH PID CONTROL

The next phase of this neural network modeling was to test the neural network performance in controlling the GCU. The performance of the I-SEP as described earlier can be enhanced by applying the backpressure at the liquid outlet to remove bulk of the gas carry under in the liquid stream. This applied back pressure caused a change in the pressure at the tangential and axial outlets. It was found during the experiment that the reduction of the GCU due to the applied back pressure is nonlinearly related to this change in the pressure at axial and tangential outlets. The trained neural network can also be used to predict these pressures at the tangential and axial outlets; the concept is to determine the inverse function of the trained neural network that could predict these pressures for a given GCU.

In other words the inverse function of the trained neural network predicts the inputs or the required manipulating variables to control the given output as shown by the dashed box in Figure 4. The mathematical representation to identify the forward dynamics of the neural network is given by the equation:

$$Y = NN(u, w)$$

where Y is the output of the trained neural network, u is the given inputs and w are the weights of the trained neural network.

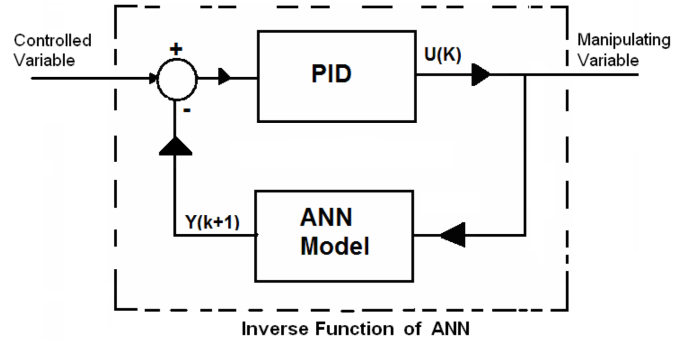

Figure 4 Inverse Function through PID Control

The inverse function of such trained neural network can then be given by the following equation:

$$u = NN^{-1}(Y, w)$$

In order to get the inverse function of the trained ANN model, a closed-loop simulation model was constructed by connecting a PID controller to the ANN model as shown in Figure 3. In Fig. 4, the input of the inverse function is the set-point of the closed-loop, which represents the desired separation performance, whilst the output of the inverse function is the output of the controller, i.e. the input to the ANN model, the steady-state of which indicates how the operational conditions, such as the pressure difference should be maintained in order to achieve the desired separation performance.

The inverse function of the trained neural network was tested with GCU as the controlled variable and P_2 as the manipulating variable, but keeping all other inputs to the neural network unchanged. The loop was tested for more than one set point of the GCU. Fig. 5 shows the case that when the GCU was set 7.58%, at steady-state, P_2 was 1.64 bar. The simulation was run for 500 seconds. However, as seen in Figure 5, the manipulated variable P_2 reached the steady-state within 50 seconds.

Figure 5 Test Result of Inverse ANN for GCU Set point :7.58%, P_2=1.64 bar
V_{ls}=1.06m/s,V_{gs}=1.71m/s,P_3=1.20 bar

The other tested values are shown in the Table 2.

Table 2 Test result of inverse of ANN (SP: GCU, Manipulated Variable: P_2)

Set Point	Test Point				Manipulated Variable P_2 (bar)	
GCU %	V_{ls} m/s	V_{gs} m/s	P_3 bar	P_2 bar	Simulated	Difference
7.58	1.06	1.71	1.20	1.64	1.64	0.00
17.53	.25	4.298	1.30	1.26	1.26	0.00
15.82	0.489	1.618	1.08	1.27	1.27	0.00
18.00	.445	4.237	1.48	1.39	1.38	0.01
6.89	.699	2.271	1.20	1.33	1.33	0.00
14.14	.507	1.625	1.08	1.20	1.19	0.01
17.46	.697	1.354	1.07	1.34	1.25	0.09
7.08	0.81	2.11	1.20	1.51	1.48	0.03

It can be seen from this table that simulated P2 values are either similar to experimental results or very close to them for the corresponding set points of GCU. This test is repeated with the pressure at the overflow, i.e. P3, taken as the manipulated variable. The corresponding results are shown in Table 3.

Table 3 Test result of inverse of ANN (SP: GCU, Manipulated Variable: P_3)

Set Point	Test Point				Manipulated Variable P3 (bar)	
GCU %	V_{ls} m/s	V_{gs} m/s	P_2 bar	P_3 bar	Simulated	Difference
7.58	1.06	1.71	1.64	1.20	1.20	0
15.82	0.48	1.61	1.27	1.0	0.93	0.07
18.00	0.44	4.23	1.39	1.48	1.48	0.00
7.93	0.79	2.13	1.53	1.20	1.14	0.06
14.14	0.50	1.62	1.20	1.08	1.08	0.00
7.57	1.01	2.19	1.81	1.47	1.48	-0.01

This test also shows that manipulated variable successfully tracked the given set point with steady-state P_3 value similar to experimental results. The results showed that inverse function of trained neural network can be obtained using the above mentioned approach. Based on the results obtained, it can be said that the inverse function of neural network can be used to control the GCU by predicting the required pressure at the tangential or axial outlet. The prediction of this pressure is helpful to the operator in adjusting the control valve position to improve the separation efficiency by controlling the GCU by applying the correct backpressure.

IV. Conclusion

The research work described in this paper has demonstrated that the separation performance of compact axial flow cyclonic separator can be modeled by using stacked neural network with reasonable accuracy on unseen data. The linear obtained through PCR showed more accuracy than other methods of linear weights determination for neural network combination. The inverse function of a stacked neural network was obtained through a PID feedback control loop. The inverse function obtained is able to predict the required pressure at the tangential or axial outlets to achieve a desired GCU. This prediction can be directly used for real-time separator operation.

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