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Predicting the Pumping Characteristics of Multiple Parallel Tube Air-Lift Pumps

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Abstract

Air-lift pumps have begun to receive a high degree of attention due to the absence of mechanical components and the potential for their use in renewable energy applications. One of the principal challenges of the air-lift pump is increasing the volume of fluid it can pump, as such it may be possible to utilise multiple parallel tubes. In such an arrangement it is necessary to have the two phases distributed to multiple tubes from a common source. However, from an analytical perspective this leads to multiple steady state solutions and hence accurately predicting the pumping characteristics of an air-lift pump becomes extremely complex.

To circumvent the analytical challenges associated with dividing a multiphase flow amongst multiple parallel tubes this work utilised an artificial neural network (ANN) (a class of artificial intelligence) to the prediction of the pumping characteristics of an air-lift pump with multiple parallel lift tubes. The results show that the neural network model provides an extremely accurate prediction of the pumping characteristics of multiple tube air-lift pumps within the training bounds. Moreover, the ANN provides insights into the pumping characteristics of multiple tube air-lift pumps outside these bounds that would be extremely difficult to achieve by analytical means.

Introduction

The use of the air-lift pump was first introduced in late 1700's [8] and involves pumping of a liquid medium through a vertical lift tube that is partly submerged in the liquid by a gas. In its simplest form air can be injected into a water-filled tube from its lower end. With a sufficiently high air flow rate a two-phase plug flow regime is realised and this lifts (pumps) the water through the tube.

Given its simplicity, this type of pump has been a standard component in small absorption refrigerators. The refrigeration capacity of these machines being limited by the pump capacity. As a result, numerous studies have been performed in order to understand the pumping performance of the single tube air-lift pump [6-8]. However, these appear to be limited in the flow rates they can achieve. To overcome this limitation, it may be possible to use multiple parallel tube air-lift pumps, an area that has received almost no attention. In achieving this, multiple tube air-lift pumps would involve the distribution of the two-phases to multiple lift tubes from a common source. However, determining the pumping capacity of such systems is difficult to realise, as analytical methods lead to multiple steady state solutions [3,10].

In light of the complexity of multiphase flow, a number of studies have utilised artificial intelligence techniques to better understand their behaviour. In this respect, numerous works have looked at identifying two-phase flow regimes from temporal pressure measurements using artificial neural networks (ANN) [1,4,11]. The advantage of an ANN model is that it does not require explicit knowledge of the physical phenomena under investigation [2] but through training can be developed to predict outputs based on a series of specified inputs. Hence, an ANN can be used to predict the unknown output values from a set of new input values previously unseen by the model [5]. The aim of this study is to predict the performance of a multiple parallel tube air-lift pump using an ANN technique.

Method

For this study the ANN consists of three interconnected layers – an input, hidden, and output layer as shown in figure 1, with each layer consisting of one or multiple nodes called neurons.

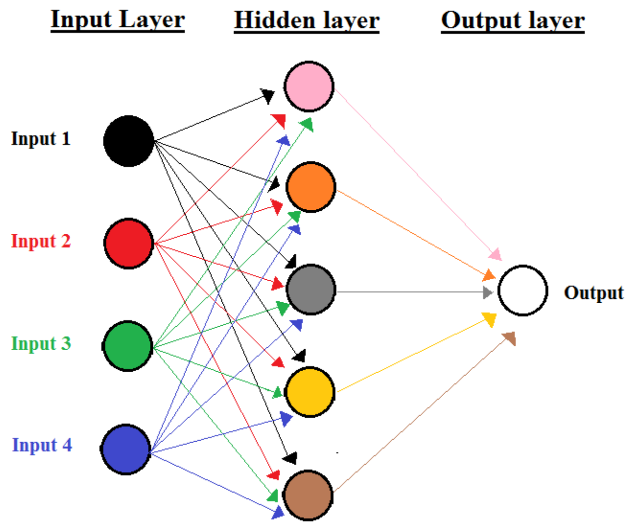

Figure 1. Schematic diagram of a typical artificial neural network

The number of nodes in the input and the output layer is equal to the total number of input and output parameters respectively, whereas the number of the nodes in the hidden layer depends upon the performance and the complexity of the network [2]**.** The input layer accepts the data from the specified source and transfers it to the nodes in the hidden or output layers which act as a summing junction for inputs and modifies the input, using equation (1).

