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Permeability estimation in heterogeneous oil reservoirs by multi-gene genetic programming algorithm

Hossein Kaydani [a], Ali Mohebbi [a,*], Mehdi Eftekhari [b]

[a] Department of Chemical Engineering, Shahid Bahonar University of Kerman, Kerman, Iran
[b] Department of Computer Engineering, Shahid Bahonar University of Kerman, Kerman, Iran

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ABSTRACT

Permeability estimation has a significant impact on petroleum fields operation and reservoir management. Different methods were proposed to measure this parameter, which some of them are inaccurate, and some others such as core analysis are cost and time consuming. Intelligent techniques are powerful tools to recognize the possible patterns between input and output spaces, which can be applied to predict reservoir parameters. This study proposed a new approach based on multi-gene genetic programming (MGGP) to predict permeability in one of the heterogeneous oil reservoirs in Iran. The MGGP model with artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS) and genetic programming (GP) model were used to predict the permeability and obtained results were compared statistically. The comparison of results showed that the MGGP model can be applied effectively in permeability prediction, which gives low computational time. Furthermore, one equation based on the MGGP model using well log and core experimental data was generated to predict permeability in porous media.

1. Introduction

Permeability is defined as a measure of the ability of a porous material to allow fluids to pass through it (Ahmed, 2001). The concept of permeability is important in determining precise reservoir description, simulation and management. So, before any modeling or calculation, the permeability of porous media must be determined. The most exact method in permeability prediction is core analysis in a laboratory by application of Darcy's law, which is expensive and time consuming (Tiab and Donaldson, 2004). To overcome this obstacle, different methods for permeability estimation have been proposed. The oldest method in permeability prediction was empirical correlations between permeability and other petrophysical properties such porosity and water saturation (Timur, 1968; Weber and Van Geuns, 1990). Although, these correlations have been used with some success in sandstone reservoirs; however, for heterogeneous formations cannot be applied (Biswas et al., 2003).

The availability of well log data in any porous media leads the attempts has been applied to predict permeability from them (Amaefule et al., 1993; Kumar et al., 2000; Al-Anazi and Gates, 2010). One of the methods, which recently has been used in petroleum engineering problem is artificial intelligent, which can be used to find the complex spatial relationship in the existence parameters of reservoir (Mohaghegh and Ameri, 1995; Aminian et al., 2000; Nikravesh, 2004; Mousavi Dehghani et al., 2008).

In the field of empirical modeling, artificial neural network (ANN) can be considered as an efficient alternative to traditional techniques in predicting permeability from well log data (Mohaghegh et al., 1996; Aminzadeh et al., 1999; Aminian et al., 2001; Tahmasebi and Hezarkhani, 2012). One of the drawbacks of ANN application was that they require the structure of the network to be identified. (Hagan and Menhaj, 1994). In order to mitigate these deficiencies, automatic designs of neural networks by optimization algorithms, such as genetic algorithm (GA) in permeability prediction have been proposed by some investigators (Saemi et al., 2007, 2008; Kaydani and Mohebbi, 2013). Kaydani et al. (2011) proposed a method, which design of topology and parameters of the neural networks as decision variables was done by using genetic algorithms. Moreover, they shows that permeability prediction based on designing separate networks for each zone is more accurately than designing single network design for all of zones. Also, fuzzy logic modeling has been applied successfully in permeability prediction of porous media (Ilkhchi et al., 2006; Abdullraheem et al., 2007; Kaydani et al., 2012). One example for using this technique in permeability prediction was

* Corresponding author. Tel./fax: +98 3412118298.
E-mail addresses: amohebbi2002@yahoo.com, amohebbi@uk.ac.ir (A. Mohebbi).

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the work done by Gedeon et al. (1997). They incorporated fuzzy IF-THEN rules into neural networks to interpolate the reservoir properties.

Despite all of the advantages of mentioned methods such as ANNs, fuzzy logic and so on, most of them suffer from not using a priori knowledge or other sources of data efficiently and some others suffer from structure dependency, which affect their output results. Furthermore, the previous models when encountering with very large dataset are slow and CPU demanding process and they miss their accuracy when a few data are available (Tahmasebi and Hezarkhani, 2012). Moreover, they do not usually give a definite function to calculate the permeability using the input values. This approach is mostly appropriate to be used as a part of petroleum software.

The aim of this study was to propose a new approach based on multi-gene genetic programming (MGGP) for estimation of permeability in porous media. The ability of MGGP to encounter with complex problems, high learning capacity and flexibility causes this algorithm can be used in most of the engineering applications. Contrary to artificial neural networks and many other soft computing tools, the MGGP enable to produce practical prediction equations, which searches a program space instead of a data space. The main advantage of the MGGP based approaches is their ability to generate prediction equations without assuming prior for of the relationship (Gandomi and Alavi, 2012a, 2012b). Therefore, one equation for permeability prediction using MGGP was generated based on well log and core experimental data in one of oil reservoirs in Iran. Finally, the performance of this model was compared among different soft computing methods.

