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EMPIRICAL MODELING OF HYDRATE FORMATION PREDICTION IN DEEPWATER PIPELINES

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ABSTRACT

Gas hydrate is a challenging problem in deep-water natural gas transmission lines. Temperature, pressure, and composition of gas mixtures in deep-water pipeline promote rapid formation of gas hydrates. The petroleum industry spends millions of dollars yearly to minimize the effects of hydrate formation on flow assurance. In this scenario, on the basis of experimental data from Sloan and Avlonits work, an artificial intelligence (AI) for methane gas hydrate of deepwater gas pipelines has been developed. This model is based on temperature and pressure conditions. The correlations between temperature and pressure are developed by using MATLAB software and then optimize with optimization techniques, such as genetic algorithm and particle swarm optimization. All correlations are computed with the existing experimental work and it satisfies that the new correlation has the minimum error with high accuracy.

Keywords: hydrate formation conditions, genetic algorithm and particle swarm optimization.

INTRODUCTION

The presence of clathrate hydrate was first discovered by Sir Humphry Davy in 1810 [1]. In 1888, Villard presented the performance data of hydrocarbon hydrates [2]. Chlorine gas in water was observed to freeze more readily than pure water. In 1934, Hammerschmidt [3] concluded that natural gas hydrates are formed in deep-water pipelines under normal thermodynamic properties, such as temperature, pressure, and flowing fluid velocity, thereby clogging the pipelines. Therefore, to avoid clogging, an approximation of hydrocarbon effect on hydrate formation temperature as a function of pressure was proposed.

The objective of the present research is to develop a gas hydrate formation prediction model that incorporates particle swarm optimization (PSO) and genetic algorithm (GA) with Gaussian equations. Long-distance pipelines are affected by hydrate formation under temperature and pressure conditions of flowing fluids and composition of gases. However, if Nitrogen (N) is increased in the mixture of gases, it works as an inhibitor. Thus, a new empirical correlation for the prediction of hydrate formation temperature in the presence of pure water and methane is studied in this research. This model helps to predict the hydrate formation conditions with flowing thermodynamic properties. The constant coefficients of the hydrate formation model were developed by using GA and PSO. The existing published data of E. D. Sloan and D. Avlonitis [4, 5] were used in this work, this model covers a wide range of pressure and temperature are 1.2 to 10.82 MPa and 259.1 to 292.35 K respectively.

REVIEWS OF EMPIRICAL METHODS

In deep-water pipelines, gas hydrates are considered undesirable solids (composed of gas molecules) that cause detrimental obstacles in the flow path [6]. The hydrates are crystalline mixture solids of natural gases that are formed at low-temperature and high-pressure conditions [7]. Gold berg [8, 9] developed an artificial intelligent (AI) technique by genetic algorithm to control the gas pipeline system, which was consisting reproduction, crossover and mutation. According to Hammerschmidt and Kobyashi *et al.* [3, 10], pressure and specific gravity are independent variables, whereas temperature is a dependent variable. A hydrate formation prediction correlation model was introduced by Kabayashi [10] in 1987. The model predicted that the hydrate formation temperature was <60 °F and the pressure was <1500 psi based on gravity curve and temperature. The statistical software Package for the Social Sciences is also used to predict hydrate formation. Ameripour and Baffufet [11] developed a correlation model to estimate hydrate formation temperature and pressure for a variety of gas hydrate formers with and without inhibitors, where regression variables such as pseudo-reduced pressure, pressure, gas specific gravity, water vapor pressure, and liquid water viscosity are employed. In a study by Nasab and co-workers empirical correlation for hydrate formation was developed using Statistical Analysis Software to correlate hydrate formation temperature with various variables, such as pressure, water vapor pressure, and specific gravity that range from 150 psi to 4300 psi, 31 to 78, and 0.6 to 1, respectively [12].

The genetic algorithm is related to a large scale of an evolutionary algorithm which helps to generate minimum optimization problems using techniques motivated by natural evolution such as inheritance, mutation, selection and crossover. And particle swarm optimization is a powerful algorithm for global optimization problems and it can tune to a small number of parameters. The population initializes randomly and it is evaluated on the objective function values. After data generation, the program changes with new data and produces the best individual near-optimum or reasonable solution.

