HYBRID MODELING OF FOAMING IN GAS PROCESSING UNITS USING ARTIFICIAL NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION

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***ABSTRACT*: *Natural gas is known as a clean and low-cost source of energy nowadays. Gas processing units are used to remove acid gas from natural gas streams in gas Industry. When foaming occurs in the system, the efficiency of the process highly decreases. In this paper, a new robust approach based on Artificial Neural Network (ANN) as a modeling tool and global optimization technique of Particle Swarm Optimization (PSO) as the optimizer is used to .model the foaming phenomenon. The proposed algorithm has the privileges of local searching ability of the ANN with the global searching ability of PSO. PSO is used to optimize the initial weights of the neural network. The PSO- ANN is applied to model the occurrence of foaming in Gas refinery plants based on a simulation data set relevant to an industrial gas refinery in Iran. Performance of the PSO- ANN is compared with ANN and the results demonstrate that the PSO- ANN model is more accurate and effective.*

Key Words: Foaming, Modeling, ANN, PSO.

1. INTRODUCTION

Acid gas removal (AGR) units are used to remove CO2 and H2S (acid gas) from sour gas in natural gas processing. When foaming occurs in the AGR system, the efficiency of the acid gas removal process extremely decreases. One of the principle causes of foaming is the formation of liquid hydrocarbons in the process. Liquid hydrocarbons are highly soluble in the amine solution and reduce the surface tension of the solution. The reduced surface tension then results in foaming. Determining the dew point of the inlet gas provides the opportunity to avoid liquid hydrocarbons entering the process [1].

Artificial neural network (ANN) is a tool widely used in modeling and control problems. The most important factor in utilizing ANN is the determination of network structure and parameters. Evolutionary algorithms such as Genetic Algorithm (GA) and Imperialist Competitive Algorithm can be employed for this determination. Recently, a new evolutionary algorithm has been proposed, called Particle Swarm Optimization (PSO) [2]. This evolutionary optimization method has shown great performance in global optimum achievement [3]. In the present work, PSO is proposed to optimize the initial weights of ANN. The simulation results demonstrate the effectiveness and potential of the new proposed PSO-ANN network for modeling and prediction of foaming conditions in an Iranian gas refinery compared with ANN using the same data.

2. Artificial Neural Network

Artificial Neural network (ANN) is a modeling tool composed of elements inspired by human nervous systems [4]. ANNs are able to express non-linear relationships using experimental input-output data. Simplified procedure of training a network is shown in Figure 1.

In network training, an input leads to a specific output; then the output is compared to a given target and based on the comparison, the network elements are adjusted until the network output matches the target [5].ANNs are structured from simple units called neurons representing processing cells in human brain. Neurons are connected together by weighted connections. Training process of the network is attained by adjusting these weights.

The approximation capabilities of the multilayer perceptron (MLP) architecture make it a popular choice for modeling cases employed by chemical, petroleum and natural gas engineers [6]. MLPs are composed of input layer, hidden layer(s) and output layer.

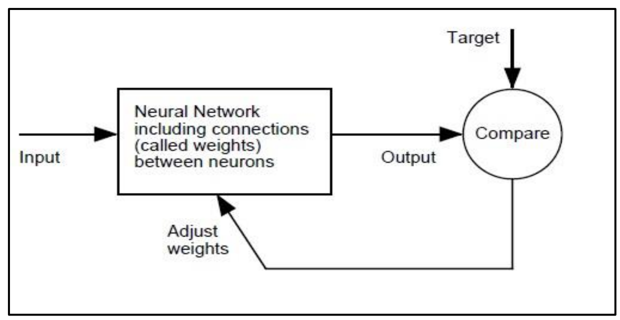

Figure 1: Simplified Procedure for Network Training.

A typical three layer MLP network with I neurons in input layer, J neurons in the hidden layer, and K neurons in output layer is illustrated in Figure 2

The number of independent input parameters affecting the target parameter(s) specifies the number of neurons in input layer and number of target parameter(s) defines the number of output layer neurons. Commonly, the optimum number of neurons in the hidden layer(s) is determined by trial and error procedure. The privilege of MLP network is its ability to express non-linear functions. Activation functions like threshold transfer function, log-sigmoid transfer function, and tan-sigmoid transfer function could be employed to incorporate non-linearity into the MLPs.

