ESTIMATING ASPHALTENE PRECIPITATION IN THE PRESENCE OF $$\rm CO_2$$ INJECTION IN OIL RESERVOIRS

SAEED AKBARI

A research submitted in partial fulfillment of the requirements for the award of the degree of Master of Engineering (Chemical)

FACULTY OF CHEMICAL ENGINEERING UNIVERSITY TEKNOLOGI MALAYSIA

MARCH 2011

To my beloved parents, thank you for always being there for me, supporting me and encouraging me to be the best that I can be.

ACKNOWLEDGMENT

First and foremost, *Syukur Alhamdulillah*, for blessing me the strength to complete this study. I wish to express my gratitude to several people that helped me during the course of my master's programme at Universiti Teknologi Malaysia.

I am particularly indebted to my project supervisor, Assoc. Prof. Dr. Gholamreza Zahedi, for his guidance, encouragement and motivation throughout this work.

I am very grateful to my parents, for their endless prayers, love and encouragement, not only during this master's programme, but also during all my life. May God protect and guide both of you. I wish to express my love and gratitude to the other members of my family, especially my brother, Omid; for their supports and endless love, through the duration of my studies.

Warmest appreciation to a wonderful friend under the same supervisor, Leila Ezzatzadegan, for her precious times, support and cares. She has gone through all the hard times with me.

I also would like to express my sincere appreciation to my best friends for being with me, understand me, all this while. Finally, thanks for those who have been contributed directly and indirectly to this work.

ABSTRACT

In this research, use of multi layer perceptron (MLP) and radial basis function (RBF) structures of artificial neural network (ANN) for prediction of asphaltene precipitation were described and the models were contrasted with the modified Hirschberg *et al.*, model. The essential data were gathered and after pre-treating was employed for training of ANN models. The performance of the best obtained model was checked by its generalization ability in predicting 30% of the unseen data. Excellent prediction with Mean Squared Error (MSE) of 0.0018 and Average Absolute Deviation (AAD %) of 1.4108 was observed. However the accuracies of RBF and MLP models may be evaluated relatively similar, it was obtained that the constructed MLP according to Levenberg-Marquardt (LM) optimization exhibited a high performance than RBF structure, and the modified Hirschberg to predict asphaltene precipitation.

ABSTRAK

Dalam kajian ini, penggunaan multi layer Perceptron (MLP), dan fungsi pangkalan jejari (RBF) struktur rangkaian saraf tiruan (JST) untuk keputusan curah hujan aspalten digambarkan dan model dibandingkan dengan diubahsuai Hirschberg dkk., Model. Data yang diperlukan dikumpulkan dan setelah pra-mengubati digunakan untuk latihan model JST. Prestasi model terbaik diperolehi diperiksa dengan kemampuan generalisasi dalam memprediksi 30% dari data yang tak terlihat. Excellent ramalan dengan Mean Squared Error (MSE) dari 0,0018 dan Rata-rata Sisihan Mutlak (AAD%) dari 1,4108 diamati. Namun ketepatan RBF dan model MLP boleh dinilai relatif sama, didapati bahawa MLP dibina sesuai dengan Levenberg-Marquardt (LM) pengoptimuman menunjukkan prestasi tinggi daripada struktur RBF, dan Hirschberg diubahsuai untuk memprediksi curah hujan aspalten.

TABLE OF CONTENT

CHAPTER	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGEMENT	iv
	ABSTRACT	V
	ABSTRAK	vi
	TABLE OF CONTENTS	vii
	LIST OF TABLES	Х
	LIST OF FIGURES	xi
CHAPTER 1	L	1
INTRODUC	TION	1
1.1 Backgroun	nd of Study	1
1.2 Problem S	Statement	3
1.3 Purpose o	f Study	4
1.4 Significan	ice of the Study	4
1.5 Objectives	S	5
1.6 Scope of S	Study	6

