

Prediction of Asphaltene Precipitation During Gas Injection Using Hybrid Genetic Algorithm and Particle Swarm Optimisation

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Abstract: Asphaltenes are precipitated and deposited during gas injection and this causes pore throat reduction, permeability reduction and wettability reversal. The result is reduced oil produced thereby leading to sizable revenue loss by field operators. To mitigate or completely prevent the occurrence of this phenomenon, this work has utilised Hybrid Genetic Algorithm Particle Swarm Optimisation-Artificial Neural Network (HGAPSO-ANN) for predicting the amount of asphaltenes deposited in the reservoir during gas injection. A number of methods are available for predicting the amount of asphaltenes deposited but some of them are either too expensive to execute or fraught with errors and deviations. This is due to the nature of asphaltene which is complicated and ambiguous. Some of the methods in existence include correlation with solvent properties, thermodynamic models and recently connectionist models (neural networks). There is however, no publication in the literature on using hybrid algorithms with neural networks to predict asphaltene precipitation during gas injection and this becomes an interesting area of research considering the enormous benefits that would be obtained from a robust hybrid asphaltene precipitation prediction model. The developed model performed well with an AARE of 0.09. This is lower than AARE values reported by Hue et al (2000), Rostami and Manshad (2010), Manshad et al (2015) which were 0.183, 0.153, and 0.121 respectively. From the results of the model it can be seen that HGAPSO-ANN is more accurate in predicting asphaltene precipitation than other existing predictive models consulted. This method can therefore, be used as a decision making tool by field operators to set up procedures for the prevention or mitigation of asphaltene precipitation during gas injection. This will help prevent revenue losses and increase profitability of recovering hydrocarbons using gas injection.

Keywords: Asphaltene Precipitation, Artificial Neural Network, Genetic Algorithm, Particle Swarm Optimization, Porous Media

1. Introduction

During oil production, organic matter is deposited and this poses a production problem. Organic material can be deposited in the reservoir, in casing, production tubing, submersible pumps, and surface equipment, thereby resulting in operational difficulties and production decrease [1]. The organic material deposited is very complicated and may be mixtures of asphaltenes, asphaltic resins, wax, oil, solid, and water.

As an oil well is produced, temperature and pressure start declining simultaneously. This causes the asphaltene

molecule to precipitate and form a sticky accumulation. The precipitated asphaltene blocks the well and flow lines thereby reducing production rate. Subsequently, valves, separators and the wellhead facilities can as well lose their performance. Even an infinitesimal amount of asphaltene can induce a noticeable decline in the performance of refinery and petrochemical units. It then becomes imperative that asphaltene precipitation be reversed or prevented in order to enhance well performance and bring about an increase in production rate [2]. Determination of the amount of precipitated asphaltenes will aid in achieving this objective.

Asphaltenes are high density polyaromatic molecules with

polydispersity property, which comprises various elements and metals present in crude oils and are surrounded and stabilised by resins. Many organic deposits in the oil reservoir are derived from asphaltenes which are precipitated as a result of low pressure, high pH, and injection of low surface tension fluids such as light paraffins, pentane, hexane, and gas condensate [3-5].

When asphaltenes are deposited in a porous media (reservoir), two major changes are produced which are changes in the porous media morphology, and changes in the surface characteristics of the porous media. Asphaltene precipitates are composed of fine particles that may aggregate and grow to a size large enough to block the throat of small pores consequently reducing absolute permeability. The deposits also induce changes in wettability from water wet to oil wet. This brings about a reduction in the absolute permeability of the porous media. Asphaltene deposition has been observed to affect permeability more than porosity [6].

A reduction in both porosity and permeability will adversely affect oil production thus making the asphaltene problem the most challenging one in petroleum hydrocarbon production [7].

Pressure depletion during primary production could induce precipitation of asphaltenes as well as changes in fluid composition during miscible displacement of oil by carbon dioxide or natural gas. Miscible gas displacement introduces some changes in the flow behaviour and equilibrium properties of the fluids which under certain conditions will precipitate asphaltenes [8]. Problems emanating from asphaltene precipitation have been encountered in many field-scale operations around the world, including those in Algeria, in the Ventura field in California, in the production tubing in the Little Creek, Mississippi, during CO₂ injection for enhanced oil recovery, and in some Iranian oil wells.

Despite several decades of studies on the mechanisms of asphaltene precipitation and deposition, there are still some controversies between researchers. There is no complete agreement on the nature of asphaltene in crude oil. Two different models emerged with a view to explaining the nature of asphaltenes in solution. The first approach is the solubility model which considers the asphaltene to be dissolved in a true liquid state [9, 10]. The second model which is the colloidal model sees asphaltenes as being solid particles which are suspended colloiddally in the crude oil and stabilised by large resin molecules [11]. Asphaltene precipitation is a thermodynamically reversible process [10] when viewed through the lens of the solubility model, but the reverse is the case with the colloidal model, which considers precipitation of asphaltene to be irreversible. The knowledge of whether it is the solubility model that is valid or the colloidal model is dependent on whether precipitation process is reversible or not.

