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Comparison of intelligent systems, artificial neural networks and neural fuzzy model for prediction of gas hydrate formation rate

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Abstract - The main objective of this study was to present a novel approach for predication of gas hydrate formation rate based on the Intelligent Systems. Using a data set obtained from flow tests in a mini-loop apparatus, different predictive models were developed. From the results predicted by these models, it can be pointed out that the developed models can be used as powerful tools for prediction of gas hydrate formation rate with total error of less than 4%.

Keywords: Artificial neural network; fuzzy Inference System; gas hydrate formation; rate model.

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Introduction

Gas hydrates are ice-like crystalline solid compounds formed from water and low molecular non-polar or slightly polar molecules (usually gases) under low temperature, but well above the freezing point of water, and elevated pressure conditions (Sloan, 1997). With the development of the natural gas industry in the 20th century, the production, processing and distribution of natural gas under high-pressure conditions were necessary. Under these conditions, it was found that the production and transmission pipelines were becoming blocked with what looked like to be ice. Hammerschmidt (Hammerschmidt, 1934). determined that hydrates were the cause of plugged natural gas pipelines.

Prediction of gas **h**ydrate **f**ormation **r**ate (HFR) plays an important role in developing models that can describe and predict the hydrate formation processes and also in studying the mechanisms of nucleation and growth of hydrate plugs in pipelines. Several studies have been performed on the measurement and modeling of hydrates formation rate based on the hydrate-former gases consumption values (Vysniauskas, et.al, 1983, Englezos, et.al, 1987, Skovborg and Rasmussen, 1994, Kashchiev and Firoozabadi, 2003).Talaghat (Talaghat, et.al,2009). proposed a new rate equation to predict gas consumption rate during hydrate formation in a flow mini-loop apparatus. However, these presented models are not accurate enough to predict HFR in pipelines and often consider only simple pure gases. Most of them require complex and time consuming computations and also a lot of input information to achieve the required information. Therefore, it is obvious that developments of new advanced prediction models are important for gas industry. These models should not have the limitations and complexities of the available models. In other words the new models should be more accurate, robust and less sensitive to noisy input data, adaptive to a new input-output information and also should require the least amount of input information. Intelligent models offer all of the above desirable characteristics. Therefore, the main objective of this study was to present models using **A**daptive **N**etwork–Based **F**uzzy **I**nference **S**ystem (ANFIS) and **M**ulti-**l**ayer **P**erceptron (MLP) for predicting the HFR of common hydrate-former gases (C1, C3, i-C4 and CO2).

Materials and methods

Artificial neural networks (multi-layer network)

Artificial neural networks (ANN) are information processing systems that have specific performance characteristics in common with biological neural networks and learn by trial and error. An ANN consists of a group of neurons (processing elements) that are organized in specific structures, which called layers. In a multi-layer network (called MLP) there are usually an input layer, one or more hidden layers and an output layer. The number of neurons in the input and output layers are equal to the number of variables that are being presented to the network as inputs and targets, respectively. Determination of the appropriate number of the existing neurons in the hidden layer(s) which are principally responsible for feature extraction is difficult and time-consuming and is often done by trial and error (Graupe, 2007, Blusari,1995, Shadravanan, 2010).

Adaptive Neural-Fuzzy Inference System (ANFIS)

A fuzzy inference system is a nonlinear system that employs fuzzy if–then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. Fuzzy logic modeling techniques can be classified into three categories, namely the linguistic (Mamdani-type) (Mamdani,et.al,1975), the relational equation, and the Takagi–Sugeno–Kang (TSK) Sugeno, 1988). In linguistic models, both the antecedent and the consequence are fuzzy sets while in the TSK model the antecedent consists of fuzzy sets but the consequence is made up of linear equations. Fuzzy relational equation models aim at building the fuzzy relation matrices according to the input–output process data.

