SPE 167620-STU

Determination of The Dew-Point Pressure (Dpp) For A Gas Condensate Fluid By Genetic Algorithm (Ga)

Bamisebi Adetiloye, University Of Ibadan, Nigeria

This paper was prepared for presentation at the SPE International Student Paper Contest at the SPE Annual Technical Conference and Exhibition held in New Orleans, Louisiana, USA, 30 September – 2 October 2013.

Abstract

In reservoir engineering, a variety of data is needed to accurately estimate reserves and forecast production. Fluid characterization consist of reservoir rock analysis and fluid analysis. The determination of gas condensate dew point pressure, gas specific gravity and producing yield is essential for fluid characterization, gas reservoir performance calculations and the design of production systems. The importance of gas condensate reservoirs has grown continuously and the condensate fluid has gained increased importance.

Traditionally, the dew-point pressure of a gas condensate is experimentally determined in a laboratory in a process called constant mass expansion (CME) test using a visual window-type PVT cell and the constant volume depletion test (CVD). However laboratory measurements , though most reliable , have been found to be laborious, costly and still subject to errors. Hence, the need for other simple and accurate methods of predicting the dew-point pressure (DPP) for a gas condensate. Thus using different equations of states (EOS), several correllations have been developed to predict the DPP of a gas condensate fluid.

This paper therefore seeks to predict the dew point pressure of a gas condensate using genetic algorithm. This is an improved, faster, simple and most accurate method of predicting the dew point pressure.

Genetic algorithm is an adaptive heuristic searching methodology, introduced on the evolutionary ideas of natural selection and genetics, which follows the Charles Darwin's principle of "Survival of the Fittest". Genetic Algorithm represents an intelligent development of a random search within a defined search space (also called as population) to obtain the optimum solution of the problems. Thus, GA would be very effective in carrying out this multi variable optimization.

INTRODUCTION

The importance of gas condensate reservoirs has grown continuously and the condensate fluid has gained increased importance. The development and operation of these reservoirs for maximum recovery require engineering and operating methods different from oil and dry gas reservoirs. The single most striking factor about gas condensate systems is that they exist either wholly or preponderantly as vapor phase in the reservoir at the time of discovery. This key fact nearly always governs the development and operating programs for recovery of hydrocarbons from such reservoirs. Therefore, a thorough understanding of the fluid properties are hence required for optimum production and management of gas condensate reservoirs.

The phase diagram for a gas condensate is somewhat smaller than that for oils and the critical point is further down the left side of the envelope. The phase diagram of a gas condensate has a critical temperature less than the reservoir temperature and a cricondentherm greater than the reservoir temperature. See fig 1. Initially, the gas condensate is totally gas, point 1. On a phase diagram, gas condensate reservoirs plot between the critical point and the cricondentherm with both their reservoir pathway and production pathway falling at some point into the 2-phase region. Initially, the gas condensate is totally gas in the reservoir. As pressure is reduced isothermally, the gas condensate reaches its first dew point (upper dew-point). At this point the first droplet of liquid is formed, that is, a substantial amount of gas phase exists in equilibrum with an infinitessimal amount of liquid phase. Upon further pressure reduction, more liquid condenses out to form free liquid in the reservoir. However there is no effective permeability to this lquid phase, hence it cannot be produced unless it's critical saturation is reached, which can rarely happen. This leads to a great loss in useful condensate which would be preferred to be gotten at surface conditions and not in the reservoir. This is a phenomenom that must be prevented from happening, thus the determination of the dew-point pressure of a gas condensate fluid is of utmost importance. If pressure is further decreased, a second dew- point(lower dew-point) will be reached and the liquid can be re-vaporized. This lower dew-point is usually below the reservoir abandonement pressure and thus would be of no interest in reservoir performance.

Traditionally, the dew-point pressure of a gas condensate is experimentally determined in a laboratory in a process called constant mass expansion (CME) test using a visual window-type PVT cell and the constant volume depletion test (CVD). However laboratory measurements, though most reliable , have been found to be laborious, costly and still subject to errors. Hence, the need for other simple and accurate methods of predicting the dew-point pressure (DPP) for a gas condensate. Thus using different equations of states (EOS), several correllations have been developed to predict the DPP of a gas condensate fluid. These correlations include; Eilerts & smith *(Eilerts, C.K et al, 1957)*, Sage & olds *(Sage, B.H. and Olds, R.H., 1947),* Organick & Golding *(Organick, E.I. and Golding, B.H., 1952)*, Nemmeth & Kennedy *(Nemeth, L.K. and Kennedy, H.T., 1967)*, A.M Elsharkawy (*Adel. M. Elsharkawy, 2001*), Hummoud & marhoun *(A.A. Humoud, 2001)* e.t.c

LITERATURE REVIEW

Sage and Olds *(Sage, B.H. and Olds, R.H., 1947*) studied experimentally the behavior of five paired samples of oil and gas obtained from wells in San Joacuin fields in California. Their investigations resulted in developing a rough correlation relating the retrograde dew point pressure to the gas-oil ratio, temperature and stock tank API oil gravity. In 1952, a correlation was presented by Organick and Golding *(Organick et al, 1952)* to predict saturation pressures, which could be a dew point or a bubble point pressure, for gas-condensate and volatile oil reservoir fluids.

Nemeth and Kennedy *(Nemeth, L.K. and Kennedy, H.T., 1966)* developed a correlation in the form of an equation, which relates the dew point pressure of a gas-condensate fluid to its chemical composition, temperature and characteristics of C**7+**. The final form of the equation contains eleven constants. The dew point pressure and temperature ranges varied from 1,270 - 10,790 psi, and 40-320F respectively. The average absolute error for the 579 experimental data points used to develop this correlation was found to be 7.4%.