Identification of crudes that can precipitate asphaltenes as well as precipitated amounts is essential so that remedial plans can be made well in advance. A number of models have been developed to predict the onset parameters of asphaltene precipitation. Hirschberg et al. [9] were the first to propose a

thermodynamic model to predict onset parameters of asphaltene precipitation. Their assumption was that crude oil is a homogeneous binary mixture of asphalt and the solvent, with the precipitated asphalt being a homogeneous solid compound. Takhar et al. [12] also presented a thermodynamic model aimed at predicting onset parameters (pressure and temperature) of asphaltene precipitation. They were able to predict the deposition of asphaltenes downhole without the need for generating data from expensive single phase downhole samples.

Rassamdana et al. [8] proposed a simple scaling equation that appeared to be capable of providing accurate predictions for asphaltene precipitation. The scaling equation provides a particularly simple, and somewhat universal, prediction for the onset of precipitation. Moradi et al. [13] also developed a scaling equation to predict asphaltene instability under gas injection without involving asphaltene properties.

Experimental methods are also available for prediction and detection of asphaltene precipitation in the reservoir during production. Joshi et al. [4] employed near-infrared (NIR) spectroscopy to characterise the asphaltene precipitation process. They were able to show that different asphaltene flocs form during depressurisation of crude oil. These flocs aggregate and deposit in the reservoir thereby clogging reservoir pores [3]. Wang et al. [14] used refractive index to predict the onset of asphaltene precipitation. They used seven crude oils representing a wide range of oil properties where they added an optical observation cell to a mercury-free pressure/ volume/temperature apparatus to extend studies of the onset of asphaltene precipitation to elevated temperatures and pressures. Findings were made for asphaltic, paraffinic, and light-to-medium gravity crude oils as a function of temperature, pressure, and mixing time.

Correlation with solvent properties where the phase behaviour of asphaltenes when particular crude has been diluted by a solvent is related to the solubility parameter of the solvent can be used to predict asphaltene precipitation. A number of researchers have obtained such correlations for crudes, tars, and distillation residues. Generally, for a given dilution ratio, the amount of asphaltene precipitated decreases as the molecular weight of the hydrocarbon diluents increases. This is because the solvent power (the ability of a solvent to dissolve asphaltenes) of a hydrocarbon increases with rising molecular weight of solvent. The reverse is the case when the effect of normal alkanes on the onset of asphaltene precipitation is analysed. Here, the dilution ratio (volume of diluent/volume of crude oil) at the onset point increases as the carbon number of light normal alkanes rises, and decreases with the carbon number of heavy normal alkanes [9, 8, 15].

De Boer et al. [16] compared the properties of some crude oils from Kuwait and the North Sea. These crudes were from fields that had the potential of precipitating and depositing asphaltenes or from fields without asphaltene problems. Most of the properties of these crudes correlate strongly with the in-situ density of the crude. De Boer [16] used these correlations to create a generalized plot of

undersaturation versus in-situ density. This plot (de Boer plot) defines regions of expected asphaltene stability and, by inference, regions where there is the potential of asphaltene deposition in the field [3].

Other prediction methods are the Soave-Redlich-Kwong (SRK), Soave-Redlich-Kwong-Plus-Huron-Vidal mixing rule (SRK+HV) and Cubic-Plus-Association (CPA) equations of state (EoS) [17], solid and scaling model for asphaltene precipitation during gas injection [18].

Artificial intelligence has proven useful as a tool for predicting amount of asphaltene precipitation. This is as a result of the failure of conventional methods in predicting asphaltene precipitation with high degree of accuracy. The latest approach in this regard is the neural network. Neural network also known as artificial neural network (ANN), represent information processing systems consisting of rough approximation and simplified simulations of biological neuron network systems [19, 20, 21]. It normally takes some inputs, processes them and gives outputs. The most important aspects of ANNs are their structure, input and output parameters, learning and testing stages, convergence, data representation and interpretation, as well as generalisation.

A number of researchers have used artificial neural networks to predict asphaltene precipitation in the reservoir under different production scenarios.

Ahmadi and Shadizadeh [22] used feed-forward artificial neural network (ANN) optimised by particle swarm optimisation (PSO) to predict asphaltene precipitation in the reservoir due to natural depletion. The results of the PSO-ANN model showed the average relative absolute deviation between the model predictions and the experimental data to be less than 4%. A comparison between the prediction of the model and the alternatives showed that the PSO-ANN model predicts asphaltene precipitation more accurately.

Ahmadi and Golshadi [23] achieved asphaltene precipitation prediction during natural depletion using a feed forward artificial neural network and hybrid of genetic algorithm and particle swarm optimization (HGAPSO). The HGAPSO-ANN model's results were almost in agreement with experimental data.

Manshad *et al.* [24] proposed an artificial neural network optimised by particle swarm optimisation to predict the amount of asphaltene precipitation during gas injection process. They observed that the developed PSO-ANN model performed better than Gaussian Process Algorithm and other previous research.