2. Multi-gene genetic programming

Genetic programming (GP) is an evolutionary computation technique that has been successfully applied for modeling of a relatively simple or complex system in all aspects of engineering (Guven and Gunal, 2008; Alavi and Gandomi, 2011; Azamathulla and Ghani, 2010, 2011). Unlike common optimization methods such as genetic algorithm, in which potential solutions are represented as numbers, genetic programming represents the potential solutions by structural based on so-called tree representation. Each of genes in GP consisting of functions (F) and terminals (T). The set of operator's F can contain the basic arithmetic operations; whereas the terminal's T contains input variables and constants of the problem. Potential solutions may be demonstrated as a rooted, labeled tree with ordered branches, using operations from the function set and arguments from the terminal set. The population of candidate solutions is modified iteratively, each iteration involving the application of some genetic operators (such as selection, crossover and mutation) in the hope of evolving new, improved candidates (Koza, 1992).

Multi-Gene Genetic Programming (MGGP) (Searson et al., 2007, 2010) is a robust variant of GP, which effectively combines the model structure selection ability of the standard GP with the parameter estimation power of classical regression. Instead of the complex rules and mathematical routines, the MGGP is able to learn the key information patterns within the multidimensional information domain with high speed. Recently, the MGGP have been used successfully for engineering modeling problems (Gandomi and Alavi, 2012a, 2012b). It has been shown that MGGP regression can be more accurate and efficient than the standard GP for modeling nonlinear problems (Gandomi and Alavi, 2012a, 2012b).

MGGP generates mathematical models of set of data by linear combinations of low order non-linear transformations of the input–output variables. Contrary to the traditional GP, which is based on the evaluation of a single tree (model) expression, each symbolic model in MGGP is a weighted linear combination of the outputs from a number of GP trees. Each of these trees may be considered to be a "gene", which each of them is a traditional GP tree. Genes are acquired incrementally by individuals in order to improve fitness (e.g. to reduce a model's root mean squared errors in a data set). The overall model is a weighted linear combination of each gene, as typically shown in Fig. 1. For each model, these coefficients are derived from the training data using ordinary least squares methods. In practice, the maximum allowable number of genes for a model (G_{max}) and the maximum tree depth (D_{max}) any gene may be specified by the user. A remarkable control can be exerted over the maximum complexity of the models evolved by MGGP in comparison with the standard GP (Searson et al., 2007, 2010).

The initial population in MGGP is constructed by creating individuals containing GP trees with different genes (between 1 and G_{max}) generated at random. In addition to the traditional GP recombination operators, during the MGGP training, genes are acquired and deleted using a tree crossover operator called two-point high-level crossover that allows the exchange of genes between individuals (Gandomi and Alavi, 2012a, 2012b). More explanation about MGGP is available in literatures (Searson et al., 2007, 2010).

3. Case study

3.1. Data acquisition and analysis

The prototype reservoir is located in an oil field in the south-west of Iran. With the data acquired, the reservoir can be classified

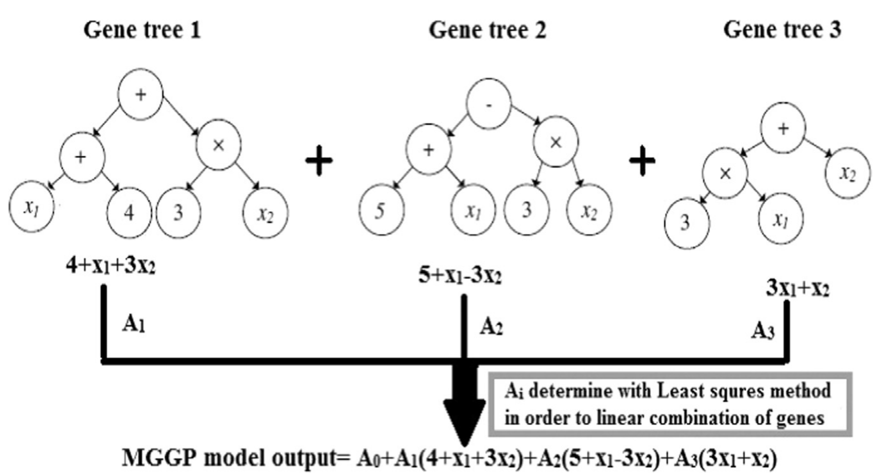

Fig. 1. The MGGP model output formulation with inputs (X_1, X_2).