$$S_i = \sum_{j=1}^{m} x_i w_{ij} + b_j \tag{1}$$

In equation (1), S_i is the net input to node j in the hidden or output layer, x_i is the input to node j, w_{ij} is the strength of the weight connection between the i^{th} node and j^{th} node, b_j is the bias associated with node j and i is the number of nodes. In order to generate relationships between the input and output a linear (purelin), hyperbolic tangent sigmoid (tansig), logarithmic sigmoid (logsig) or radial basis (radbas) transfer function can be used. The most common transfer functions for a non-linear relationship are the logsig and tansig functions which are given by equations (2) and (3) respectively.

$$f(S_j) = \frac{1}{1+e^{-Sj}} \tag{2}$$

$$f(S_j) = \frac{e^{Sj} - e^{-Sj}}{e^{Sj} + e^{-Sj}} \tag{3}$$

With an ANN the relationship between the data in the input and output layers is established using a ‘training’ process consisting of three steps, training, testing and validation. For the training, a set of known input and output values are given to the network, the model adjusts the weight between the nodes until the desired output is obtained [9]. This iterative method of adjusting the weights is termed as epoch. Subsequently, the ANN undergoes testing and validation to determine if unseen input data can be presented to the network to determine output.

In order to train the ANN, it was necessary to develop a data set with a number of input variables. For this study four input parameters were chosen for this purpose: air flow rate, tube diameter, number of tubes, and submergence ratio, with the output parameter being the amount of liquid pumped. To achieve this an experimental setup, schematically shown in figure 2, was developed. In this system compressed air and water at room temperature were used as the working fluids for all the tests.

The experimental setup consists of multiple 500 mm long clear acrylic lift tubes (1) having their lower end fixed at the lower tank (2). The upper end of the lift tube is connected to a separator tank (3) from where the pumped liquid is directed towards a measuring cylinder (4) to measure the amount of the liquid pumped in a given time. The liquid is pumped by injecting air (5) supplied to the sparger (6) through one of three rotameters (7) that are used to measure the air flow rate. After lifting the liquid, the air is released to the environment through a small opening (8) provided at the top of the separator tank. Water is supplied to the pump from a reservoir tank (9) by a separate water supply (10) with a constant head (11). The reservoir tank was placed on an adjustable stand (12) that could be fixed at different heights in order to vary the submergence ratio which is defined as the ratio between the height of the liquid filled in the lift tube (H_L) to the total height of the lift tube (H_T).

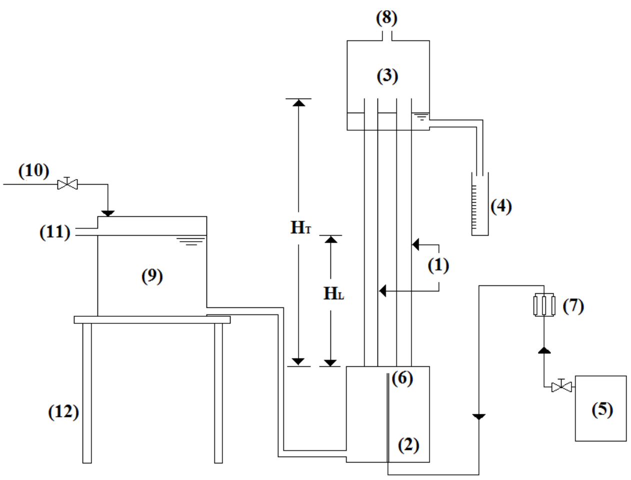

Figure 2. A schematic diagram of the experimental setup

To develop a sufficiently rich data set for the ANN model, a total of 1044 data points were collected from experiments performed on an air-lift pump with 1, 2 and 3 tubes with configurations shown in table 1 and with air flow rates between 0.5 and 50 l/min at each configuration.

As described earlier, the network was trained with four input parameters to determine the rate at which water was pumped. In doing this the input data was randomly divided into three sets consisting of 70% for training using the Levenberg-Marquardt back propagation (LM-BP) algorithm [12], 15% for validation and 15% for testing. The training set was used to develop and adjust the weights and the bias of the network, the validation set was used to ensure the accuracy of the developed model and the testing set was used to check the final performance of the developed network.