To adjust the values of weights of the network for training the MLP-ANN, a proper learning algorithm should be utilized. Back-Propagation (BP) training algorithm is one of the most commonly used algorithms due to its high performance in lowering the generated error [7]. In a feed forward neural network with BP algorithm, a set of input data is introduced to the network and the outputs are estimated by back propagation algorithm. In the next step the difference between the actual and the estimated output values, i.e. error, is calculated and the network starts going backward to adjust the weights. When all the weights are updated, the network returns the forward propagation to estimate new output for the network. Error calculation and weight adjustment steps

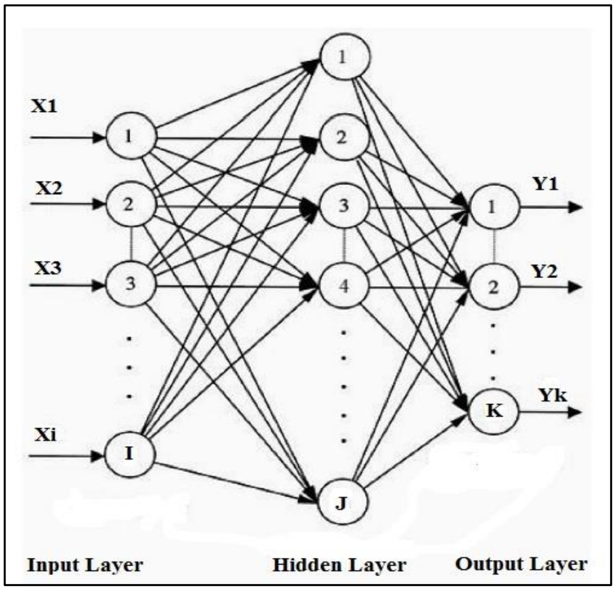

Figure 2: A Typical MLP Network

continue until the generated error reaches a minimum [8].

A three layered feed-forward neural network with back propagation algorithm can estimate any nonlinear function to an arbitrary accuracy

The BP algorithm uses the gradient descent method to minimize the error and is vulnerable to get trapped into a local minimum, making it entirely dependent on initial settings (weights). This problem can be alleviated by global searching ability of the evolutionary algorithms such as PSO [9].

3. Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) introduced by Kennedy and Eberhart [9], is a strong evolutionary algorithm for solving global optimization problems**.** PSO is the model of the motion of a group of birds and fishes [10]. Works done by other authors proves that PSO acts more efficient compared to other optimization techniques [11]. Finally, PSO has low number of parameters for train and its implementation is easy [12]. PSO is summarized in the following simple steps [11]:

1. Initialization of the swarm particles randomly such that each particle has an reasonable velocity;
2. Calculation of the cost function for each particle;
3. Comparison of the value of each particle with its best position (pbest). If the current value of the particle is better than the pbest value, the position of the particle and pbest are bartered ;
4. Updating the particle position and the cost function of global best (gbest);
5. Updating the velocity and position of particles after steps 1 to 4;
6. Continuing steps 1 to 5 until stopping conditions are met i.e. the appropriate cost function.

4. Model Development

The purpose of the present study is to develop a (PSO-ANN) model to estimate the conditions of foaming phenomenon in an absorber column of a gas sweetening plant. To develop the network, a sum of 400 data points were collected from dynamic plant simulation relevant to a gas refinery in Iran.- The operating ranges of the collected dataset for foaming conditions are given in Table 1.

Table 1: Input Parameters Features.

Parameters	Min	Max
P_{abs} (bar a)	6	77
F_a (m3/hr)	130	220
T_a (oC)	35	54

In this model, Temperature of gas stream (T_g) and Gas dew point temperature (GDPT) are considered as functions of absorber pressure (P_{cont}), amine flow (F_a) and amine temperature (T_a):

$$\mathrm{Tg}\,,\mathrm{GDPT} = \mathrm{f}\,(\mathrm{Pabs}, \mathrm{Fa}, \mathrm{Ta}) \qquad \text{eq. (1)}$$

The datasets of input and output parameters of the model are shown in Figures 3 & 4 respectively. Before developing the model, all the collected input data points (except Z_g dataset) were normalized between 0 and 1as the preprocessing step using the following equation:

$$\mathrm{Xnorm} = \frac{(\mathrm{Xi} - \mathrm{Xmin})}{(\mathrm{Xmax} - \mathrm{Xmin})} \qquad \text{eq. (2)}$$

In which X_{max} and X_{min} are the maximum and minimum values of variable X_i in the data sets. Input data normalization is of great importance because the input parameters have different physical units and range and should be utilized having the same order).

In the next step the normalized dataset were divided into three sub data sets including training data, validation data, and test data. The training dataset is used to tune the weights of the network and train the model. The validation dataset is employed to avoid over-fitting. The test set is utilized to evaluate the estimation ability of the model. To determine the best structure for the network there is no certain procedure; therefore trial and error is performed and the best network topology is chosen based on correlation coefficient (R-value) and mean square error (MSE) criteria in this study. A back propagation ANN with a single hidden layer is employed to develop the model. The network is trained by the Levenberge-Marquardt (LM) technique and tan-sigmoid and linear transfer functions have been assigned to hidden layer and output layer respectively. Number of hidden neurons is Selected to be 5 which means the best topology for the model is 4-5-2.