CHAPTER 2	7
LITERATURE REVIW	7
2.1 Asphaltene	7
2.2 Carbon Dioxide	9
2.2.1 Chemical and Physical Properties of CO2	9
2.3 Models for Asphaltene Precipitation	10
2.4 Pressure and Temperature Effects on Asphaltene Stability	13
2.5 Modified Hirschberg Model	14
2.5.1 Model Description	15
2.6 Neural Network	17
2.6.1 Learning Rule	19
2.6.2 Neural Network Structure	20
2.6.3 Multi Layer Perceptron	24
2.6.4 Radial Basis Function Neural Network	26
2.7 Over Fitting and Under Fitting Problems	28
CHAPTER 3	30
METHODOLOGY	30
3.1 Research Methodology	30
3.2 Parameter Selection and Data Collection	32
3.3 Modeling Procedure	34
3.4 Evaluating Error in Training and Validation Parts	35
3.5 Sensitivity Analysis	35
CHAPTER 4	36

viii

MODEL DEVELOPMENT	36
4.1 Introduction	36
4.2 MATLAB Version 7.10.0.499 (R2010a)	37
4.3 Neural Network Toolbox	38
4.4 Dividing Data	38
4.5 Preprocessing and Postprocessing on the Data	39
4.5.1 Min and Max (mapminmax)	40
4.5.2 Mean and Stand. Dev. (mapstd)	41
4.5.3 Principal Component Analysis (processpca)	41
4.6 Backpropagation Algorithms	43
4.7 Procedure of Modeling in MLP Structure of ANN	43
4.7.1 Preprocessing on the Data	44
4.7.2 Network Setup	44
4.7.3 Training Back Propagation	45
4.7.4 Modeling Procedure	46
4.8 Modeling by RBF Structure of ANN	48
CHAPTER 5	50
RESULTS AND DISCUSSION	50
5.1 Result Overview	50
5.1.1 General Rule in This project to Train MLP Netwo	rk of ANN 51
5.1.2 Trainlm	52
5.1.3 Traingdx	56
5.1.4 Resilient Backpropagation (trainrp)	58
5.1.5 Comparison of Best Result of Different Training A	Algorithms 59
5.2 RBF Structure of ANN	60
5.3 Comparing the Result of MLP, RBF, and the Solubility	y Models 62

ix

5.4 Characterization and Performance of the Best Model	63
5.5 Sensitivity Analysis	68
CHAPTER 6	71
CONCLUSION AND RECOMMENDATION	71
6.1 Conclusion	71
6.2 Recommendation	72
REFRENCES	73
APPENDIX A	81
APPENDIX B	84
APPENDIX C	86

X

LIST OF TABLES

TABLE NO.	TITLE	PAGE
4.1	Summary of different type of preprocessing methods	40
5.1	Different number of neurons in hidden layer.	53
5.2	Effect of input normalization method on the predictive performance.	54
5.3	Effect of different training option on the performance of network.	56
5.4	Summary of best result of ANN model by using traingdx algorithm.	57
5.5	Summary of best result of ANN model by using trainrp algorithm.	58
5.6	Comparison of performance of optimum MLP with various algorithms for testing data.	60
5.7	Average Absolute Deviation (AAD%) for ANN and solubility model	62
5.8	Characteristics of the ANN networks	64
5.9	Statistical performance of ANN model	65
0.1	Weight value associated with the neuron in output layer.	86
0.2	Bias value associated with each neuron in each layer layer.	86
0.3	Weight value associated with each neuron in hidden layer.	87

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
2.1	"Long diagram" shows that the asphaltenes include the crude oil material highest in molecular weight, polarity, and/or aromaticity	8
2.2	Pressure-Temperature phase diagram for carbon dioxide	10
2.3	Natural neurons	18
2.4	a) Single neuron b) Simple Single –layer Perceptron, Abbreviated Notation	21
2.5	Three types of activation function	25
2.6	A three layers Feed-forward artificial neural network architecture	25
2.7	The RBF neural network	27
2.8	Over fitting and under fitting problems	29
3.1	Research methodology	30
3.2	Input and output variables of the network	33
3.3	Modeling flow chart	34
4.1	Training procedure	47
4.2	Flow chart of modeling by RBF structure of ANN	49
5.1	Performance of the RBF network based on the number of hidden neurons	61
5.2	Performance of the RBF network based on the spread for 24 neurons in the hidden layer	61
5.3	ANN model structure	64
5.4	Prediction result of ANN model for Train Data vs. experimental data	66
5.5	Prediction result of ANN model for Test Data vs. experimental data	66
5.6	Relative Error for Train and Test data	67
5.7	Comparing the effect of changes in different variables on production rate (-%5)	69
5.8	Comparing the effect of changes in different variables on production rate $(+\%5)$	70