Based on the TSK model, an Adaptive Network based Fuzzy Inference System (ANFIS) has been introduced by Jang (Jang, 1993).ANFIS is fuzzy inference system implemented as neural network. Each layer in the network corresponds to a part of the fuzzy inferencesystem (FIS) namely input fuzzification, rule inference and fire strength computation, and output defuzzification. The main advantage of this kind of representation is that the FIS parameters are encoded as weights in the neural network and, thus, can be optimized via powerful well known neural net learning methods. This model is mostly suited to the modeling of nonlinear systems. It combines the recursive least-square estimation and the steepest descent algorithms for calibrating both premise and consequent parameters iteratively.

In a TSK model with a rule base of M rules, each giving p antecedents, the ith rule can expressed as:

Rule i : If x_i is f_1^i and...and x_p is f_p^i ,then y^i(X) =

$$c_0^i+c_1^i x_1+c_2^i x_2+\ldots+c_p^i x_p=C_i X \qquad (1)$$

where i = 1, 2, . . . , M, c_j^i (j = 0, 1, . . , p) are the consequent parameters, y^i(X) is the output of the ith rule, and f_k^i (k = 1, 2, . . , p) are fuzzysets.

The overall output, y(X), of the model is obtained by combining the outputs from the M rules in the following prescribed way:

$$y(X) = \frac{(\sum_{i=1}^{M} f^i(x) y^i(x))}{\sum_{i=1}^{M} f^i(x)} = \frac{\sum_{i=1}^{M} f^i(x)(c_0^i+c_1^i x_1+c_2^i x_2+\cdots+c_p^i x_p)}{\sum_{i=1}^{M} f^i(x)} \qquad (2)$$

where the $f_i(X)$ are rule firing level (strengths), defined as:

$$f^i(X) = T_{k=1}^{p} \mu_{f_k^i}(x_k) \qquad (3)$$

in which T denoted a t-norm, usually minimum or product.Fig.1provides an example of a simple FIS represented in an ANFIS network. In ANFIS architecture, a FIS is described in a layered, feed-forward network structure, where some of the parameters are represented by adjustable nodes (represented as rectangular entities in the figure) and the others as fixed nodes (represented as spherical entities in the figure). The raw inputs are fed into the nodes of layer 1 that represent the membership functions. The parameters in this layer are called premise parameters and they are adjustable. The second layer represents the t-norm operators that combine the possible input membership grades in order to compute the firing strength of the rule. At least in the basic ANFIS method these parameters are not adjustable. The third layer implements a normalization function to the firing strengths producing normalized firing strengths. The fourth layer represents the consequent parameters that are adjustable. The fifth layer represents the aggregation of the outputs performed by weighted summation. It is not adjustable (Fuzzy logic toolbox for use with MATLAB user guide, 2007, Zadeh, 1984).

Development of models

To develop ANFIS and MLP models 467 data obtained from flow mini-loop apparatus (Table 1) were used with a random selection (350 data as train set and the 117 data as test set). This combination was selected based on trial and error to achieve best results.

Table 1. Ranges of the input variables used in developing the ANFIS and MLPmodels

Parameter	Hydrate- Former	Minimum	Maximum
Temperature (K)	C1, C3	277.15	277.15
	i-C4	275.15	275.15
	CO2	280.15	280.15
Pressure (MPa)	C1	5	8
	C3	1	2
	i-C4	1	2
	CO2	4	7
Molecular Weight (gr/mol)	C1,C3, i-C4, CO2	16.043 (C1)	58.123 (i-C4)
Time (min)	C1,C3, i-C4, CO2	0	185

To develop an intelligent system, the most important physical skill required is to make a decision what the principal inputs and output(s) of the system are. In this study, the input parameters were temperature, pressure, molecular weight of hydrate-former, and time. The desirable output of the models was the hydrate formation rate (gas consumption amount). To achieve this goal, two models of ANFIS and MLP were developed.