Model verification is the final and the most important step in the model development. In this study, R-value and MSE are chosen as the criteria for accuracy determination of the model. The model is accurate as the R-value approaches 1 and MSE approaches 0.

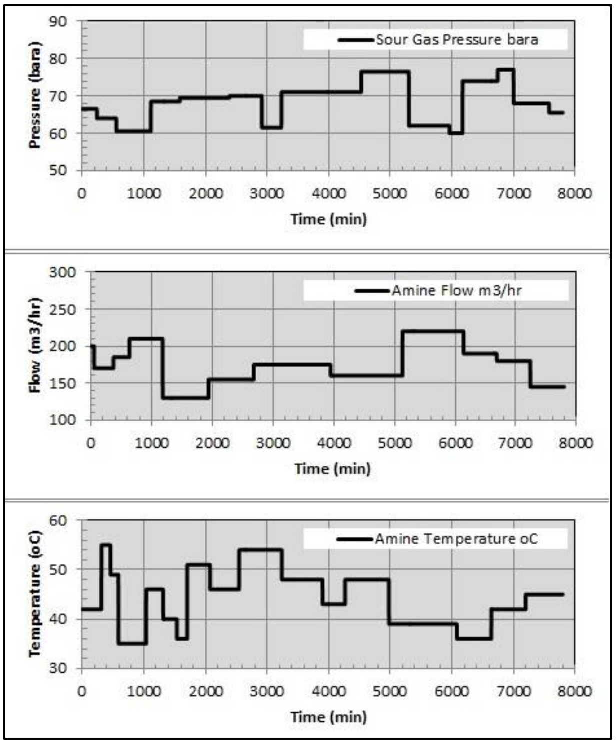

Figure 3: Variation of Plant Input Parameters.

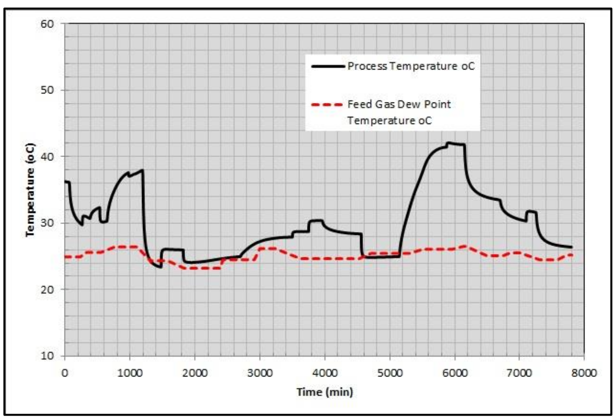

Figure 4: Variation of Plant output Parameters.

R-value and MSE are defined by equation 7&8 respectively:

$$R-\text{value} = 1-\frac{\sum_{i=1}^{n}(y_i-ye)^2}{\sum_{i=1}^{n}(y_i-ya)^2} \qquad \text{eq. (3)}$$

$$MSE = \frac{\sum_{i=1}^{n}(y_i-ye)^2}{n} \qquad \text{eq. (4)}$$

In the above equations, n is the number of data points, y_i is the real value of foaming condition, y_e is the estimated value of foaming condition, and y_a is the average of plant data.

5. RESULTS AND DISCUSSION

The performance of the constructed models was evaluated on the basis of R-value and MSE analyses. R-value and MSE values for the both ANN and PSO-ANN models are tabulated in Table 2. According to the table 2 the performance of the PSO-ANN model is more accurate than that of ANN model.

Table 2: Performance of the designed models.

Simulator Outputs	ANN	PSO-ANN
R-Value	0.9569	0.9842
MSE	0.008654	0.003218

The normalized predicted output and real plant data of foaming conditions, are compared in Figures 5 & 6 for ANN and PSO-ANN models respectively.

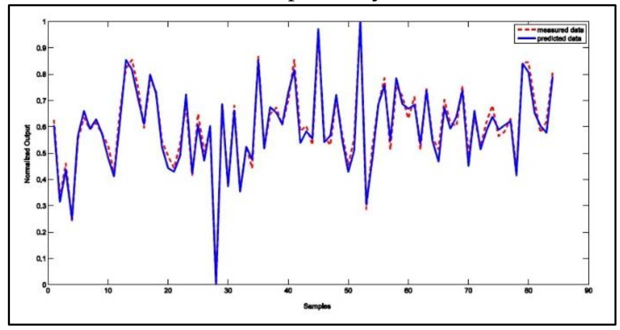

Figure 5: Comparison of normalized predicted data and real plant data in ANN model.