LIST OF ABBREVIATIONS

Abbreviation:	
EOR	Number of neurons in hidden layer
EOS	Equation of state
ANN	Artificial neural network
ANFIS	Adaptive neuro fuzzy inferance system
MLP	Multi layer perceptron
ANN	Artificial neural network
ANFIS	Adaptive neuro-fuzzy inference system
RBF	Radial basis function
FCM	Fuzzy c-means clustering
FIS	Fuzzy inference system
AAD (%)	Average absolute deviation(%)
Sub-ANFIS	ANFIS-based subtractive clustering algorithm
MLP	Multi layer perceptron
MSE	Mean squared error
GDX	Gradient decent algorithm
LM	Levenberg–Marquardt algorithm
RP	Resilient back propagation
TSK	Takagi-Sugeno-Kang
ANFIS_FCM	ANFIS-based fuzzy c-means clustering algorithm
NH	Number of neurons in hidden layer
HLT	Hidden layer transfer function
OLT	Output layer transfer function
LR	Learning rate
MSE_TEST	Mean squared error value for testing data
MSE_TRAIN	Mean squared error value for training set
T_T (sec)	Consumed time for training part (second)
NORM_F	Normalization function
MLP_LM	Multi layer perceptron structure trained by trainlm function

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Petroleum consists of a complex mixture of hydrocarbons of various molecular weights, plus other organic compounds. There is a very general classification scheme which is used to define the various component typically found in petroleum fluids. The scheme is specifically designed to address special phase behavior and solid deposition issues. In general, petroleum constituents are classified under two major groups, namely the well defined and volatile C_6^- fraction and the poorly defined and relatively nonvolatile C_6^+ fraction. The C_6^+ fraction is more complex than C_5^- due to the multiple isomer combinations available to hydrocarbon with increasing chain length. This group of component is classified as paraffins (P), naphthenes (N), aromatics (A), resins (R), and asphaltene (A). Among of these constituents, asphaltenes are possibly the most studied and yet least understood materials in the petroleum industry. The word "asphaltene" was coined by Boussingaultin in 1837 when he noticed that the distillation residue of asphaltenes.

Strictly speaking, asphaltenes are the crude oil components that meet some procedural definition.

A common definition is that asphaltenes are the material that is (1) insoluble in n-pentane (or n-heptane) at a dilution ratio of 40 parts alkane to 1 part crude oil and (2) re-dissolves in aromatic solvents such as toluene, benzene and xylene. Asphaltene aggregation problems are encountered both in the reservoir and during transport and processing of petroleum fluids. Asphaltene can cause reservoir impairment, plugging of walls and flow lines through deposition, separation difficulties, and fouling in facilities. Deposition in the oil wellbore and tubing are identify very difficult and expensive to remove. The main factors that influenced to the deposition are:

- i. Temperature drop acidizing
- ii. Pressure drop
- iii. Action of metallic ions
- iv. Rich gas
- v. Mixing of crude streams
- vi. Incompatible organic chemicals
- vii. Miscible flooding-such as CO₂ (EOR)

Enhanced oil recovery (EOR) has been known as tertiary recovery of oil. CO_2 Flooding applied in the EOR system to recover oil. Normally, CO_2 has been flooded as immiscible and miscible form.

One interest question of oil industry is "how much" asphaltene will precipitate under certain condition. By answering this, a proper solution may take to prevent this problem. Of course "prevention is better than cure". Consequently, using an appropriate model is unavoidable. Taking into account the dissimilar approaches, different models have been developed; thermodynamic molecular solubility model (Hirschberg *et al.*, 1984; Yang *et al.*, 1999), thermodynamic colloidal model (Leontaritis and Mansoori, 1987), thermodynamic micellization model (Pan and Firoozabadi, 1998; Pan and Firoozabadi, 2000), solid line model (Nghiem *et al.*, 1998), statistical association theory (SAFT) (Chapman *et al.*, 2004; Paricaud *et al.*, 2002).

Although there are a lot of models to estimate asphaltene precipitation, the predictive capabilities of these models are poor especially in the presence of CO_2 . Established models suffer from the difficulty in characterizing asphaltene fraction (Hammami and Ratulowski, 2007).