Setup	No of tube(s)	Diameter of tube (mm)	Submergence Ratio
1	1	14	0.748
2	1	14	0.51
3	1	14	0.272
4	1	10	0.748
5	1	10	0.51
6	1	10	0.272
7	2	10	0.748
8	2	10	0.51
9	2	10	0.272
10	3	10	0.748
11	3	10	0.51
12	3	10	0.272

Table 1. Experimental configurations used for the design of the network

Now, in the initial phase of the ANN modelling, the number of the neurons in the hidden layer is normally not known. As such, they are estimated by varying their number and calculating the error for each set of neurons. In this study, the number of the neurons in the hidden layer was varied from 2 to 30 and the error for each case was estimated using the mean square error (MSE) as given by equation (4).

$$MSE = \frac{1}{n}\sum_{m=1}^{n}(Y_{Exp,m} - Y_{Pred,m})^2 \tag{4}$$

where n is the number of data points, Y_{Exp} is the experimental value and Y_{Pred} is the predicted value from the network and the estimation of the neurons in the hidden layer was estimated using two transfer functions: tansig and logsig.

As shown in figure 3, the network with 24 hidden neurons and using tansig transfer function showed the least error. Therefore, the developed model used tansig as the transfer function and consisted of 4 neurons in its input layer, 24 neurons in its hidden layer and 1 neuron in its output layer. The convergence of the optimum model is shown in figure 4.

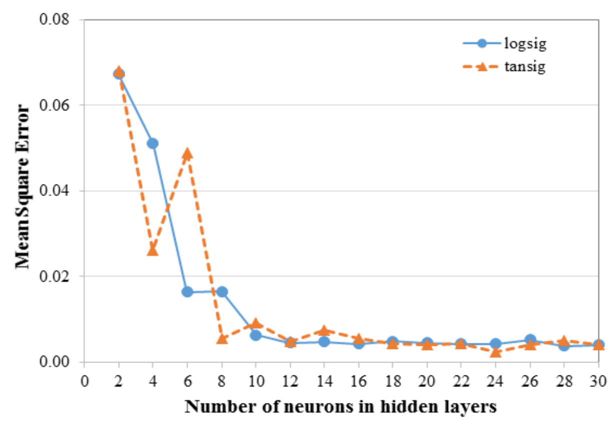

Figure 3. Determination of the number of neurons in the hidden layer

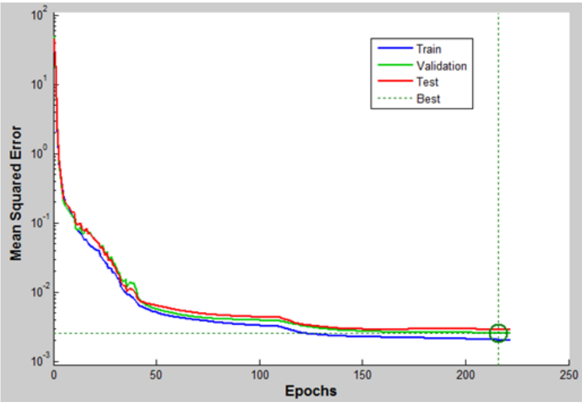

Figure 4. MSE versus epoch with 4-24-1 network configuration

Results and Discussions

In formulating an ANN it is important to understand the consistency of its predictions when applied to the data used in the development phase of the model and for the prediction of the unseen data. In this respect, the performance of the optimum model was assessed by calculating the coefficient of determination (R^2) and mean squared error in each phase. The performance of the model is shown in table 2 and shows a high value of R^2 and MSE for all the data sets, thus indicating a strong predictive capacity.

Data	No of Data points	MSE	R^2
Training	730	0.00215160	0.99933
Test	157	0.00289613	0.99903
Validation	157	0.00257442	0.99925
Total Data	1044	0.00250516	0.99999

Table 2. Performance of ANN model for training, validation, testing and all data sets.

Exploring this further, figure 6 shows a normalised comparison between the optimum ANN predicted values and the experimental values. From this it can be seen that the optimum model shows good prediction values when compared with the values for different experimental set up.