In 2001, A.M Elsharkawy *(Adel. M. Elsharkawy, 2001)* presented an empirical model to estimate the dew point pressure of gas condensate reservoirs as a function routinely measured gas analysis and reservoir temperature. The prediction of the dew point pressure was done as a function of the reservoir temperature, composition of the mixture, molecular weight and specific gravity of the heptane plus fraction. The proposed model has an ARD of 0.44%, average absolute deviation (AAD) of 7.68% in comparison to other methods.

In the same year, Hummoud and Marhoun *(A.A. Humoud, 2001)* also presented an empirical correlation to predict the dew point pressure of gas condensate from readily available data. This correlation relates the dew point pressure of the gas condensate to its reservoir temperature, pseudo reduced pressure and temperature, primary separator gas – oil ratio, primary separator temperature and pressure and relative densities of separator gas and heptane plus fraction.

First pioneered by John Holland in the 70s, Genetic Algorithms has been widely studied, experimented and applied in many fields in engineering worlds. Not only does GAs provide an alternative method to solving problem, it consistently outperforms other traditional methods in most of the problems link. David Goldberg, who was able to solve a difficult problem involving the control of gas-pipeline transmission for his dissertation *(Goldberg, 1989).* Holland's original work was summarized in his book.

The GA for optimum distributions of gas injection rates for maximizing the oil production was examined by Martinez and Moreno *(Martinez et al, 1994).* They employed GA based optimization approach for gas injection and got around 20% increment in productivity of the whole field of Corpoven S. A (CORPOLAG).

Romero et al. (2000) introduced modified GA for with the help of predefined geological data and structural model to achieve best prediction of reservoir performance. Their approach preceded the use of refining local search techniques such as Hill Climbers or Gradient Optimizers to induce the global optimum value of reservoir models by GA.

Furthermore, *(Fichter, 2000)* applied GA to the portfolio optimization in oil and gas field. They compared GA with rank and cut methodology and purely random search approach, to acquire the optimum values for the project size and other complexities (that is, contractual obligations for minimum participation within a region).They ensured the effectiveness and accuracy of GA with the incremental project size and number of simulations.

GA approach was applied for optimizing the performance of hydrocarbon producing wells *(Tavakkolian et al, 2004).* They developed the MATLAB code, based on GA to define the optimum size of tubing and the depth at which tubing size should vary, size of choke, number of separators and separators pressure. Their research aimed to optimize all these parameters to obtain maximum economical profit or maximum fractional liquid recovery with improved hydrocarbon production.

The GA model for viscosity prediction *(Hajizadeh et al., 2007)* has also been employed. For prediction of optimum value of viscosity (centipoise) he used four parameters, as model input that is, pressure (psia), temperature (°F), reservoir fluid gas oil ratio (scf/bbl of stock tank oil) and oil density (gm/cc). He compared his model with two Iranian PVT reports for the field located in Khuzestan and three fluid characterization reports, which together provided 89 data points for reservoir fluid viscosity. The model took around 18 hours run time and more than 2 billion run to predict the viscosity, which was quite accurate one.

GENETIC ALGORITHMS

An algorithm is an effective method expressed as a finite list of well-defined instructions for calculations, data processing and automated reasoning. Starting from an initial state and initial input, the instructions describe a computation that, when executed, will proceed through a finite number of well-defined successive states, eventually producing "output" and terminating at a final ending state.

Genetic algorithms attempt to find solutions to problems by mimicking biological evolutionary processes, with a cycle of random mutations yielding successive generations of "solutions". Thus, they emulate reproduction and "survival of the fittest". In genetic programming, this approach is extended to algorithms, by regarding the algorithm itself as a "solution" to a problem.

The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population 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. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

Initialization

Initially many individual solutions are (usually) randomly generated to form an initial population. The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, allowing the entire range of possible solutions (the search space). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions.

Reproduction

The next step is to generate a second generation population of solutions from those selected through genetic operators: **crossover (also called recombination), and/or mutation.** For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. By producing a "child" solution using the above methods of crossover and mutation, a new solution is created which typically shares many of the characteristics of its "parents". New parents are selected for each new child, and the process continues until a new population of solutions of appropriate size is generated. These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions.

Although Crossover and Mutation are known as the main genetic operators, it is possible to use other operators such as regrouping, colonization-extinction, or migration in genetic algorithms.

Termination

This generational process is repeated until a termination condition has been reached. Common terminating conditions are:

a. A solution is found that satisfies minimum criteria.
b. Fixed number of generations reached.

c. The highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results.
d. Manual inspection.
e. Combinations of the above.

APPLICATION OF GENETIC ALGORITHMS

Genetic algorithms are often viewed as function optimizers although the range of problems to which genetic algorithms have been applied is quite broad.

GA's have been used for problem-solving and for modeling. GA's are applied to many scientific, engineering problems, in business and entertainment, including: optimization, petroleum engineering, automatic programming, machine and robot learning, economic models, immune system models, ecological models, population genetic models and social systems.

GA – DPP PREDICTION MODEL

The el-sharkawy model still (Adel M. Elsharkawy, 2001) remains the most accurate correlation for the prediction of the dew point pressure for a gas condensate fluid. Therefore, the genetic algorithm will be based on this model, though it could also be extended to other models to check their accuracies.

The cost equation to screen our population is the el-sharkawy model and a penalty based on the given DPP value.

Based on the above model, the dew point pressure for a gas condensate fluid is a function of several variables which include reservoir temperature, mole fraction of all the components of the gas (C_1 to C_6), mole fraction of the heptane-plus (C_{7+}) fraction, Specific gravity of the C_{7+} fraction and molecular weight of the C_{7+} fraction.