1.2 Problem Statement

Carbon dioxide (CO_2) flooding has been used as a commercial process for enhanced oil recovery (EOR) since the 1970s (Yin, 2000). Significant amounts of residual oil can be recovered by this procedure. Normally, CO_2 has been flooded as immiscible and miscible form. The miscibility of CO_2 depends to the reservoir pressure. Reservoirs pressure which higher than Minimum Miscibility Pressure (MMP) of CO_2 , could formed CO_2 miscible with oil. Although, CO_2 flooding bring a good recovery, but miscible CO_2 flooding have to handle with carefully to avoid asphaltene precipitation in the production systems. It known that, asphaltene will be precipitated if occur any changes in pressure, composition and some other factors. Miscibility of CO_2 will make asphaltene to precipitate, due to changing the crude oil composition and making oil to be acidic (changing in PH). As a result, a special investigation is needed to control CO_2 concentration in the systems during flooding. This investigation can lead to a robust model to monitor asphaltene behavior.

1.3 Purpose of Study

 CO_2 Injection is one of the most common enhanced oil recovery methods. In this process, CO_2 acts as a solvent, lowering the viscosity of the oil and making it mobile. Thus significantly it can lower the irreducible oil saturation. However, CO_2 flooding processes cause many changes in the flow and phase behavior of the reservoir fluids and can significantly favor the precipitation of asphaltenes. Even though the literature is considerable on the subject, few studies have been reported on the simulation of asphaltene phase behavior changes caused by CO_2 addition.

1.4 Significance of the Study

Although there are many models to predict asphaltene precipitation but most of them have an error to some extent, to predict phase behavior of asphaltene. Because of the difficulty in characterizing asphaltene fraction, the predictive capabilities of most models are poor. In enhanced oil recovery (EOR) projects by CO_2 flooding, predicting asphaltene precipitation will be more complicated because another strange component has been added to the oil. Carbon dioxide has its own unique behavior and shows an extraordinary performance to enhanced oil recovery in compare with other substances like N₂ and some chemical materials, when they are in contact with crude oil. In this project ANN approach has been examined to predict asphaltene precipitation. It will be well worth employing these methods to catch good result, because this type of modeling is independent of understanding characterization of asphaltene.

1.5 Objectives

The objective of this study is to examine ANN approach to find a robust model, to predict asphaltene precipitation weight percent in the presence of CO_2 in oil reservoirs. The model should be able to predict the output of the model as a result of changing in pressure, temperature, mole fraction of CO_2 in liquid, and oil composition.

1.6 Scope of Study

Scope of this study is described as below:

- i. Choice of inputs and output of the black box. Based on literature review, 33 parameters were chosen as inputs of the model and asphaltene precipitation weight percent examined as output variable.
- ii. Data collection. The data sets were collected from the six samples of the oil.
- iii. Development of different models of ANN. These structures have been built based on different types of multi layer perceptron algorithms and radial basis function of ANN. The complete process model is programmed and simulated in MATLAB R2010a.
- iv. Training and validation of each model by using experimental data. From the experimental data file, seventy and thirty percent of all data observations were selected for training and estimating the generalization ability of the model, respectively.
- v. Comparing result of best models with a solubility model. After finding the best model of each structure, their prediction ability will be compared by a solubility model. Their performance has been evaluated based on a statistic criterion and the best one was chosen for future investigations.
- vi. Analysis on best model sensitivity towards changes in process input variables, like temperature, pressure, mole percent of CO_2 in liquid, and component of the oil.

REFERENCES

- Ali L.H., Ghannam, A. K. (1981) Investigations into Asphaltenes in Heavy Crude Oils.I.effect of temperature on percipitation by alkane solvents. Fuel Sci. Technol. Int 60:1043-1046.
- Andersen S.I. (1994b) Effect of Precipitation Temperature on the Composition of n-Heptane Asphaltenes. Fuel Sci. Technol. Int 12:51-74.
- Andersen S.I.B., Kulbir S. (1990) *Influence of temperature and solvent on the precipitation of asphaltenes*. Fuel Science & Technology International 8:593-615.
- Bar, Yam Y. (1997) Dynamics of Complex Systems Addison-Wesley.
- Boer R.B.d., Klaas L., Eigner M.R.P., Bergen A.R.D.v. (1995a) Screening of Crude Oils for Asphalt Precipitation: Theory, Practice, and the Selection of Inhibitors. SPE Production & Operations 10:55-61. DOI: 10.2118/24987-pa.
- Boer R.B.d., Leerlooyer K., Eigner M.R.P., Bergen A.R.D.v. (1995b) Screening of Crude Oils for Asphalt Precipitation: Theory, Practice, and the Selection of Inhibitors. SPE Production & Operations 10. DOI: 10.2118/24987-pa.
- Buckley J.S. (1999) Predicting the Onset of Asphaltene Precipitation from Refractive Index Measurements. Energy & Fuels 13:328-332. DOI: 10.1021/ef980201c.