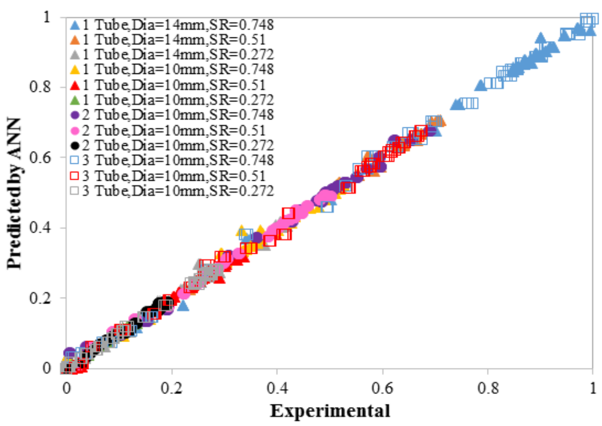

Figure 6. Predicted values from ANN model versus experimental values for all the data sets

Now, in order to check the flexibility of the ANN model it was tested for its ability to predict the pumped water flow rate based on an unseen data set within the training bounds. In the first instance, the ANN was set the task of predicting the liquid pumped by an air-lift pump with 2 and 3 lift tubes of 10 mm diameter, submergence ratios of 0.51 and 0.748 and air flow rates that had not been previously tested. Figures 7 and 8 show the comparison between the prediction made by the ANN and the experimental data for 2 and 3 tubes. Given that the testing was for data with the training bounds, the results show good agreement between the experiment and the ANN prediction, as one would expect.

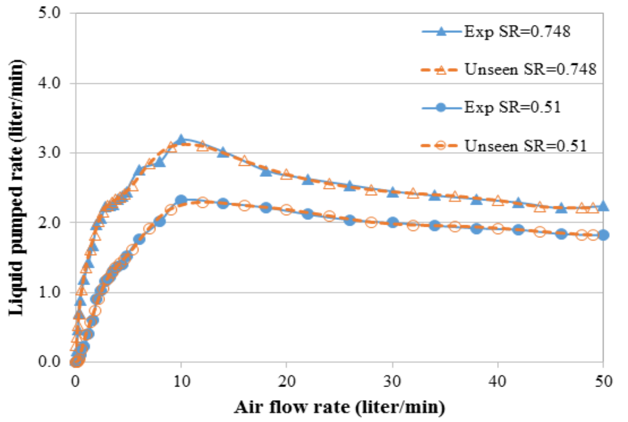

Figure 7. Predicted values of unseen data from ANN model versus experimental values for 2 tubes

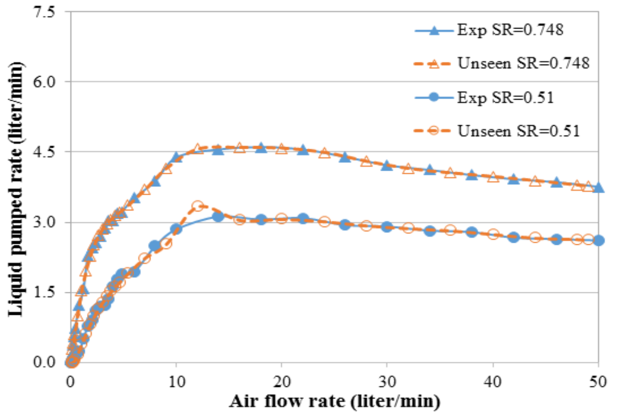

Figure 8. Predicted values of unseen data from ANN model versus experimental values for 3 tubes.

Following on from this, the performance of the multiple tube air-lift pump for an unseen submergence ratio (0.6) was evaluated using the ANN. As shown in figures 9 and 10, the model suggests that the pumping capacity would lie between that of pumps of submergence ratios of 0.51 and 0.748, as one might expect.

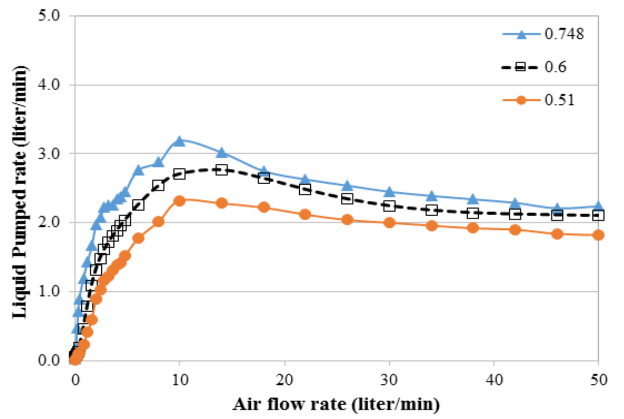

Figure 9. Predicted values for 0.6 submergence ratio from ANN model versus experimental values for 2 tubes.