METHODOLOGY

The proposed methodology is summarized in following five key steps as shown in following

Figure-1. In the first step to finding the experimental data that showing the temperature and pressure conditions for hydrate formation. In the second step is developing hydrate formation conditions by the help of GA and PSO algorithm discussed as bellow.

The volume *(v)* and pressure *(P)* of gas in the pipeline are calculated by the developed objective function with the help of PSO and GA algorithms.

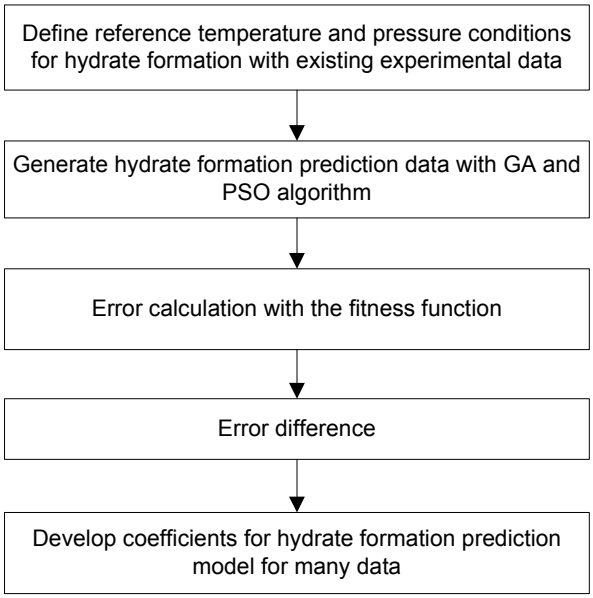

Figure-1. Methodology.

To observe the point at which the hydrate formation conditions are formed, the developed correlation coefficient values were generated at a constant temperature, pressure, and molecular weight. Abbasi *et al.* [13] developed correlation Equations based on polynomial and Fourier equations, which were used to develop new correlations for hydrate formation temperature as a function of pressure. Polynomial and Fourier equations were used in PSO and GA to optimize mutations of hydrate formation correlation coefficients. The properties of methane gas will be determined by flowing gas in pipelines. The polynomial equation can be described in terms of degrees. The number of coefficients and the polynomial degree *n* provide the highest prediction variable. Those were examined by different parameters, such as one and three sets of polynomials and Fourier series respectively with PSO algorithm.

Here are discussing Gaussian equation based prediction of hydrate formation conditions with same program arrangement as defined in Abbasi *et al* [13, 14] and discussed as above. The Gaussian-based correlation is obtained as follows:

$$T = \left\{ \begin{array}{l} a_1 e^{-\left(\frac{P-a_2}{a_3}\right)^2} + a_4 e^{-\left(\frac{P-a_5}{a_6}\right)^2} + a_7 e^{-\left(\frac{P-a_8}{a_9}\right)^2} \\ + a_{10} e^{-\left(\frac{P-a_{11}}{a_{12}}\right)^2} + a_{13} e^{-\left(\frac{P-a_{14}}{a_{15}}\right)^2} \end{array} \right\} \quad (1)$$

where; *a* is the developed coefficient which is illustrated in Table-1, *e* is the exponential function, *T* is the flowing temperature in the pipeline, and *P* is the pressure of the flowing fluid. The dynamics of particle change position is based on the time evaluation and the free movement of particles at different times.

In the third and fourth steps, are determining the error, fitness function and difference of error. This information is challenging because the same particle will have different locations/positions at different times, and the dynamics of particle change position [13]. The mean square error (MSE) equation is used to find the error difference between existing data and generated results. The MSE equation is used to examine the accuracy of correlations and compare the prediction results with the experimental data.