Zendehboudi *et al.* [21] also used Artificial neural networks (ANNs) joined with imperialist competitive algorithm (ICA) and particle swarm optimisation (PSO) to approximate asphaltene precipitation and deposition with and without CO₂ injection. They showed that ICA-ANN attains more reliable outputs compared with PSO-ANN, the conventional ANN, and scaling models.

This study used Hybrid Genetic Algorithm Particle Swarm Optimisation (HGAPSO) to optimise feed forward artificial neural network. It came up with a predictive model namely, Hybrid Genetic Algorithm Particle Swarm Optimisation

Artificial Neural Network (HGAPSO-ANN) for forecasting the amount of precipitated asphaltenes during gas injection. The model demonstrated its superiority over several existing asphaltene prediction models.

2. Neural Networks

Artificial neural networks (ANNs) are processing devices (algorithms or actual hardware) that are loosely modelled after the neuronal structure of the mammalian cerebral cortex but on much smaller scales. A large ANN might incorporate hundreds or thousands of processor units, contrary to a mammalian brain that has billions of neurons with a corresponding increase in magnitude of their overall interaction and emergent behaviour.

ANNs, as computational methods are used to analyse complex systems with nonlinear relationships with the help of a number of input-output training patterns from the experimental data [22]. A reliable and strong network can be obtained only if correct data pre-processing, correct architecture selection and correct network training are achieved.

Commonly encountered neural networks are multilayer feed forward neural networks (MLPFFN) and recurrent neural networks (RNN). However, feed forward neural networks have proven more useful in both computational intelligence and petroleum engineering. In feed forward neural networks, the neurons are organized in different layers, and each of the neurons in one layer can receive an input from units in the previous layers without loss of generality. A three-layered feed-forward neural network with back propagation algorithm can approximate any nonlinear continuous function to an arbitrary accuracy. Figure 1 shows three layered feed forward neural network with back propagation algorithm for approximation of nonlinear functions with acceptable level of accuracy.

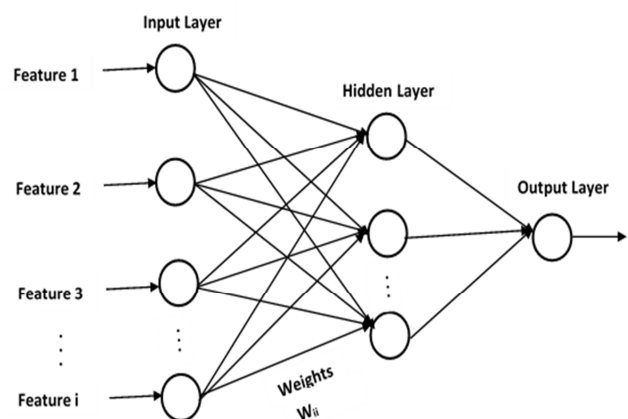


Figure 1. Structural design of three-layer feed-forward ANNs.

In predictive modelling, the goal is to map a set of input patterns onto a set of output patterns. Neural networks are able to accomplish predictive modelling by learning from a series of input/output data sets made available to the network.

The trained network then applies what it has learned to approximate or predict the corresponding output. Some statistical parameters such as mean squared error, correlation coefficient, coefficient of determination etc. are normally carried out to examine performance of network. The mean squared error of a network (MSE) is as follows:

$$MSE = \frac{1}{2} \sum_{K=1}^G \sum_{j=1}^m [Y_j(K) - T_j(K)]^2 \quad (1)$$

where m is the number of output nodes, G is the number of training samples, $Y_j(K)$ is the expected output, and $T_j(K)$ is the actual output. The data used are divided into training data set, testing data set, and validating data set [22].

The developed model performance can be checked by calculation of average absolute relative errors (AARE).

$$AARE = \sum (abs(Y - X)/X)/N \quad (2)$$

In the above equation, Y is predicted weight of asphaltene precipitation and X is experimental weight. When for a model AARE approaches zero, the model accuracy will increase and the network error will decrease [24].

3. Genetic Algorithm

A genetic algorithm (GA) is a metaheuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA).

The GA is a global search procedure that searches from one population of points to another. As the algorithm continuously samples the parameter space, the search is directed toward the area of the best solution so far. This algorithm has been shown to perform exceedingly well in obtaining global solutions for difficult non-linear functions like ANN [25].

In a genetic algorithm, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimisation problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible.

The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a *generation*. In each generation, the fitness of every individual in the population is evaluated; the fitness is usually the value of the objective function in the optimisation problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population [26].

GAs encode candidate solutions as binary strings. Each string (chromosome) is built by chaining a number of sub-

strings, each sub-string representing one of the candidate solution's features.

Biological genes are comparable to the sub-strings encoding the parameters, with each binary digit related to the nucleotides composing the DNA. The genotype can be identified with one single chromosome because a single bit-string is capable of being described by one individual.