Bulsari A.B. (1995) Neural Networks for Chemical Engineers Elsevier Science Inc.

- Burke N.E., Hobbs R.E., Kashou S.F. (1990) Measurement and Modeling of Asphaltene Precipitation (includes associated paper 23831). SPE Journal of Petroleum Technology 42. DOI: 10.2118/18273-pa.
- Chapman W.G., Sauer S.G., Ting D., Ghosh A. (2004) Phase behavior applications of SAFT based equations of state--from associating fluids to polydisperse, polar copolymers. Fluid Phase Equilibria 217:137-143.
- Chen K.T., Chou C.H., Chang S.H., Liu Y.H. (2008) *Intelligent active vibration control in an isolation platform.* Applied Acoustics 69:1063-1084.
- Chung T.-H. (1992) *Thermodynamic Modeling for Organic Solid Precipitation*, SPE Annual Technical Conference and Exhibition, 1992 Copyright 1992, Society of Petroleum Engineers Inc., Washington, D.C.
- Edmonds B., R.A.S. Moorwood, R. Szczepanski, X. Zhang, M. Heyward, and R. Hurle. (1999) Measurement and prediction of asphaltene precipitation from live oils, 3rd International Symposium on Colloid Chemistry in Oil Production, Asphaltenes and Waxes Deposition (ISCOP'99), Mexico.
- Fotland P. (1996b) Precipitation of asphaltenes at high pressures; experimental technique and results. Fuel Science and Technology 14:313-325.
- Fuhr B.J., C. C., L. C., H. K., A. I.M. (1991) Properties of Aspahltenes from a Waxy Crude. Fuel Science and Technology 70:1293–1297.
- Geman S., Bienenstock E., Doursat R. (1992) Neural Networks and the Bias/Variance Dilemma. Neural Computation 4:1-58. DOI: doi:10.1162/neco.1992.4.1.1.

- Gonzalez D.L., Ting P.D., Hirasaki G.J., Chapman W.G. (2005) Prediction of Asphaltene Instability under Gas Injection with the PC-SAFT Equation of State†Energy & Fuels 19:1230-1234. DOI: 10.1021/ef049782y.
- Hagan M.T., Demuth H.B., Beale M.H. (1996) *Neural network design* Vikas Publishing House Pvt. Ltd., New Delhi.
- Hammami A., Chang-Yen D., Nighswander J.A., Stange E. (1995) An experimental study of the effect of paraffinic solvents on the onset and bulk precipitation of asphaltenes.Fuel Science and Technology International 13:1167 1184.
- Hammami A., Phelps C.H., Monger-McClure T., Little T.M. (1999) Asphaltene Precipitation from Live Oils: An Experimental Investigation of Onset Conditions and Reversibility. Energy & Fuels 14:14-18. DOI: 10.1021/ef990104z.
- Hammami A., Ferworn K.A., Nighswander J.A., OverËš S., Stange E. (1998) Asphaltenic crude oil characterization: an experimental investigation of the effect of resins on the stability of asphaltenes. Petroleum Science and Technology 16:227-249.
- Hammami A., Ratulowski J. (2007) Precipitation and Deposition of Asphaltenes in Production Systems: A Flow Assurance Overview, in: O. C. Mullins, et al. (Eds.), Asphaltenes, Heavy Oils, and Petroleomics, Springer New York. pp. 617-660.
- Hamouda A.A., Chukwudeme E.A., Mirza D. (2009) Investigating the Effect of CO2 Flooding on Asphaltenic Oil Recovery and Reservoir Wettability. Energy & Fuels 23:1118-1127. DOI: 10.1021/ef800894m.
- Haskett C.E., Tartera M. (1965a) A Practical Solution to the Problem of Asphaltene Deposits-Hassi Messaoud Field, Algeria. SPE Journal of Petroleum Technology 17. DOI: 10.2118/994-pa.