The genetic algorithm, which is well suited for multi variable optimization will be used to optimize and achieve the dew point pressure. The following variables will be optimized;

- Reservoir temperature
- mole fraction of the heptane-plus (C7+) fraction
- Specific gravity of the heptane-plus (C7+) fraction and
- Molecular weight of the heptane-plus (C7+) fraction

The function for the dew point pressure can be represented by;

DPP = **f** $(Tr, xC_1, xC_2, xC_3, xC_4, xC_5, xC_6, xC_{7+}, S.GC_{7+}, M.WC_{7+})$ **Eqn 1.0**

The representative function for the algorithm is therefore reduced to;

DPP = **f** $(Tr, xC_{7+}, S.GC_{7+}, M.WC_{7+})$ **Eqn 1.1**

Each of the above variables was represented in the chromosome for the algorithm. Using binary GA, each chromosome is 30-bit long with reservoir temperature (6-bits), mole fraction of C_{7+} fraction (9-bits), specific gravity of C_{7+} fraction (7-bits), molecular weight of C_{7+} fraction (8-bits). Each set of population contains eight (8) chromosomes, with each chromosome containing thirty (30) genes. This yielded an [8 x 30] matrix and consequently an initial population of 240.

The algorithm then proceeds to rank the chromosomes generated in descending order by cost (i.e. best to worst). The last four chromosomes are then eliminated and the remaining best four are reproduced using cross-over and mutation operators. The reproduction of four new chromosomes was carried out using a single point crossover and mutation rate of 5%. Thereafter, the cost is re-evaluated again and the iteration continues.

After several runs and trials, the maximum number of generations was fixed to be 1000. This means that within 1000 generations of a run, we should achieve the best value of our DPP.

RESULT AND DISCUSSION

Genetic algorithm written on MATLAB was used to predict the dew point pressure for 14 gas condensate samples and the result is shown below.

The GA was able to predict the temperature, molecular weight of C7+ fraction, S.G of C7+ fraction, mole fraction of C7+ and the resulting dew point pressure. Also the average relative deviation and absolute relative deviation between the experimental values and the GA output for each sample was done. The average relative deviation and absolute relative deviation for the samples range between 0.21% - 31.76% with exception of sample M1. Samples M1 and 2_11 have the highest deviations and this corresponds with other values from other methods used to predict DPP. This could be due to errors from the actual experimental values.

Table (3) shows the results of the DPP predicted by GA and other methods for the same set of 14 samples. It shows that GA prediction gives the closest value to the actual dew point pressures.

Table (4) shows comparison between predicted dew point pressures from GA and other methods for some samples. This table indicates that dewpoint pressures calculated from GA closely match the experimental ones for most of the samples. It also shows that the calculated dewpoint pressure from GA compare well with that from equation of states. The following seven samples were selected because they represent the lowest and highest temperature, lowest and highest molecular weight of the C_{7+}, lowest and highest density of C_{7+}.

Table (5) also shows comparison of the average relative deviations (ARD), average absolute deviations (AAD), root mean square errors (RMSE) and correlation coefficient (COR) in percentage between the GA output, other correlations and equations of states. It is obvious that GA closely matches the experimental values having the highest correlation coefficient (99.347%), the lowest average absolute deviation (1.28%) and root mean square error (3.71%).

The accuracy of the GA shown by the tables was also confirmed as seen in the crossplots (fig 5 - 9) of the measured value against the genetic algorithm result.

Knowing the fact that there is uncertainty in the measured data as stated earlier, we can summarize that the accuracy of the GA for the prediction of dew point pressure is excellent and out performs all other correlations and equations of states.

CONCLUSION

On the basis of the literature review, extensive research and actual work done, the following conclusions have been reached:

1. Genetic Algorithm is an efficient tool for the determination of the Dew point pressure of a gas condensate fluid with high accuracy compared to experimental values and other correlations.

2. The Genetic Algorithm approach yields accurate prediction of the DPP with an average absolute deviation of 1.09% among all other tested correlations.
3. Genetic Algorithms provide a rich and capable environment for solving many search, optimization, and design problems in various fields of Petroleum Engineering. The larger the space of possible solutions, the more effective is the use of this approach.

RECOMMENDATION

It is recommended that GA approach should be extended to develop an entirely new model/correlation hence improving its accuracy.

The GA should also be extended to account for the optimization of all the variables, this gives a larger search space for optimization and hence might yield more accurate DPP values.

ACKNOWLEDGEMENTS

I wish to express my profound gratitude to my parents (Mr & mrs A.A. Bamisebi), my supervisor (Mrs Princess Nwankwo) and my Head of department (Dr Falode O.A.).

I also express my sincere thanks to Mr Chukwuka of the department of Electrical/Elcetronics Engineering, who out of his extremely tight schedule made out time for me as regards to the development of the algorithm.

REFERENCES

1. Andre C. Marta*. "Parametric Study of a Genetic Algorithm using an Aircraft Design Optimization Problem".* Dept. of Aeronautics and Astronautics, Stanford University, Stanford, California 94305
2. De Jong, K. A. (1975), "*An Analysis of the Behavior of a class of Genetic Adaptive Systems"*. PhD thesis, University of Michigan
3. Eilerts, C.K et al (1957), "*Phase relations of gas condensate fluids, test results, apparatus and techniques",* American Gas Assn, New york.