Several other encoding procedures have been investigated to determine the most appropriate choice with Holland opting for the binary coding. His choice is due to binary coding allowing maximum number of schemata to be processed per individual. However, the mapping to binary coding introduces Hamming cliffs onto the search surface.

Although non-binary representations may be more natural for some problem domains and may reduce the computational burden of the search, it is seldom used for continuous function optimisation as it has been shown that solutions are too easily disrupted (the Hamming cliff issue). Researchers are therefore, less likely to use disruptive coding such as Gray coding.

A number of generational replacements are employed by canonical GAs with elitism and steady-state replacement the popular alternatives. Both alternatives seek to improve the preservation of good genetic material at the expense of a reduced search space exploration.

The best solution (s) are directly copied into the new population in the case of elitism while only a fraction of the population is replaced at each generation for the steady-state replacement alternative.

Selection of individuals for reproduction is based on their fitness with the roulette wheel selection procedure normally adopted. Other available selection schemes are fitness ranking and tournament selection [27].

4. Particle Swarm Optimisation

Particle swarm optimisation (PSO) is a computational method that optimises a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. The solution to problems is obtained by having a population of candidate solutions and moving these particles around in the search space according to simple mathematical formulae over the particle's position and velocity. The population of candidate solutions is referred to as particles. The movement of each particle is determined by its local best-known position, but is also guided toward the best-known positions in the search-space. These positions are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

The goal of PSO is to converge to the global optimum of some multidimensional and complex nonlinear functions. This is achievable by randomly distributing the particles over the search space. Particles search space and keep paths of their position to arrive at the global optimum solution.

PSO was introduced by Eberhart and Kennedy in 1995 as an optimisation process for simulating social behaviour, and as a stylised representation of the movement of organisms in

a bird flock or fish school. The algorithm was simplified and it was observed to be performing optimisation [28, 24].

PSO is a metaheuristic as it makes few or no assumptions about the problem being optimised and can search very large spaces of candidate solutions. However, metaheuristics such as PSO do not guarantee an optimal solution is ever found. Also, PSO does not use the gradient of the problem being optimised, which means PSO does not require that the optimisation problem be differentiable as is required by classic optimisation methods such as gradient descent and quasi-Newton methods.

PSO, like other optimisation methods has a fitness evaluation function that takes each particle's position and assigns it a fitness value. The position of highest fitness value visited by the swarm is called the global best. Each particle remembers the global best, and the position of highest fitness value that it has personally visited, which is called the local best.

One popular improved PSO which has wide application in science and engineering is the canonical PSO with inertia weight. In the canonical PSO, each particle i has position z_i and velocity v_i that is updated at each iteration according to Eq. (3)

$$V_i = \omega V_i + C_1 \phi_1 (P_i - Z_i) + C_2 \phi_2 (P_g - Z_i) \quad (3)$$

where ω is the inertia weight, p_i is the best position found so far by particle p_i , and p_g is the global best so far found by the swarm. ϕ_1 and ϕ_2 are weights that are randomly generated at each step for each particle component. C_1 and C_2 are positive constant parameters called acceleration coefficients (which control the maximum step size the particle can achieve).

The position of each particle is updated at each iteration by adding the velocity vector to the position vector.

$$Z_i = Z_i + V_i \quad (4)$$

The inertia weight ω (which is a user-defined parameter), in combination with c_1 and c_2 , controls the contribution of past velocity values to the current velocity of the particle. A large inertia weight biases the search towards global exploration, while a smaller inertia weight directs towards fine-tuning the current solutions (exploitation). A balance can be reached between the global and the local search by the selection of a suitable inertia weight and acceleration coefficients.

The PSO algorithm can be modelled following these 5 main steps:

1. Initialize the position vector z and associated velocity v of all particles in the population randomly. Then set a maximum velocity and maximum particle movement amplitude in order to decrease the cost of evaluation and to get a good convergence rate.

2. Evaluate the fitness of each particle via the fitness function. There are many options when choosing a fitness function and trial and error is often required to find a good one.

3. Compare the particle's fitness evaluation with the particle's best solution. If the current value is better than

previous best solution, replace it and set the current solution as the local best. Compare the individual particle's fitness with the population's global best. If the fitness of the current solution is better than the global best's fitness, set the current solution as the new global best.

4. Change velocities and positions by using equations (3) and (4).

5. Repeat step 2 to step 4 until a stopping criterion is satisfied or a predefined number of iterations is completed.

Particle size (n), inertia weight (ω) and maximum iteration number (t) are important factors in PSO [27].

5. Development of HGAPSO-ANN

Genetic algorithm has been successfully used to solve a range of problems, but it has the disadvantage of being a time consuming process especially if used for large-scale optimisations that require several function evaluations for convergence. This will lead to high computational efforts and cost. To tackle this problem, genetic algorithm and particle swarm optimization is combined into a single algorithm. This combination allows the harnessing of the benefits from the appropriate characteristics and searching abilities of both algorithms in predicting desired parameters. In this research, the hybrid of genetic algorithm (GA) and particle swarm optimization (PSO) reoptimised by ANN named HGAPSO-ANN, was carried out to forecast asphaltene precipitation during gas injection process. This is a modification of the model originally proposed by Juang [29]. Figure 2 portrays the schematic representation of the introduced hybrid genetic algorithm and particle swarm optimization approach [23].