RESULTS AND DISCUSSIONS

All the values of the common parameters in each algorithm were the same; for instance, the population size was 200 and the iteration was 1000. The aim of balancing input variables is to examine PSO and GA based generated results. The standard binary code for GA is evaluated as its fitness scaling, seed selection, random selection crossover, and mutation. The mutation was 0.4; the friction of population was 0.5; the variable limit was ±1000; and the minimum cost was -9999999. In the PSO, the cognitive and social components were c1 and c2 (i.e., 0.8 and 0.8-c1, respectively). The variables c1 and c2 are constants and could be changed between personal and population, respectively. Inertia weight determines how the previous velocity *(v)* of particle influences the velocity *(v)* in the next iteration [13]. Table-1 shows the constant coefficients of the correlation, which are optimal variables obtained by PSO and GA, respectively. These constant coefficients are used for many data or universally for adopted data in this work.

Table-1. The Constant coefficients of correlation for minimized optimization by Gaussian equation.

Coefficients	Gaussian equation	
	GA	PSO
a_1	272.82	0.2125
a_2	273.11	0.0128
a_3	273.48	0.0315
a_4	274.28	0.0168
a_5	274.56	0.0053
a_6	275.28	-0.0295
a_7	275.66	-0.0069
a_8	275.68	-0.0026
a_9	276.48	0.0371
a_{10}	278.5	0.0702
a_{11}	279.72	-0.0049
a_{12}	280.47	0.0651
a_{13}	281.2	0.0315
a_{14}	282.67	0.0401
a_{15}	285.45	0.0044

The plots in Figure-2 to **Figure-5** show the prediction of hydrate formation conditions. These plots were developed by using PSO and GA. These graphs were showing the correlations of hydrate formation temperature as a function of pressure. In Figure-2, the generated data of hydrate formation temperature are compared with the existing experimental data temperature of [4, 5]. The prediction tool results are close to the existing prediction model results of hydrate formation, with a minimum error of 8.7752% and 2.2778% in Figure-2 and **Figure-3** respectively. The Figure-3 correlation is measured in PSO. The error in Figure-4 is 0.6%, which satisfies the fitting value and error difference with Gaussian correlation results.

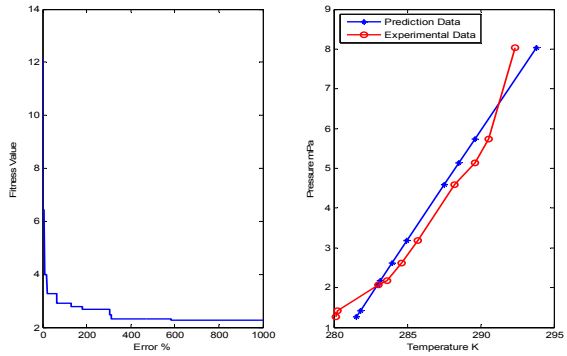

Figure-2. Comparison of Gaussian based result of the newly developed method for predicting hydrate formation temperature with derived data of [5] with GA.

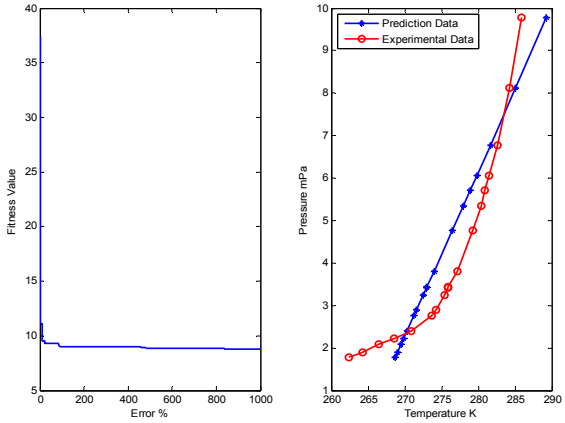

Figure-3. Comparison of Gaussian based result of newly developed method for predicting hydrate formation temperature with derived data of [4] with GA.