In MLP model, HFR was a function of temperature (T), pressure (P), molecular weight of hydrate-former (MW_{hf}), time (t) therefore, the model has 4 and 1 neurons in its input and output layers, respectively:

$$HFR = f_{\text{MLP and ANFIS}}(T, P, MW_{hf}, t) \quad (4)$$

Based on the importance of optimum architecture determination in developing multi-layer neural networks [14], four elements that contain these architectures have been investigated to developed the desirable models: 1) number of hidden layers, 2) number of neurons in each hidden layer, 3) activation function of each layer and 4) training algorithm, which determines the final value of the weights and biases.

Several neural network architectures were tested to find out the best accuracy. Finally, a multi-layer network with two hidden layers was found to be suitable to consider the relationship indicated in equation (4). The optimum numbers of the neurons in the first and second hidden layers were determined 18 and 5 and tangent-sigmoid and linear transfer functions were used as activation (transfer) functions of the hidden layers and output layer, respectively. In the network were developed in this study, the Bayesian regularization (automated determination of optimal regularization parameters) in combination with Levenberg-Marquardt training algorithm, was used to improve the generalization power of ANN. This kind of regularization has been implemented in the function "trainbr".

ANFIS model on the basis of the subtractive clustering algorithm with inputs and output similar to MLP model was developed.

The fuzzy HFR modeling system used in this study is a multi-input single output (MISO) Takagi-Sugeno system. Because of large number of input variables, scatter partitioning was used to avoid "curse of dimensionality" problem instead of grid partitioning.

Table 2 shows the details of optimal fuzzy model designed for ANFIS model. This arrangement was also selected by trial and error procedure.

Table 2. Characteristics of fuzzy model for ANFIS.

Parameter	Operator
AND	prod
OR	probor
Implication	prod
Aggregation	max
Difuzzification	wtaver

Hybrid optimization method was used to optimize generated **f**uzzy **i**nference **s**ystems (FIS). The best models of ANFIS and MLP were selected according to minimum total average absolute deviation percent (TAAD%). The performance of ANFIS and MLP configuration was evaluated based on calculating the total average absolute deviation percent (TAAD%):

$$TAAD\% = \frac{100}{N} \times \left| \frac{\sum_{i=1}^{N}\left(y_i^{exp} - y_i^{cal}\right)}{y_i^{exp}} \right| \quad (5)$$

Where y_i^{exp} and y_i^{cal} are target and model output for the ith output, and N is the total number of events considered.

Results and discussions

Table 3 shows the features and functions of designed models compared with the actual results and the latest presented model (Talaghat model). TAAD% is the overall average of absolute deviation for normalized data and R is the correlation coefficient for normalized data. Figures 2 to 5 show the results of testing ANFIS and MLP models compared with experimental results in this study, and Talaght model. Moreover, four different types of gas hydrates, including CO_2, C_1, C_3, and i-C_4 at different pressures are illustrated .

Table 3. Error analysis of different models

	TAAD%	R
ANFIS Model	3.3523	0.9998
MLP Model	3.7849	0.9997
Talaghat Model	14.9	0.9901

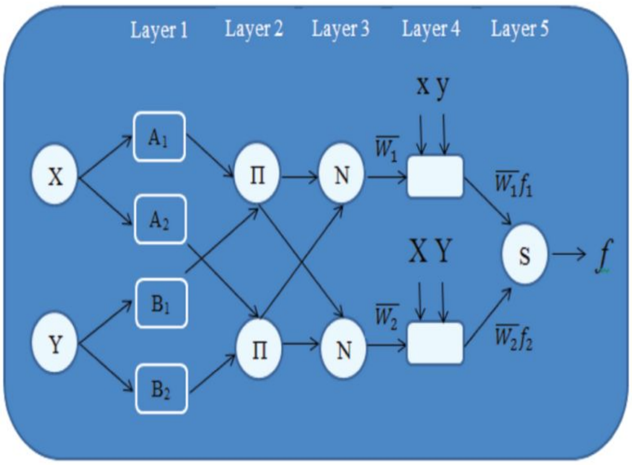

Figure 1. ANFIS structure.