The detailed design algorithm of HGAPSO consists of three major operators: enhancement, crossover, and mutation.

In each generation, after the fitness values of all the individuals in the same population are calculated, the top-half best-performing ones are marked. These individuals are considered elites. Instead of reproducing the elites directly to the next generation as elite GAs do, they are first enhanced. The enhancement operation is synonymous with the maturing phenomenon in nature, where individuals will become more suitable to the environment after acquiring knowledge from the society. The usage of enhanced elites as parents allows the generated offspring to achieve better performance than those bred by original elites.

The crossover operation allows the production of well performing individuals. In this operation, parents are selected from the enhanced elites only. To select parents for the crossover operation, the tournament selection scheme is used, where two enhanced elites are selected at random, and their fitness values compared to select the elite with better fitness value as one parent. The same procedure is followed to select the other parent. Performing crossover on the selected parents yields two offspring. Some commonly used crossover techniques are k-point crossover, and flat crossover. This study utilised two-point crossover operation.

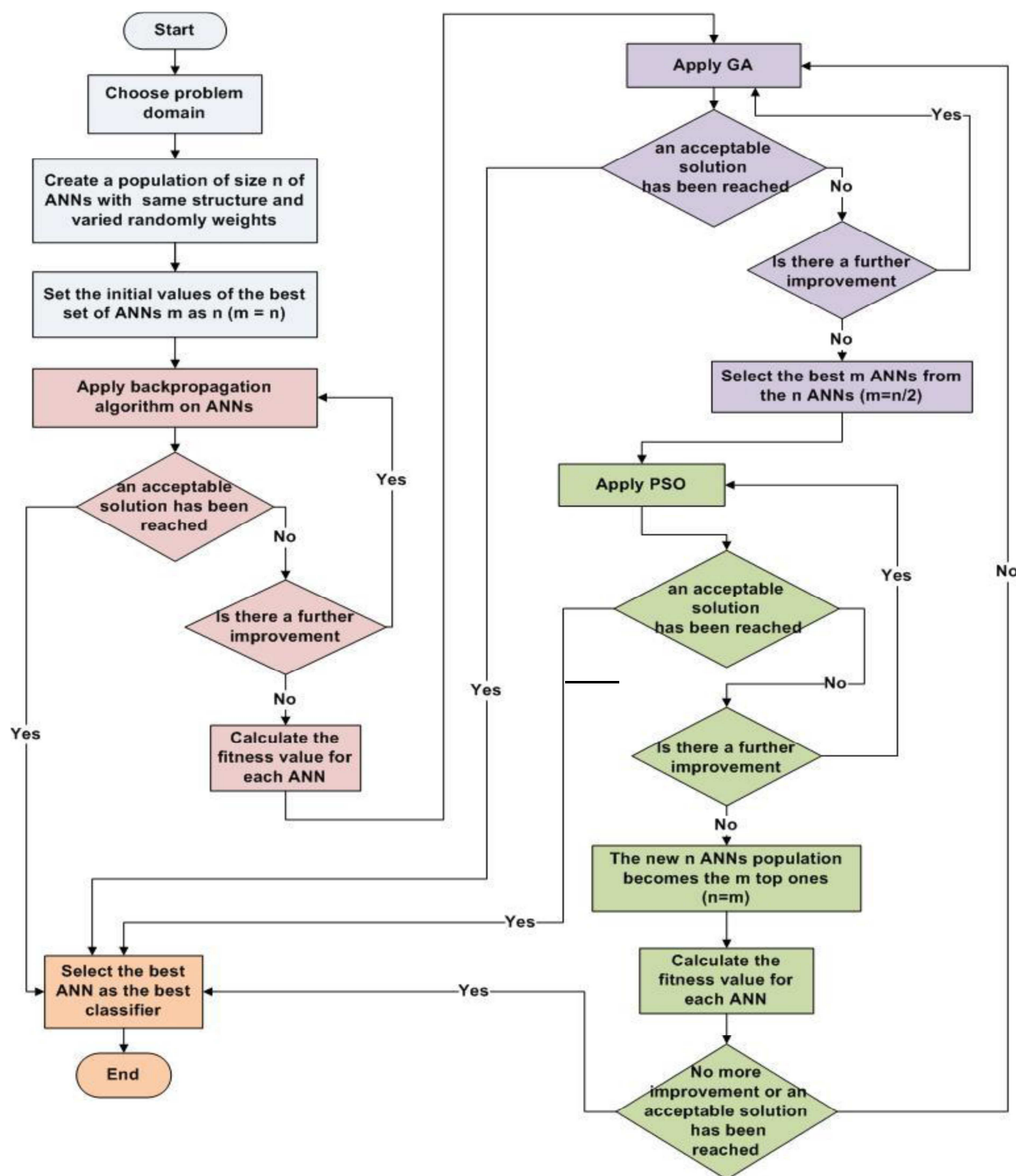


Figure 2. Flow chart of HGAPSO-ANN [23].