- Haskett C.E., Tartera M. (1965b) A Practical Solution to the Problem of Asphaltene Deposits-Hassi Messaoud Field, Algeria. SPE Journal of Petroleum Technology 17:387-391. DOI: 10.2118/994-pa.
- Hirschberg A., deJong L.N.J., Schipper B.A., Meijer J.G. (1984) *Influence of Temperature and Pressure on Asphaltene Flocculation* 24. DOI: 10.2118/11202-pa.
- Hu Y.-F., Li S., Liu N., Chu Y.-P., Park S.J., Mansoori G.A., Guo T.-M. (2004) Measurement and corresponding states modeling of asphaltene precipitation in Jilin reservoir oils. Journal of Petroleum Science and Engineering 41:169-182.
- Idem R.O., Ibrahim H.H. (2002) *Kinetics of CO2-induced asphaltene precipitation from various Saskatchewan crude oils during CO2 miscible flooding.* Journal of Petroleum Science and Engineering 35:233-246.
- Kalantari-Dahaghi A., Gholami V., Moghadasi J., Abdi R. (2008) Formation Damage Through Asphaltene Precipitation Resulting From CO2 Gas Injection in Iranian Carbonate Reservoirs. SPE Production & Operations 23. DOI: 10.2118/99631-pa.
- Kokal S.L., Sayegh S.G. (1995) Asphaltenes: The Cholesterol of Petroleum, Middle East Oil Show, 1995 Copyright 1995, Society of Petroleum Engineers, Inc., Bahrain.
- Lang R.I.W. (2006) A future for dynamic neural networks, Cybernetics, University of reading, UK.
- Lasne D., Barreau A., Behar E. (1987) *Phase behaviour laboratory investigation of CO2-hydrocarbon mixtures for enhanced oil recovery modelling*, Proceedings of the 4th European Symposium on Enhanced Oil Recovery, Hamburg, Germany.
- Leontaritis K.J., Mansoori G.A. (1987) Asphaltene Flocculation During Oil Production and Processing: A Thermodynamic Collodial Model, SPE International Symposium on

Oilfield Chemistry, 1987 Copyright 1987 Society of Petroleum Engineers, Inc., San Antonio, Texas.

Long R.B. (1981) The Concept of Asphaltenes, Chemistry of Asphaltenes. pp. 17-27.

- Macmillan, D J., Tackett, J E., Jessee, M A., Monger M., T G. (1995) A unified approach to asphaltene precipitation: laboratory measurement and modeling.
- Madaeni S.S., Zahedi G., Aminnejad M. (2008) Artificial neural network modeling of O2 separation from air in a hollow fiber membrane module. Asia-Pacific Journal of Chemical Engineering 3:357-363. DOI: 10.1002/apj.155.
- Mansoori G.A. (1994) The occurrance of asphaltene throughout production cycle: *A comprehensive description of mechanism and factors influencing heavy organic deposition,* 6th International Petroleum Exhibition and Conference, Abu Dhabi. pp. 282–292.
- Mansoori G.A., Jiang T.S., Kawanaka S. (1988) *Asphaltene deposition and its role in petroleum production and processing*. Arabian Journal for Science and Engineering 13:17-34.
- Nghiem L.X., Coombe D.A., Farouq Ali S.M. (1998) Compositional Simulation of Asphaltene Deposition and Plugging, SPE Annual Technical Conference and Exhibition, 1998 Copyright 1998, Society of Petroleum Engineers Inc., New Orleans, Louisiana.
- Norgaard M., Ravn O., Poulsen N.K., Hansen L.K. (2000) Neural Networks for Modelling and Control of Dynamic Systems Springer, Berlin and New York.
- Pan H., Firoozabadi A. (1998) Complex Multiphase Equilibrium Calculations by Direct Minimization of Gibbs Free Energy by Use of Simulated Annealing. SPE Reservoir Evaluation & Engineering 1. DOI: 10.2118/37689-pa.