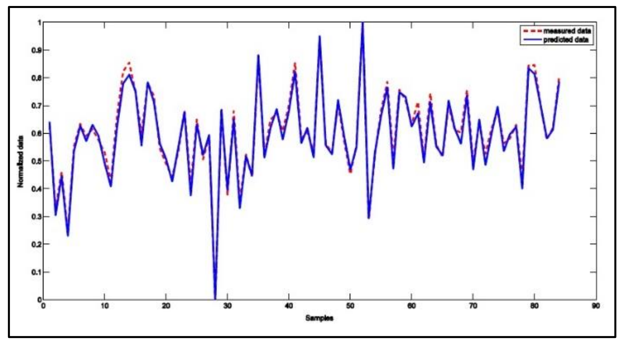

Figure 6: Comparison of normalized predicted data and real plant data in PSO-ANN model.

It can be observed that the results of PSO-ANN model are in better agreement with plant data in comparison to that of traditional ANN model.

The better performance and accuracy of the PSO-ANN model is due to the combination of local searching ability of ANN and global searching capability of PSO.

6. CONCLUSIONS

In this study, the conditions of foaming phenomenon are well-predicted by means of a hybrid model designed on the basis of Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) modeling tools. The model is structured using ANN, while PSO has the role of weight initialization for ANN network. The results of the designed model show that the agreement of real plant data with the predicted outputs of PSO-ANN model is reasonably better than that of traditional ANN network. The better performance of PSO-ANN model is due to the combination of local searching ability of ANN and global searching capability of PSO.

7. Nomenclature

ANN	Artificial Neural Network
PSO	Particle Swarm Optimization
gbest	Global Best Position
pbest	Personal Best Position
Obj Fcn	Objective Function
P abs	Absorber Pressure
Fa	Amine Flow
Ta	Amine Temperature
R – Value	Correlation Coefficient
MSE	Mean Square Error

8. REFERENCES

1. Zubarev, D. I., "Pros and cons of applying proxy models as a substitute for full reservoir simulations," *SPE 124815, in Proceedings of the SPE Annual Technical Conference and Exhibition held in New Orleans, Louisiana, USA,* (2009).
2. Bjorndalen, N., Kuru, E. and Schiozer, D. J., "Application of Neural Network and Global Optimization in History Matching," *Journal of Canadian Petroleum Technology*, PETSOC-08-11-22-TN, **Vol 47** (2008).
3. Cullick, A. S., Johnson, D. and Shi, G., "Improved and More-Rapid History Matching With a Nonlinear Proxy and Global Optimization", *SPE 101933, SPE Annual Technical Conference and Exhibition held in San Antonio, Texas, U.S.A.*, 24–27 September (2006).
4. Zhang, X., Hou, H., Wang, D., Mu, T., Wu, J. and Lu, X., "An Automatic History Matching Method of Reservoir Numerical Simulation Based on Improved Genetic Algorithm," *International Workshop on Information and Electronics Engineering (IWIEE), Procedia Engineering* 29, 3924 – 3928 (2012).
5. Vapnik, V., Golowich, S., Smola, A., "Support vector method for function approximation, regression estimation, and signal processing," In: *Mozer, M.C., Jordan, M.I., Petsche, T. (Eds.), Advances in Neural Information Processing Systems 9. MIT Press, Cambridge, MA,* pp. 281–287 (1997).
6. Samui, p., "Application of Least Square Support Vector Machine (LSSVM) for Determination of Evaporation Losses in Reservoirs", *Engineering*, **3**, 431-434 (2011).
7. Elmabrouk, S. Kh., "Application of function approximations to reservoir engineering," *Ph.D. thesis, Department of Petroleum Engineering, University of Regina* (2012).
8. Shi, D.F. and Nabil, N.G., "Tool wear predictive model based on least squares support vector machines," *Mechanical Systems and Signal Processing*, **vol. 21**, pp. 1799-1814 (2007).
9. Kennedy, J., Eberhart, R., "Particle Swarm Optimization, Purdue School of Engineering and Technology Indianapolis," *IN 46202-5160, Washington, DC 20212 , IEEE* (1995).
10. Riazi, S. H., Heydari, H., Ahmadpour, E., Gholami, A. and Parvizi, S., "Development of novel correlation for prediction of hydrate formation temperature based on intelligent optimization algorithms," *Journal of Natural Gas Science and Engineering* 18, 377 – 384 (2014).
11. Mohamed, L., Christie, M. and Demyanov, V., "Reservoir Model History Matching With Particle Swarms," *Institute of Petroleum Engineering, Heriot–Watt University, Edinburgh, UK*, SPE 129152 (2010).
12. Martinez-Soto, R., Rodriguez, A., Castillo, O. and Aguilar, T., "Gain Optimization for Inertia Wheel Pendulum Stabilization using Particle Swarm Optimization and Genetic Algorithms," *International Journal of Innovative Computing, Information and Control*, **Vol. 8** (2012).