The occurrence of mutation in HGAPSO is in association with the crossover operation. Mutation is an operation whereby the allele of a gene is altered randomly with resultant new genetic materials being introduced into the population. However, mutation should not be used all the time otherwise; the algorithm will become little more than a random search. In this work, uniform mutation was adopted, that is, the mutated gene is drawn randomly, uniformly from the corresponding search interval [29].

This model used HGAPSO to train ANN to predict asphaltene precipitation during CO₂ injection process. The

model had 15 input variables (mole percentage of C1- C6), oil specific gravity, reservoir temperature, reservoir pressure, mole percentage of other component, mole percentage of solvent, mole percentage of the heavy fractions (C7 +), and weight of asphaltene precipitate as desired output. As shown in table 1, 80 experimental data sets (temperature, pressure, oil composition, specific gravity, and the other properties) from five different crude oil samples were used. After the data preprocessing, 75 data sets were selected for network training.

Table 1. Crude oil samples characterization data.

Component	Oil 1	Oil 2	Oil 3	Oil 4	Oil 5
Nitrogen	0.57	0.51	0.05	0.23	0.27
H ₂ S	0	0	0	0	0.03
CO ₂	2.46	1.42	6.47	8.53	1.66
Methane	36.37	6.04	9.58	21.72	30.44
Ethane	3.47	7	12	20.8	7.92
Propane	4.05	6.86	6.83	4.82	5.53
i-Butane	0.59	0.83	0.87	1.35	0.87
n-butane	1.34	3.35	3.78	3.47	2.51
i-pentane	0.74	0.7	1.42	1.68	1.03
n-pentane	0.83	3.46	2.62	2.11	1.49
Hexane	1.62	3.16	4.95	2.53	7.43
Heptane +	47.96	66.68	51.43	32.76	40.82
API stock tank oil	19	24	30	37	22.3043
Asphaltene content wt. %	16.8	9	2.8	0.4	6.64
Test pressure, psi	3034.7	514.7	2814.7	3514.7	1500
Test temperature, F	212	218	225	225	205

Source: [24].

6. Results and Discussions

Hybrid Genetic Algorithm Particle Swarm Optimization Artificial Neural Network (HGAPSO-ANN) Model.

Data sets from five different crudes originally gathered by Manshad *et. al* [25] were normalized and used for the development of this model. The data sets were divided into training, testing and validation sets.

Hybrid genetic algorithm particle swarm optimization (HGAPSO) was used to train feed forward neural network for the prediction of asphaltene precipitation during gas injection. In this model, fifteen (15) parameters which comprise pressure, temperature, oil composition and other parameters were used as inputs to the network with weight of precipitated asphaltene as output of the developed network.

The optimisation of the developed neural network using HGAPSO was to achieve better optimisation results and finally generate a network with good predictive ability. The HGAPSO-ANN algorithm was run with a population size of 100. Eighty (80) data sets were used for development of the network. The random number generator chose 75 data points for network training and the remaining 5 data points kept for checking network integrity and robustness.

Recombination of the genetic material from two good “parent” chromosomes in order to make two better offspring is referred to as Crossover. In order to find the optimum crossover rate, different crossover probabilities were investigated. Crossover probabilities of 0.5, 0.6, 0.7, 0.8, 0.85, 0.9, and 0.95 were investigated. Best performance was obtained with a crossover probability of 0.9. It was however observed that the performance analysis of the output showed reduced convergence with increasing crossover rate.

Trapping at local maxima is overcome by mutation. This is the process where the bits at one or more randomly selected positions of chromosomes are altered. Mutation rates of 0.05, 0.04, 0.02, 0.01, 0.005, 0.003, 0.0003, and 0.0001 were implemented to obtain the optimum mutation rate. Unlike

crossover probabilities, increasing the mutation rate yielded better solutions.

In this work, uniform crossover probability was set to 0.9 and optimum uniform mutation rate was 0.02.

HGAPSO-ANN was evaluated with 3, 5, 7, 9 and 11 neurons in the hidden layer. The result obtained by using the different number of neurons in the hidden layer is displayed in table 2.

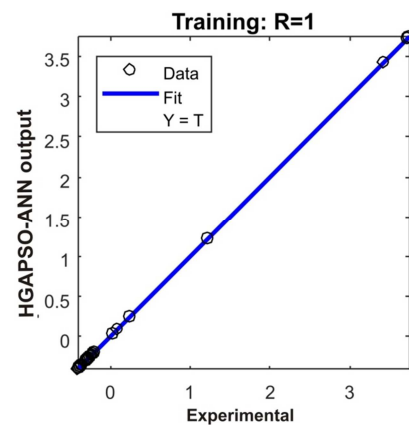
The performance of the network increased from 3 hidden neurons to 7. This is obvious from the reduced MSE both in training and testing periods. Beyond 7 neurons in the hidden layer, network performance begins to decline as represented by the increased MSE in training and testing periods. Thus, the optimum HGAPSO-ANN model requires 7 neurons in the hidden layer. The overall network architecture is 15-7-1, ie 15 inputs into the network, 7 neurons in the hidden layer and 1 output in the output layer.