- Pan H., Firoozabadi A. (2000) Thermodynamic Micellization Model for Asphaltene Precipitation From Reservoir Crudes at High Pressures and Temperatures. SPE Production & Operations 15. DOI: 10.2118/60842-pa.
- Pan H.a.A.F. (1997) Thermodynamic micellization model for asphaltene precipitation from reservoir crudes at high pressures and temperatures, SPE Annual Technical Conference and Exhibition, San Antonio, TX.
- Panagou E.Z., Kodogiannis V., Nychas G.J.E. (2007) Modelling fungal growth using radial basis function neural networks: The case of the ascomycetous fungus Monascus ruber van Tieghem. International Journal of Food Microbiology 117:276-286.
- Paricaud P., Galindo A., Jackson G. (2002) Recent advances in the use of the SAFT approach in describing electrolytes, interfaces, liquid crystals and polymers. Fluid Phase Equilibria 194-197:87-96.
- Potter C.W., Negnevitsky M. (2006) Very short-term wind forecasting for Tasmanian power generation. Power Systems, IEEE Transactions on 21:965-972.
- Quah J.T.S., Ng W.D. (2007) Utilizing Computational Intelligence for DJIA Stock Selection, Neural Networks, 2007. IJCNN 2007. International Joint Conference on. pp. 956-961.
- Shakhashiri. (2008) Carbon dioxide, chemical of the week.
- Simon R., Rosman A., Zana E. (1978) *Phase-Behavior Properties of CO2 Reservoir Oil* Systems 18. DOI: 10.2118/6387-pa.
- Stankiewicz A.B., M.D. Flannery, N.A. Fuex, G. Broze, J.L. Couch, S.T. Dubey, S.D. Iyer, J., Ratulowski a.J.T.W. (2002) *Prediction of asphaltene deposition risk inE&Poperations*, Proceeding of 3rd International Symposium on Mechanisms and Mitigation of Fouling in

- Takhar S., P.D. Ravenscroft, and D.C.A. Nicholl. (1995) *Prediction of asphaltene deposition during production—Model description and experimental details*, European Formation Damage Conference.
- Tamhane D., Wong P.M., Aminzadeh F., Nikravesh M. (2000) Soft Computing for Intelligent Reservoir Characterization, SPE Asia Pacific Conference on Integrated Modelling for Asset Management, Copyright 2000, Society of Petroleum Engineers Inc., Yokohama, Japan.

The MathWorks Inc. (2010a) Neural Network Toolbox The MathWorks, Inc.

- Ting P.D. G.J.H., and W.G. Chapman. (2003) *Modeling of asphaltene phase behavior with the SAFT equation of state*. Pet. Sci. Technol 21:647–661.
- Vafaie-Sefti M., Mousavi-Dehghani S.A. (2006) *Application of association theory to the prediction of asphaltene deposition*: Deposition due to natural depletion and miscible gas injection processes in petroleum reservoirs. Fluid Phase Equilibria 247:182-189.
- Wang J.X., Brower K.R., Buckley J.S. (1999) Advances in Observation of Asphaltene Destabilization, SPE International Symposium on Oilfield Chemistry, Society of Petroleum Engineers, Houston, Texas.
- Wang S., Civan F. (2005) Preventing Asphaltene Deposition in Oil Reservoirs by Early Water Injection, SPE Production Operations Symposium, Society of Petroleum Engineers, Oklahoma City, Oklahoma.
- Werner A., Behar F., De Hemptinne J.C., Behar E. (1996) Thermodynamic properties of petroleum fluids during expulsion and migration from source rocks. Organic Geochemistry 24:1079-1095.

- Wilhelms A., Larter S.R., Schulten H.R. (1993) Characterization of asphaltenes by pyrolysisfield ionization mass spectrometry--some observations. Organic Geochemistry 20:1049-1062.
- Yang Z., Ma C.F., Lin X.S., Yang J.T., Guo T.M. (1999) Experimental and modeling studies on the asphaltene precipitation in degassed and gas-injected reservoir oils. Fluid Phase Equilibria 157:143-158.
- Yin Y.R.Y., A. T. (2000) AsphalteneDeposition and Chemical Control in CO2 Floods, 2000 SPE/DOE Improved Oil Recovery Symposium, Tulsa, OK.
- Zahedi G., Mohammadzadeh S., Moradi G. (2008) Enhancing Gasoline Production in an Industrial Catalytic-Reforming Unit Using Artificial Neural Networks. Energy & Fuels 22:2671-2677. DOI: 10.1021/ef800025e.
- Zahedi G., Elkamel A., Lohi A., Jahanmiri A., Rahimpor M.R. (2005) *Hybrid artificial neural network--First principle model formulation for the unsteady state simulation and analysis of a packed bed reactor for CO2 hydrogenation to methanol.* Chemical Engineering Journal 115:113-120.
- Zhang L.Y., Breen P., Xu Z., Masliyah J.H. (2006) Asphaltene Films at a Toluene/Water Interface. Energy & Fuels 21:274-285. DOI: 10.1021/ef0603129.