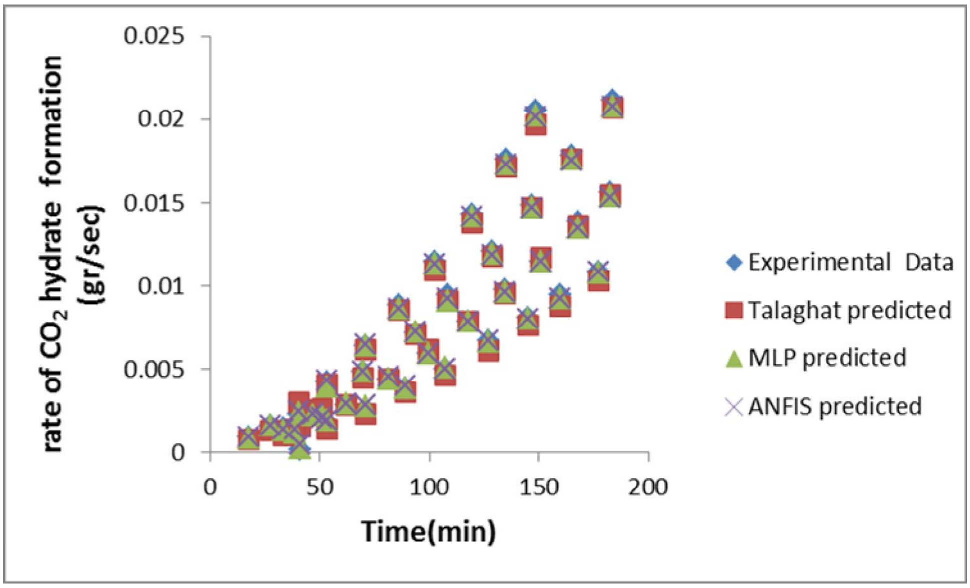

Figure 2. Rate of CO_2 hydrate formation as a function of time at 280.15 K and different pressure.

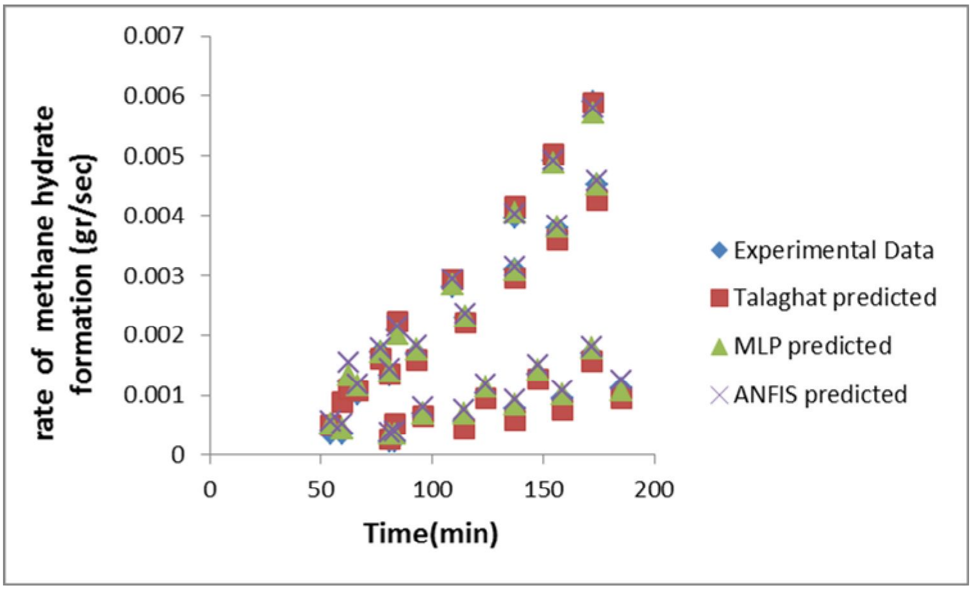

Figure 3. Rate of Methane hydrate formation as a function of time at 277.15 K and different pressure.