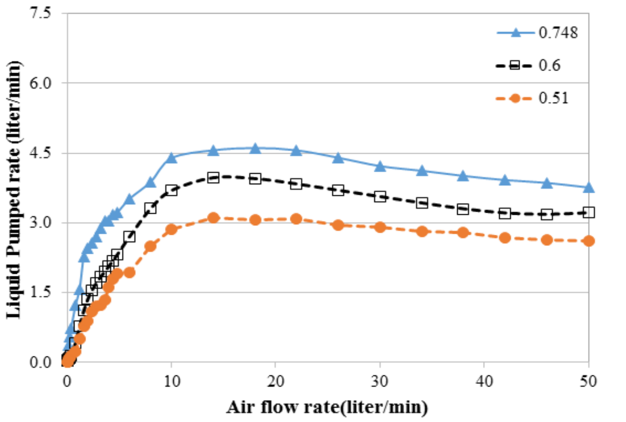

Figure 10. Predicted values for 0.6 submergence ratio from ANN model versus experimental values for 3 tubes.

Previously, it was shown that an ANN provided an accurate prediction of the pumped liquid flow rate within the bounds of the data it was trained with. However, if the ANN is provided with inputs outside the bounds of the training set, one would expect a less accurate prediction. That said, with a robust network it should be able to provide insights into possible outcomes that would be extremely difficult to realise by traditional methods.

Hence, to examine the ANN capabilities outside the training bounds the ANN was used to predict the performance of an air-lift pump with four lift tubes at the submergence ratio of 0.748. Now, in the previous results it could be seen that an increase in the number of lift tubes reduces the performance of the pump at low air flow rates but improves it at higher air flow rates. Essentially the air flow needs to be divided amongst multiple tubes which delays the onset of plug flow, where the pump tends to perform best. Based on this, one would expect to see a four tube air-lift pump to exhibit lower pumping rates at low air flow rates and higher rates at higher air flows. As such, figure 11 shows the predictions of the ANN for the multiple air-lift pump operating with four lift tubes compared to that of three lift tubes and illustrates the behaviour one would expect. In this respect the ANN provides an insight into the characteristics of the air-lift pump when operating with four lift tubes which, as stated previously, would be extremely difficult to achieve by analytical means.

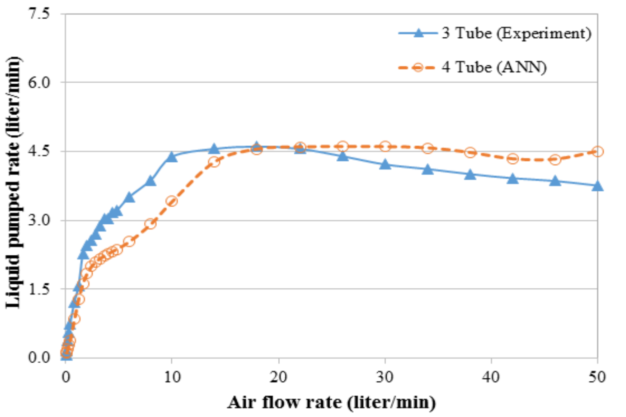

Figure 11. Predicted values for 4 tube air-lift pump from ANN model

Conclusion

In this study, an ANN was developed to predict the pumping characteristics of multiple tube air lift pumps. The ANN was trained, tested and validated against the experimental data that were taken from the studies performed with single and multiple tubes and an optimum ANN was identified. The results showed that the ANN was able to predict the performance of air lift pumps based on unseen values of air flow rate, tube diameter, number of tubes and submergence ratio extremely accurately. Moreover, it was shown that the ANN could provide insights into the performance of air lift pumps with design parameters outside the training bounds.

Given the capability and flexibility of the ANN technique it presents an alternative approach to designing and analysing the performance of multiple parallel air lift pumps. This is of particular significance, as analytical approaches are at best cumbersome and at worst unable to facilitate this prediction.

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