4. Elsharkawy, A. M. (2001), “*Predicting the dew point pressure for gas condensate reservoirs: empirical models and equations of state”*, Kuwait university, P.O Box 5969, Kuwait
5. Fichter D (2000). “*Application of Genetic Algorithms in Portfolio Optimization for the Oil and Gas Industry*”. SPE 62970-MS.
6. Goldberg, D.E. (1983), “*Computer Aided Gas Pipeline Operation Using Genetic Algorithms and Rule Learning”* PhD dissertation, U. of Michigan, Ann Arbor, Michigan.
7. Goldberg, D. E. (1989), “*Genetic Algorithms in Search, Optimization, and Machine Learning”.* Reading, MA: Addison-Wesley.
8. Hajizadeh. Y (2007). “*Viscosity prediction of crude oils with genetic algorithms*”. SPE 106763-MS.
9. Holland, J. H. (1975), *Adaptation in Natural and Artificial Systems,* University of Michigan Press, Ann Arbor.
10. Humoud, A.A., SPE, Saudi Aramco, and M.A. Al-Marhoun, SPE, King Fahd U. of Petroleum and Minerals, *A New Correlation for Gas-condensate Dewpoint Pressure Prediction,* SPE 68230
11. Martinez E, Moreno W, Moreno J, Maggiolo R (1994), “*Application of Genetic Algorithm on the Distribution of Gas-Lift Injection”*. SPE 26993-MS.
12. Nemeth, L.K. and Kennedy, H.T. (1966), *“A Correlation of Dewpoint Pressure with Fluid Composition and Temperature,”* paper SPE 1477 presented at SPE 41st Annual Fall Meeting held in Dallas, Tex.
13. Organick, E.I. and Golding, B.H. (1952), *“Prediction of Saturation Pressures for Condensate-Gas and Volatile Oil Mixtures,”* Trans., AIME Vol. 195, 135-148.
14. Pedersen, K. S., Thomassen, P., and Fredenslund, A. (1988), *‘Characterization of gas condensate mixtures’*, presented at the 1988 AIChE Spring National Meeting, New Orleans, Louisiana, March 6-10, 1988.
15. Potsch, K.T. and Braeuer, L. (1996), *“A Novel Graphical Method for Determining Dewpoint Pressures of Gas Condensates,”* Paper SPE 36919, presented at the 1996 SPE European Conference held in Italy, October 22-24.
16. Randy L. Haupt &Sue Ellen Haupt (2004), “*Practical Genetic Algorithms”, second edition*
17. Reamer, H. H. and Sage, B. H. (1950), *‘Volumetric behavior of oil and gas from Louisiana Field’*, Trans., AIME, Vol. 189, 1950, 261-268.
18. Romero C, Carter J, Gringarten A, Zimmerman R (2000), “*A Modified Genetic Algorithm for Reservoir Characterisation”*. SPE 64765-MS.

19. Sage, B.H. and Olds, R.H. (1947), *"Volumetric Behavior of Oil and Gas from Several San Joaquin Valley Fields,"* Trans., AIME Vol. 170, 156-173.
20. Tavakkolian M, Jalali F and Emadi M (2004). "*Production Optimization using Genetic Algorithm Approach"*. SPE 88901-MS.

APPENDIX: EQUATIONS, TABLES AND FIGURES

ELSHARKAWY MODEL AND CONSTANTS

$$\mathbf{P_d = A_0 + A_1\,T_f + A_2\,xH_2S + A_3\,xCO_2 + A_4\,xN_2 + A_5\,xC_1 + A_6\,xC_2 + A_7\,xC_3 + A_8\,xC_4 + A_9\,xC_5 + A_{10}\,xC_6}$$

$$\mathbf{+ A_{11}\,xC_7 + A_{12}\,MW_{7+}\,A_{13}\,\gamma_{7+} + A_{14}\,(xC_{7+}.\,MW_{7+}) + A_{15}\,(MW_{7+}/\gamma_{7+}) + A_{16}\,(xC_{7+}.MW_{7+}/\gamma_{7+}) + A_{17}}$$

$$\mathbf{\{xC_{7+}/(xC_1 + xC_2)\} + A_{18}\,\{xC_{7+}/(xC_2 + xC_3 + xC_4 + xC_5 + xC_6)\}\ldots}$$

Where; $\mathbf{P_d}$ = DPP (psia)

$\mathbf{T_f}$ = reservoir temperature (°F)

'x' = composition expressed as mole fraction

$\mathbf{MW_{C7+}}$ = molecular weight of the C_{7+}

$\boldsymbol{\gamma_{7+}}$ = specific gravity of the C_{7+} fraction.

The constants A_0 through A_{18} are;

$\mathbf{A_0 = 4268.85, A_1 = 0.094056, A_2 = -7157.87, A_3 = -4540.58, A_4 = -4663.55, A_5 = -1357.56}$

$\mathbf{A_6 = -7776.10, A_7 = -9967.99, A_8 = -4257.10, A_9 = -1417.10, A_{10} = 691.5298, A_{11} = 40660.36}$

$\mathbf{A_{12} = 205.26, A_{13} = -7260.32, A_{14} = -352.413, A_{15} = -114.519, A_{16} = 8.133, A_{17} = 94.916}$ **and**

$\mathbf{A_{18} = 238.252}$

In the above empirical model, $\mathbf{A_{17}}$ and $\mathbf{A_{18}}$ account for the interaction between heavy fraction and light fraction, and heavy fraction and intermediate fraction.