Figures 3, 4, and 5 show network performance during training testing and validation.

HGAPSO-ANN network performed satisfactorily during training with a regression value of 1 and an almost unity value during testing. The fit lines for training testing and validation are identical with the line $Y=T$. This is a statement on the reliability of the network. It shows that there seems to be no difference between the values predicted by the network and experimental values.

Table 2. Performance of HGAPSO-ANN based on the number of hidden neurons.

Number of neurons	Training		Testing		Network Architecture
	R ²	MSE	R ²	MSE	
3	0.9985	0.0182	0.9974	0.0184	15-3-1
5	0.9995	0.0164	0.9985	0.0165	15-5-1
7	1.0000	0.0140	0.9997	0.0143	15-7-1
9	0.9958	0.0176	0.9956	0.0179	15-9-1
11	0.9996	0.0711	0.9986	0.0714	15-11-1

**Figure 3.** Network performance during training.

The scatter plot of the HGAPSO-ANN network (Figure 6) shows that there is good agreement between model output and experimental data for asphaltene precipitation during gas injection.

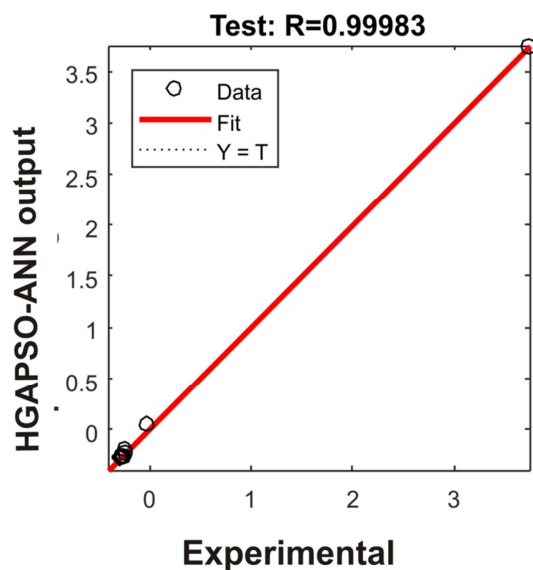


Figure 4. Network performance during testing.

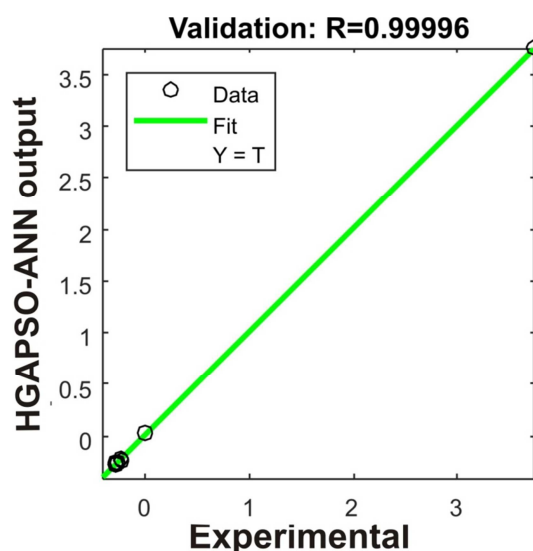


Figure 5. Network performance during data validation.

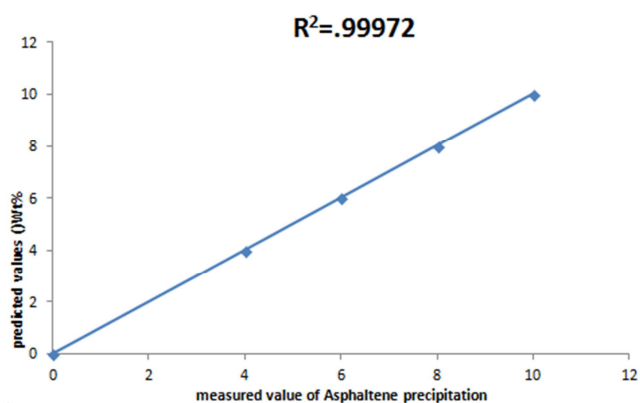


Figure 6. Scatter plot of HGAPSO-ANN model prediction values versus measured value.