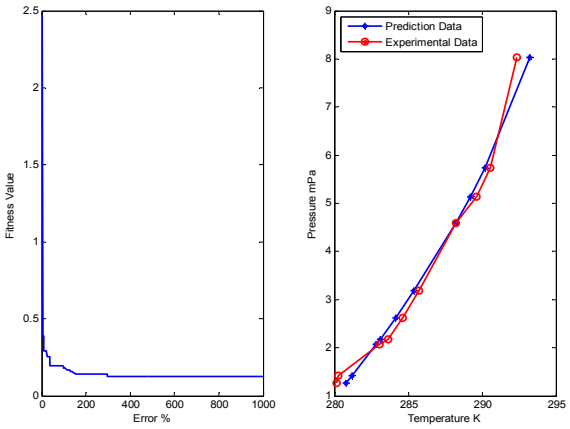

Figure-4. Comparison of Gaussian based result of the newly developed method for predicting hydrate formation temperature with derived data of [5] with PSO.

Figure-5 is plotted in PSO with the help of Gaussian Equation. This graph shows that the developed correlation for hydrate formation temperature is approximately similar to the existing data. The graph's fitting value is <2 and its error is 0.1%. In **Figure-5**, the predicted hydrate formation temperature is almost similar with existing experimental data and satisfying the prediction model for hydrate formation.

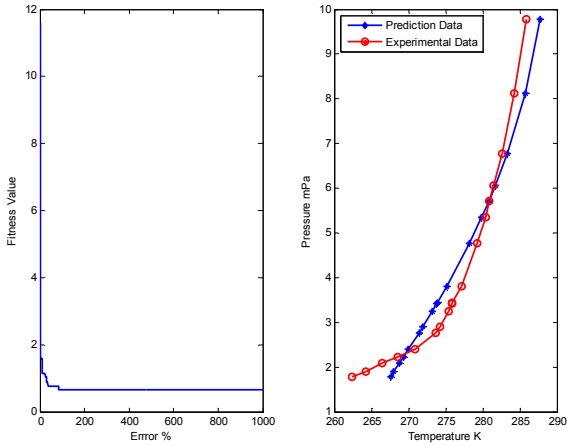

Figure-5. Comparison of Gaussian based result of developed method for predicting hydrate formation temperature with data of [4] with PSO.

Table-2. The Error calculation for hydrate formation prediction model.

	Gaussian	
	GA	**PSO**
A	8.7752	0.6
B	2.2778	0.1

The second phase of correlations is developed by GA with Gaussian Equation, as illustrated in Figure-4. The error (%) is <10 with a fitness value of <9. The predicted hydrate formation temperature and the developed prediction temperature of hydrate formation under the function of pressure are approximately equal to the existing data of E. D. Sloan and D. Avlonitis. These results indicate that the equation (1) correlation provides the best prediction of hydrate formation temperature conditions with minimum error. The Table-2 and Figure-6 are illustrating the error difference in between existing data and prediction data for the hydrate formation model.

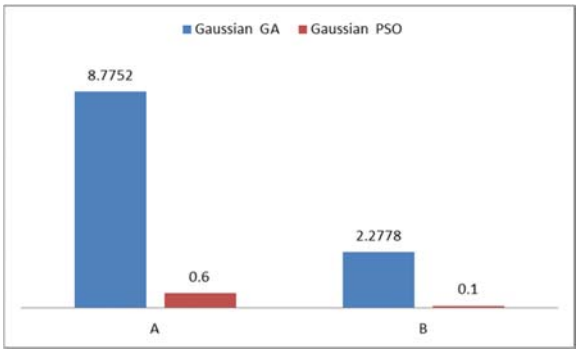

Figure-6. Comparison of error with GA and PSO results.

CONCLUSIONS

An empirical modelling for prediction of hydrate formation temperature was described in this paper. This paper proposed a novel application for methane gas hydrate based on the adopted data from [4, 5]. All correlations are performed at a range of pressure and temperature is 1.2 to 10.82 MPa and 259.1 to 292.35 K respectively. This new correlation can be applied to predict the hydrate formation of various temperature and pressure conditions of deep-water pipelines. The new correlation was modified by using PSO and GA algorithms with developed correlation equations and constant coefficients as shown in Table-1. Gaussian equation with PSO and GA are giving best results and obeying existing experimental data. The proposed correlation shows accurate results across all pressure and molecular weight of flowing gases. The developed constant coefficient could be helpful in the prediction of various hydrate formation temperature and pressure conditions.

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