	Min	Max	Ave
Dew point pressure, psia	1560	11830	4390
Reservoir temperature, °F	40	340	190
Molecular weight of C7+	106	253	142
Specific gravity of C7+	0.72	0.85	0.77
Composition mole fraction			
Methane	0.194	0.952	0.773
Ethane	0.016	0.210	0.060
Propane	0.000	0.123	0.031
Butane	0.000	0.508	0.011
Pentane	0.000	0.123	0.011
Hexane	0.000	0.087	0.012
Heptane plus	0.000	0.17	0.454
Hydrogen sulphide	0.000	0.281	0.004
Carbon dioxide	0.000		0.015
Nitrogen	0.000	0.127	0.011

Table 1: Properties of gas condensate samples used in this study (Adel.M. Elsharkawy, 2001)

GA PARAMETER	VALUE/TYPE
Algorithm type	Binary GA
Total chromosome length i. Reservoir temperature ii. Specific gravity of C_{7+} fraction iii. Molecular weight of C_{7+} fraction iv. Mole fraction of C_{7+} fraction	30-bit 6-bit 7-bits 8-bits 9-bits
No of chromosomes	Eight (8)
Population	8x30 (240)
Cost equation	El-sharkawy
Selection	Ranking by descending order (best to worst)
Crossover	Single point
Mutation	5%
Max no of generations	1000

Table 2: Parameters for the Genetic algorithm.

Sample	A1	E1	T1	M1	45	66
Experimental	3095	3345	2651	3337	8750	11830
Genetic algorithm	3088.64	3354.81	2628.97	4967.48	8752.67	11829.92
Elsharkawy	3220	3345	2655	6541	8643	12081
Organick & Golding	2650	3850	2620	2750	7055	7800
Nemmeth & kennedy	2823	2507	2792	4144	9136	5545
SRK-EOS 1	3104	3342	2911	6808	9850	12914
SRK-EOS 2	3077	2790	2902	4739	9599	12689
PR-EOS 1	2833	3206	2682	5947	9172	11738
PR-EOS 2	2815	2603	2675	4909	9138	11426

Sample	2_4	2_5	2_6	2_7	2_8	2_9	2_10	2_11
Experimental	5780	5229	4203	4173	5219	4172	4160	7871
Genetic algorithm	5780.65	5228.22	4203.13	4173.02	5219.38	4171.07	4162.38	6858,84
Elsharkawy	5808	5349	4270	4170	5179	4173	4139	6734
Organick & Golding	3468	4270	3674	3740	4054	3808	3520	4800
Nemmeth & kennedy	5492	5062	4054	3983	4932	4061	4063	7128
SRK-EOS 1	5602	5147	4152	4153	4823	4089	4055	6208
SRK-EOS 2	6500	5141	4157	4152	4830	4098	4105	6762
PR-EOS 1	5096	5330	4256	4243	4709	3855	4159	6183
PR-EOS 2	5427	5307	4258	4242	4712	3863	4235	6374

Table 3: DPP prediction for study samples by GA and other methods

Ref	Sage & Olds	Al-Mahross	Kurata & Katz	El-sharkawy	Reamer & Sage	El-sharkawy	Pedersen 1988
	A-1	M-1	T-1	66	E-1	45	Mix 2_4
Res. Temperature,°F	40	337	60	271	220	224	246
Composition Mole fraction							

Hydrogen sulphide	0.00	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000
Carbon dioxide	0.00	0.065	0.0045	0.0097	0.001	0.0018	0.0864
Nitrogen	0.00	0.1171	0.0038	0.0041	0	0.0015	0.0071
Methane	0.8238	0.7906	0.8300	0.8616	0.9522	0.8657	0.7085
Ethane	0.0428	0.0162	0.0376	0.0355	0.0168	0.0383	0.0853
Propane	0.0351	0.0035	0.0144	0.0154	0.0091	0.0197	0.0495
Iso-Butane	0.0161	0.0008	0.0089	0.0046	0.0026	0.0049	0.0075
n-butane	0.0303	0.0010	0.0000	0.0046	0.0033	0.0072	0.0126
Iso-pentane	0.0060	0.0004	0.0436	0.0026	0.0016	0.0034	0.0041
n-pentane	0.0068	0.0004	0.0000	0.0020	0.0011	0.0040	0.0040
Hexane	0.0099	0.0006	0.0308	0.0035	0.0025	0.0057	0.0046
Heptane plus	0.0292	0.0039	0.0263	0.0564	0.0098	0.0478	0.0304
Molecular weight C7+	125	161.9	**106**	**253**	122.6	200	155.3
Specific gravity C7+	0.74	0.8	0.733	**0.85**	**0.723**	0.8311	0.8311
Measured dew point pressure, psia	3095	3337	2651	11830	3345	8750	5780
Calculated dewpoint pressure, psia							
GENETIC ALGORITHM	**3088.64**	**4967.48**	**2628.97**	**11829.92**	**3354.81**	**8752.67**	**5780.65**
Elsharkawy	3220	6541	2655	12081	3345	8643	5808
Organick & Golding	2650	2750	2620	7800	3850	7055	3468
Nemmeth & Kennedy	2823	4144	2792	5545	2507	9136	5492
SRK-EOS (1)	3104	6808	2911	12914	3342	9850	5602
SRK-EOS (2)	3077	4739	2902	12689	2790	9599	6500
PR-EOS (1)	2833	5947	2682	11738	3206	9172	5096
PR-EOS (2)	2815	4909	2675	11426	2603	9138	5427

Table 4: Comparison between GA & various methods of calculating dewpoint pressures using some gas condensate samples used in this study.

					SRK - EOS		PR - EOS	
	Genetic algorithm	**El-sharkawy**	**Organick & Golding**	**Nemmeth & kennedy**	**Method 1**	**Method 2**	**Method 1**	**Method 2**
ARD %	**-1.03%**	-0.48%	-16.97%	-8.73%	-0.60%	-0.48%	-4.09%	-4.66%

AAD %	**1.09%**	2.13%	19.29%	10.22%	5.50%	6.46%	2.20%	6.32%
RMSE %	**3.57%**	4.30%	22.37%	17.04%	8.16%	8.46%	8.21%	9.12%
COR %	**99.397%**	99.165%	93.886%	75.723%	97.475%	98.377%	97.989%	98.28%

Table 5: Accuracy of GA compared to other correlations and equations of states.