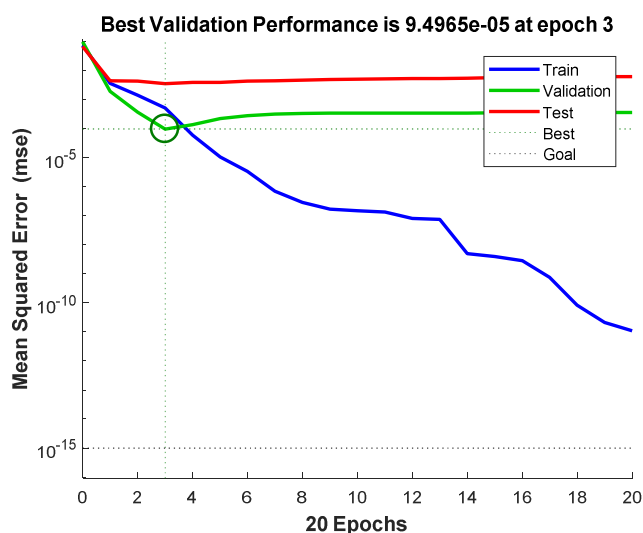


Figure 7. Performance Plot of HGAPSO-ANN model.

The determination coefficient R^2 of 0.99972 is also an indication that the network performed well. Excellent model performance is represented by an R^2 value greater than 0.9. When R^2 value is in the range of 0.8-0.9, the model performance is equally good. An R^2 value of less than 0.8 however, indicates an unsatisfactory performance.

Sensitivity analysis of the model inputs and output is shown in Figure 8. Here, it can be seen that pressure has the most effect on asphaltene precipitation with temperature having a significant but lesser effect than pressure. This is in agreement with literature and a pointer to the significant role that pressure plays in asphaltene precipitation.

Effect on Asphaltene precipitation

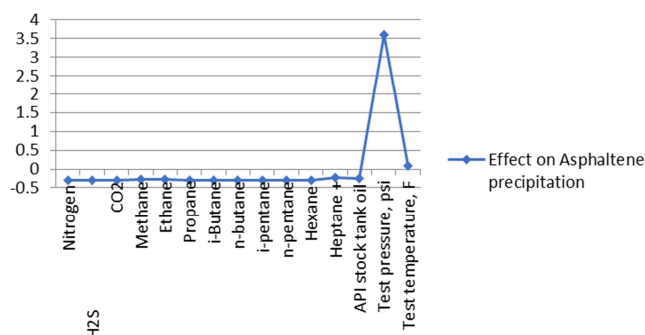


Figure 8. Effect of input variables on asphaltene precipitation.

Comparison of Developed Model with Existing Ones.

A model has been developed in this study with the aim of arriving at a better model which will surpass existing models. A comparison of the developed model with existing models is shown in table 3.

From this table, HGAPSO-ANN has an average absolute relative error (AARE) of 0.09. It can be clearly seen that HGAPSO-ANN has smaller error and as such is better at predicting asphaltene precipitation. Comparing HGAPSO-ANN with existing models such as Hu et al. [30], Rostami and Manshad [31], Manshad et al. [24] clearly show that HGAPSO is superior in predicting asphaltene precipitation.

Table 3. Comparison of HGAPSO-ANN with Existing Models.

Name	Model	AARE
Hu et al. [31]	Scaling	0.183
Manshad and Edalat [23]	Polydispers Molecular Thermodynamic	0.150
Rostami and Manshad [32]	Gaussian Process	0.153
Manshad et al [25]	ANN-PSO	0.121
Present Study	HGAPSO-ANN	0.090

7. Conclusions and Recommendations

Artificial intelligence has gained wide acceptance and found applications in different fields. The use of artificial neural networks to predict different phenomena in petroleum engineering is becoming popular. This is due to their ability to forecast phenomenon to different degrees of accuracy.

In this work, artificial neural network trained by hybrid genetic algorithm particle swarm optimisation has been used to forecast asphaltene precipitation during gas injection. The study has thus, come up with a predictive model namely, hybrid genetic algorithm particle swarm optimisation-artificial neural network (HGAPSO-ANN).

From this model, it can be concluded that HGAPSO-ANN is an excellent tool for forecasting asphaltene precipitation.

Combining the two algorithms (Genetic Algorithm and Particle Swarm Optimisation) overcomes the challenge of high computational efforts and costs that would result if a GA-ANN were used especially when large scale optimisations are involved. The determination coefficient from testing HGAPSO-ANN is 0.99970 with a very small MSE of 0.0143. Hybrid Genetic Algorithm Particle Swarm Optimisation-Artificial Neural Network (HGAPSO-ANN) is therefore, of high integrity in forecasting asphaltene precipitation due to its ability to integrate global search and local search abilities of genetic algorithm and particle swarm optimisation. By designing and testing several different network architectures, the best architecture has been found to be 15-7-1 based on statistical parameters (R^2 and MSE).

A comparison of the developed networks with existing models demonstrates the superiority of HGAPSO-ANN in forecasting amounts of precipitated asphaltenes. This is due to the very small AARE of HGAPSO-ANN which approaches zero.

HGAPSO-ANN should therefore, be used in forecasting asphaltene precipitation.

Future work should concentrate on combining different algorithms with artificial neural networks to investigate the possibility of obtaining a better and more accurate model for the prediction of asphaltene precipitation when gas injection is used to increase oil production to meet the ever increasing energy demands of an energy hungry world.

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