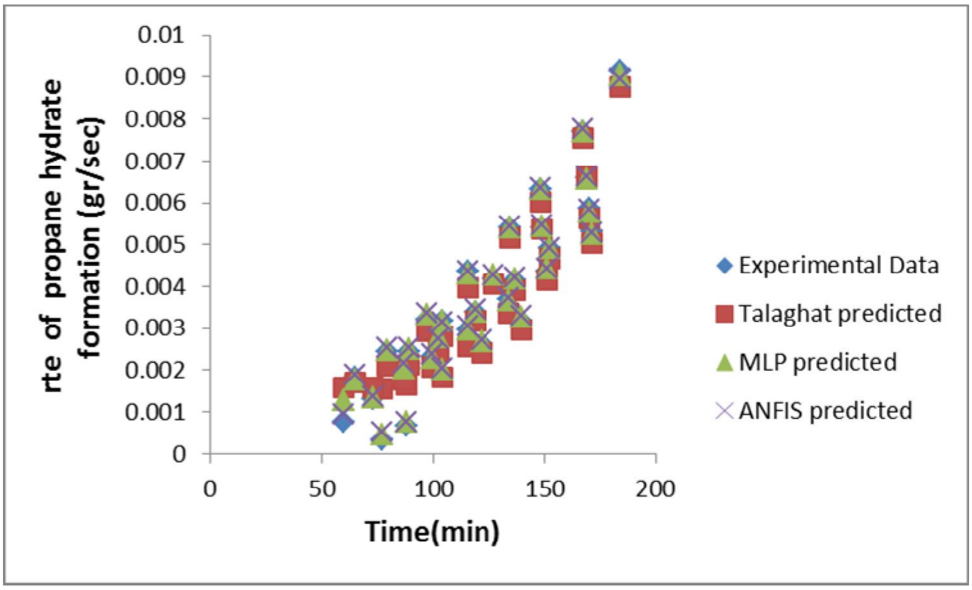

Figure 4. Rate of Propane hydrate formation as a function of time at 277.15 K and different pressure.

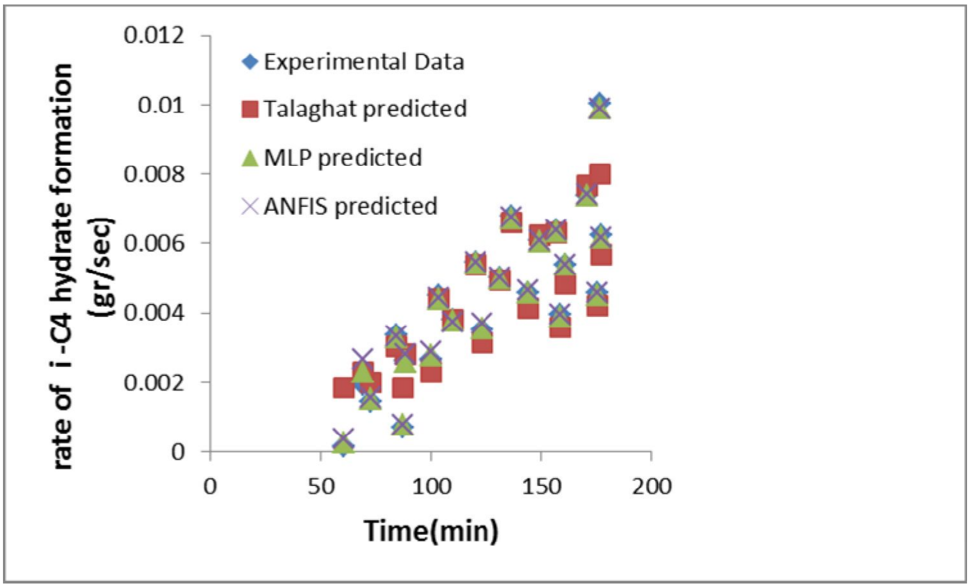

Figure 5. Rate of Iso-butane hydrate formation as a function of time at 275.15 K and different pressure

Figures 6 and 7 show an accurate the relationship between experimental results and those predicted by MLP and ANFIS. The developed ANFIS and MLP models are more accurate than other investigated models because of the integration of fuzzy logic systems with the capability of learning in artificial neural networks which leads to the adaptability of the model with this issue.