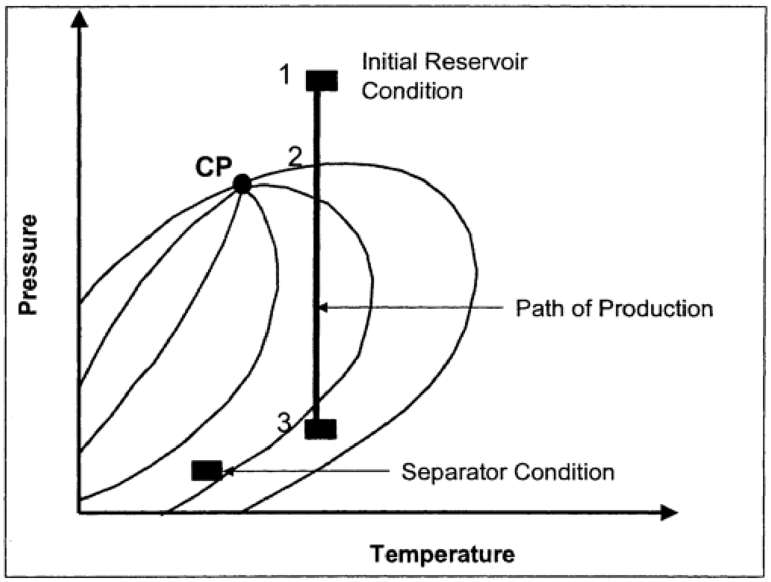

Fig 1 Phase diagram of a typical gas condensate showing line of isothermal reduction of reservoir pressure

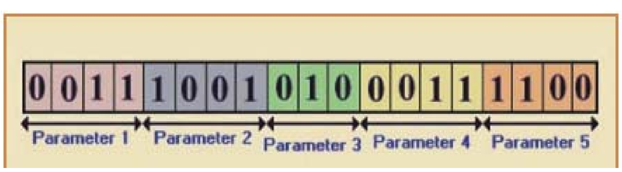

Fig 2 A typical binary chromosome with 5 genes (Shahab Mohaghegh, JPT October 2000)

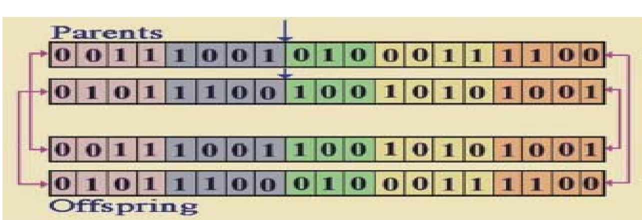

Fig 3 Chromosome reproduction using 'single point cross-over' (Shahab Mohaghegh, JPT October 2000)

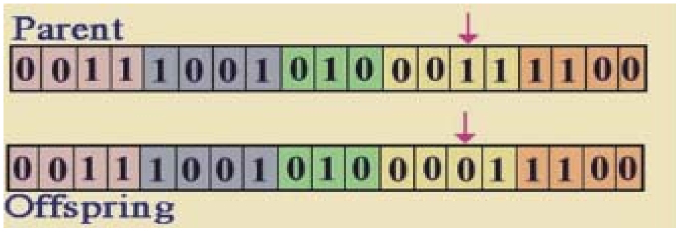

Fig 4 Chromosome reproduction using mutation (Shahab Mohaghegh, JPT October 2000)

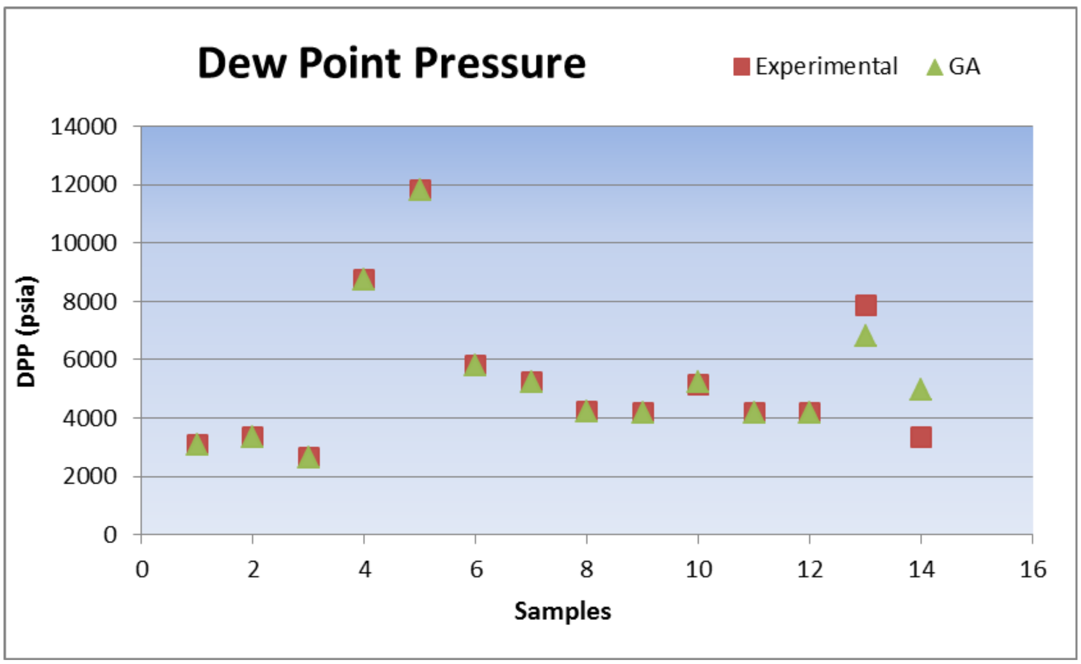

Fig 5: Crossplot of Dew point pressures for experimental values against GA result