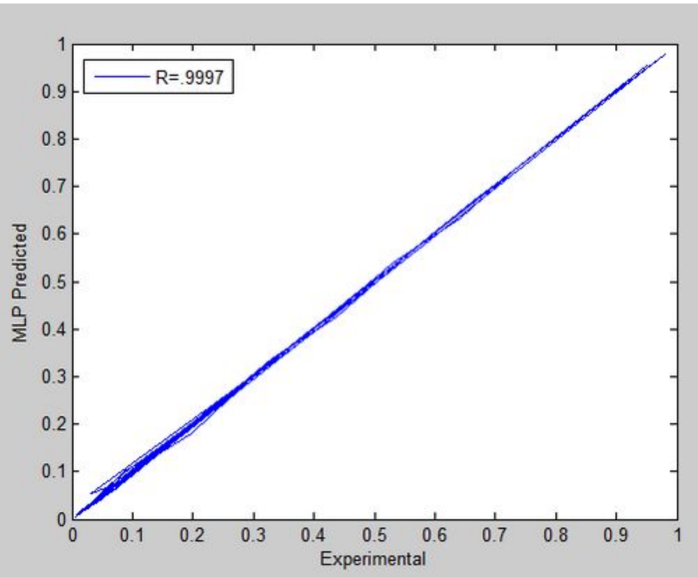

Figure 6. Experimental data versus MLP model outputs.

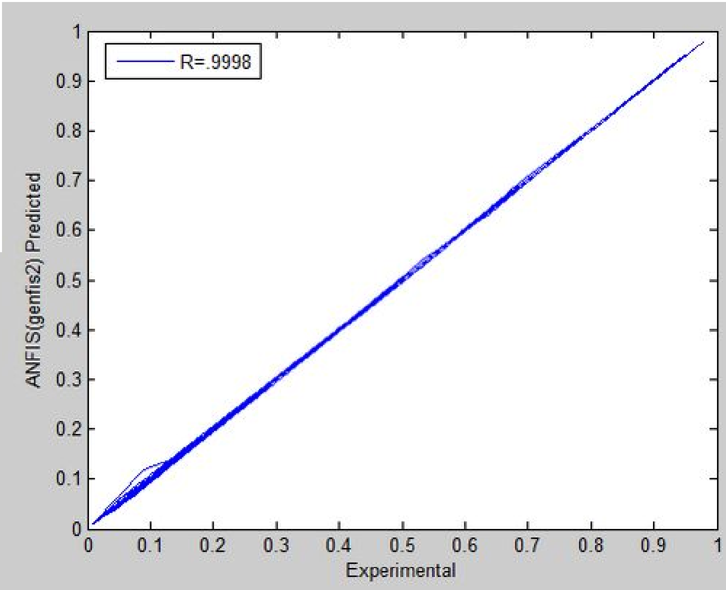

Figure 7. Experimental data versus ANFIS model outputs.

CONCLUSION

Gas hydrate formation in production wells and transmission pipelines and consequent plugging of these lines have been a major flow-assurance concern of the oil and gas industry for the last 75 years. Gas hydrate formation rate is one of the most important topics related to the kinetics of the process of gas hydrate crystallization. In this work, utilization of the adaptive Artificial Neural neural fuzzy inference system an Network (Multi-layer Perceptron) techniques for predicting the hydrate formation rate have been investigated.

From the results of this study, it can be pointed out that the developed ANFIS and MLP models are able to predict the hydrate formation rate of the main hydrate-formers such as C1, C3, i-C4 and CO2 and can be used in gas industry.

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