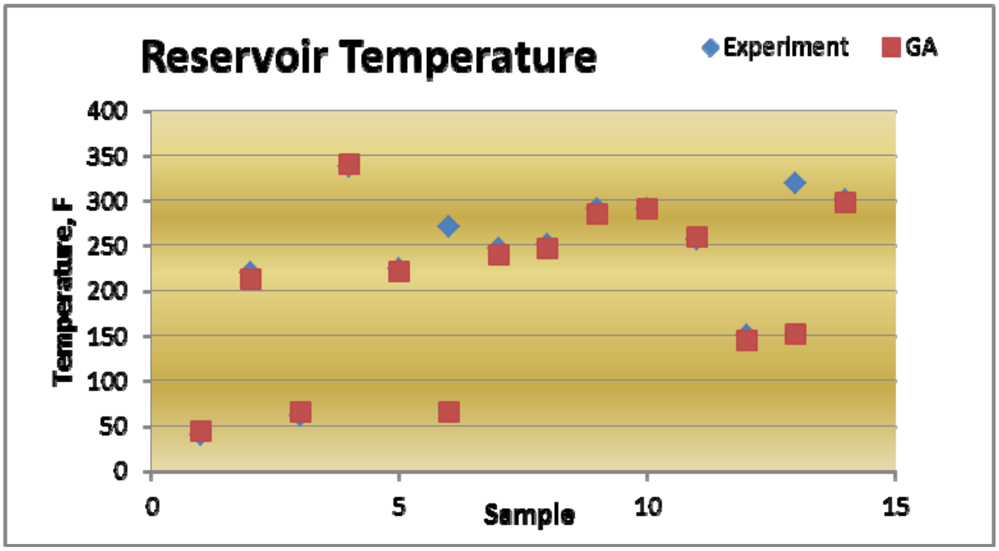

Fig 6: Crossplot of Reservoir temperature for experimental values against GA result

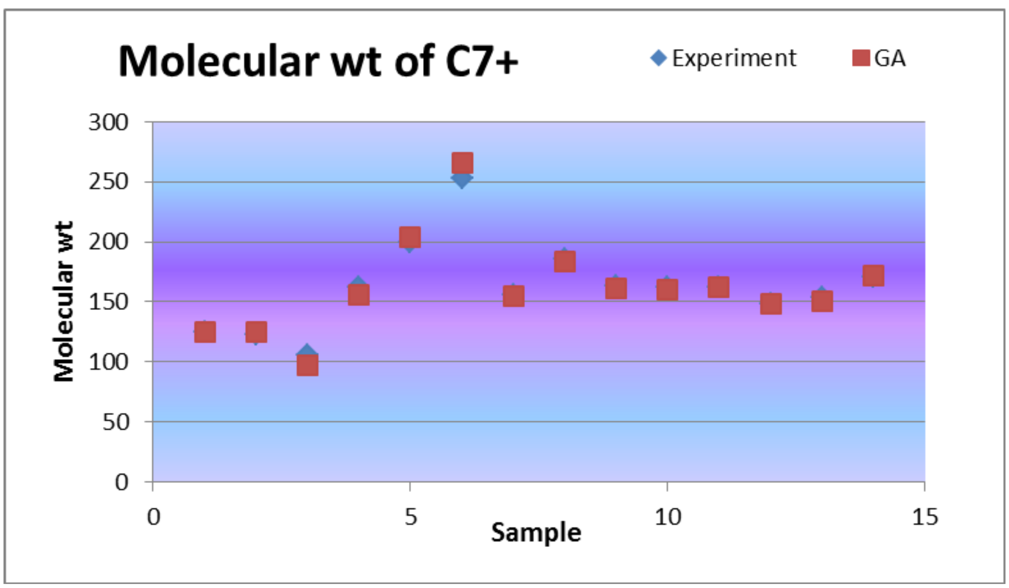

Fig 7: Crossplot of Molecular weight for experimental values against GA result

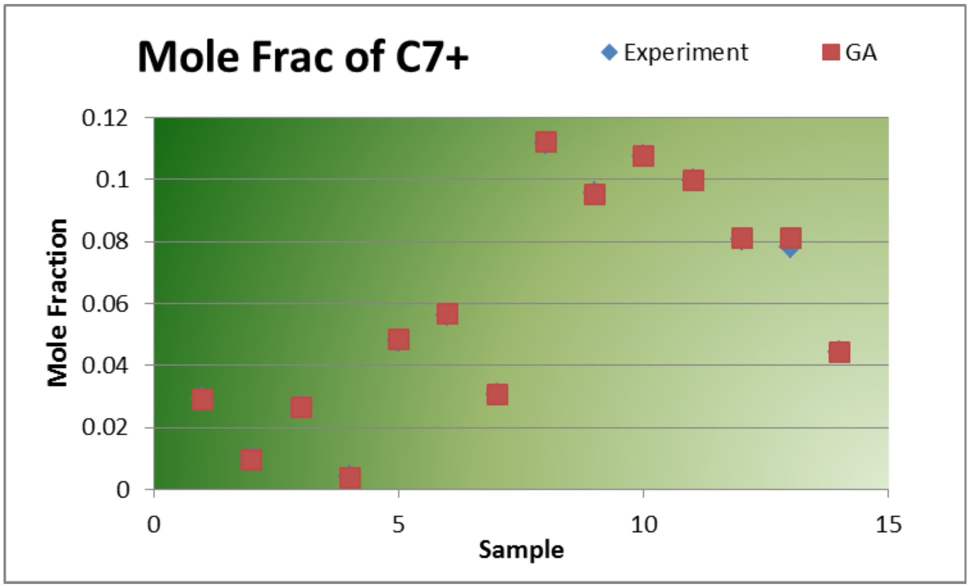

Fig 8: Crossplot of Mole fraction of C7+ for experimental values against GA result

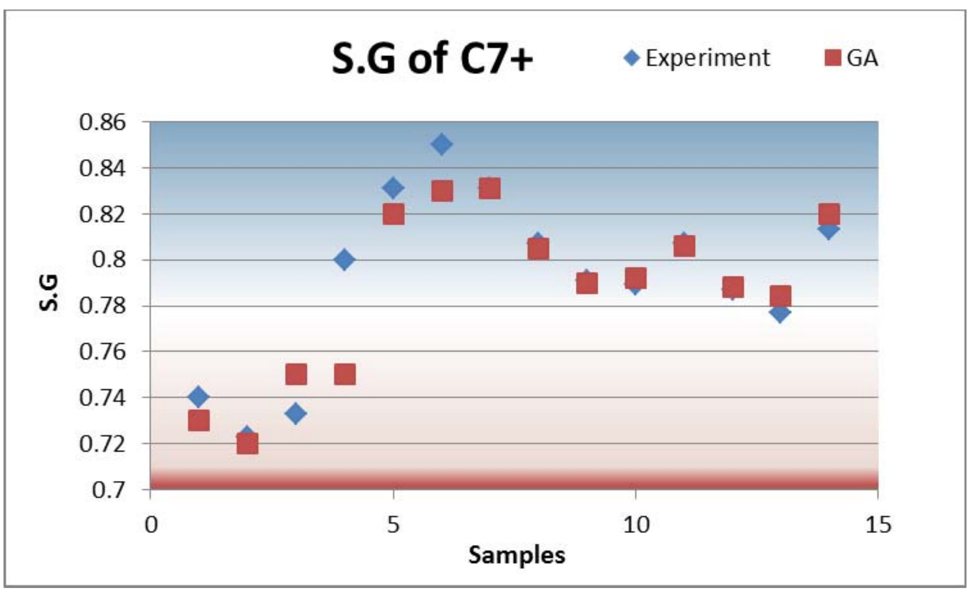

Fig 9: Crossplot of Specific gravity of C7+ for experimental values against GA result

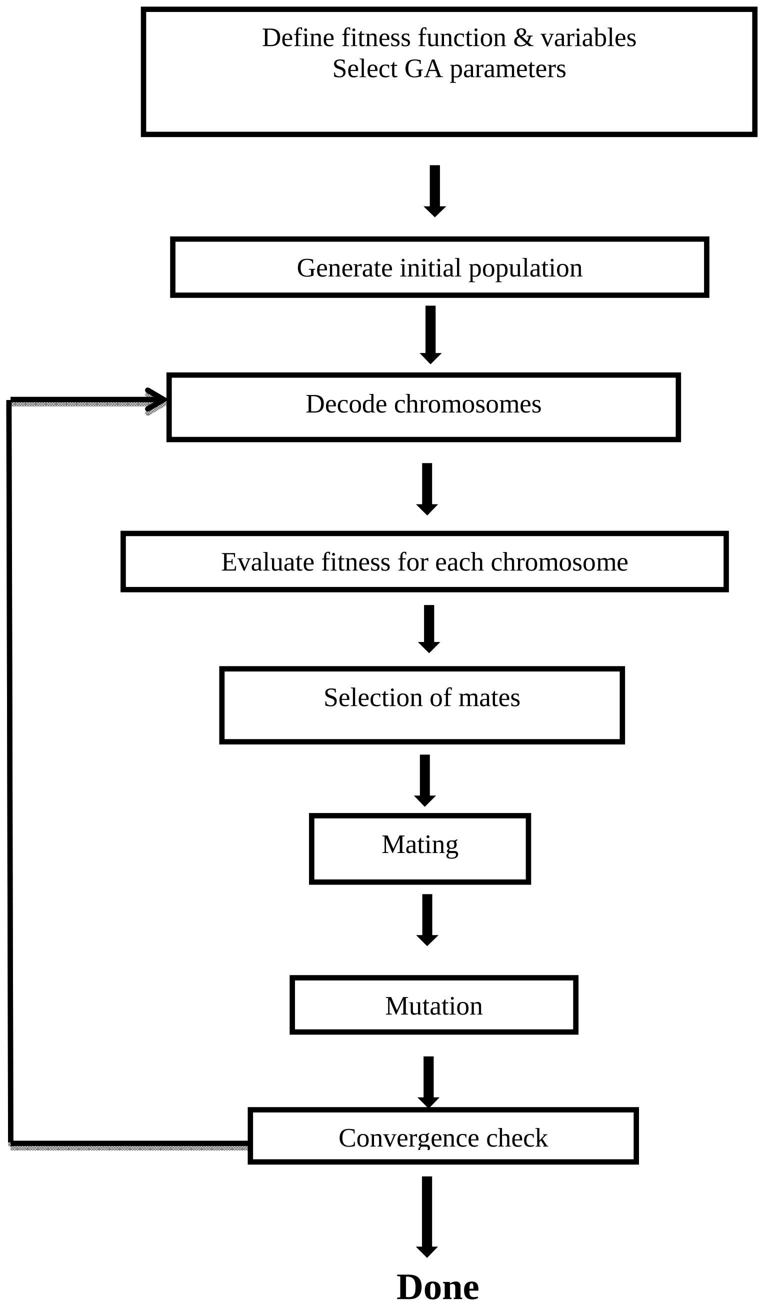

Fig 10: Flow chart showing the pathway for the genetic algorithm