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# Development a new mathematical model to estimation fracture gradient using genetic algorithms and with Gene Expression Programming approach in one of the fields in Persian Gulf

**Ahmad Ganji[1], Ezzatalah Kazemzadehe[2] and Hamed Nazari[1]**

1. Department of Petroleum and Gas Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

2. Department of Research and Development Department of Upstream Petroleum Industry, Research Institute of Petroleum Industry (RIPI), Tehran, Iran

**kazemzadehe@ripi.ir**

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## INTRODUCTION

Estimation of pore pressure and fracture pressure gradient are necessary for a successful and safe well design. During over balance drilling operation mud weight should keep between pore pressure and fracture pressure, upper than pore and lesser than fracture. This pressure interval is called mud window. Fracture pressure gradient is upper limit of downhole pressure while drilling. Accurate knowledge of fracture gradient plays a major role in the selection of casing point which is critical in drilling of an oilwell. There are two methods for estimation of fracture gradient; direct and indirect. The direct method estimate fracture gradient with using of Leak-off test (LOT) data. On the other hand the indirect method is based on analyzing of well logging / drilling data and developing a mathematical correlation with using these data [1, 2, and 3].

During years many studies have done for developing a general method for prediction of fracture gradient. Hubbert and Willis who are pioneer of these studies claimed for developing a fracture in wellbore should pressure exerted on formation be upper than minimum principle stress (assumed overburden in max principle stress) [4]. Matthews and Kelly published a fracture gradient relationship with overburden gradient equal with 1 psi/ft [5]. Eaton reviewed the works of Mathews and Kelly, and Hubbert and Willis. He assumed overburden pressure and poisson ratio are depth-dependent [6]. Anderson et al., developed a model based on Biot's stress/strain relationships for an elastic porous media [7]. Sadiq and Nashawi, suggested a method using neural networks for estimation the fracturegradient [8]. Halomoan et al.

presented a new method to predict fracture gradient by correcting Matthew and Kelly and Eaton's correlations [9].

## ARTIFICIAL INTELLIGENCE AND GENE EXPRESSION PROGRAMMING (GEP)

In recent years artificial intelligence (AI) has had a rapid evolution. Improving in mathematical algorithm and computer pressing helped to developing of AI of all engineering sciences. One application of artificial intelligence is finding a solution to very complex and nonlinear problems. AI has several sub-sets which Evolutionary Algorithm (EA) is one of them. EA inspires biological evolutionary for solving a problem. EA itself has several sub-se which all are based on biological evolutionary. Genetic algorithm (GA), Genetic programing (GP) and Gene Expression Programming (GEP) are belonging to a same family of EA, but nature of its answers is different [10, 11]. GEP developed by Ferrera in 2001 for overcoming of limitation of GA and GP. Main steps of GEP have shown schematically in followed fig 1 [12, 13].

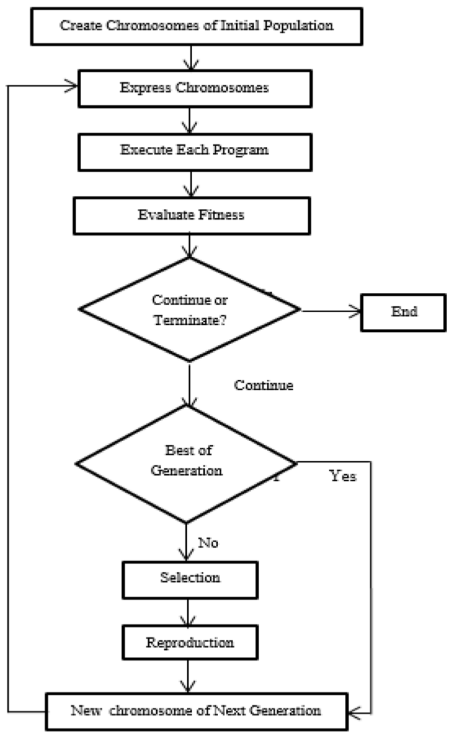


**Figure 1: GEP algorithm steps**

## STUDY METHOD

The information used in this study is from a field located in the Persian Gulf. The data obtained from two directional wells drilled in Kangan and upper Dalan formations (here well named A and B). Used data originate from well loggign and final drilling reports. Raw data needed to some modification for wellbore environmental effects. This modification did with Geolog® software. Corrected data used for calcualtion of fracture pressure gradient based on Eton's model. Data from well A inputs into a GEP software package to developing a model for prediction of fracture gradient for each formation separately. All well A data was 4300 that 75% of data used for training and 25% remained for testing. Fig (2) to (5) show results of trainaing and testing for Kangan and Upper Dalan. Statistcial analysis of each formation in training and testing show in table (1).

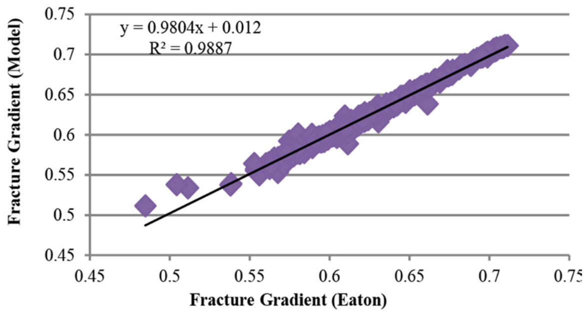


**Figure 2: Training data for the Kangan Formation**

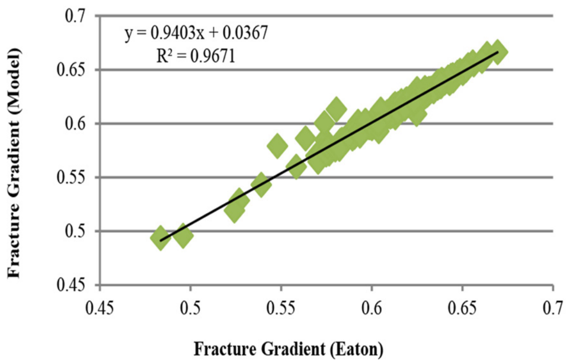


**Figure 3: Testing data for the Kangan Formation**

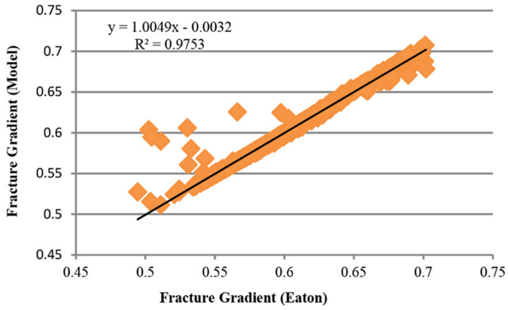


**Figure 4: Training data for the upper Dalan Formation**

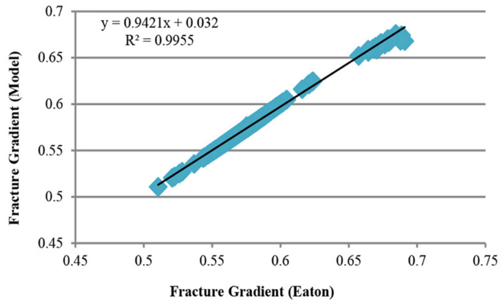


**Figure 5: Testing data for the upper Dalan Formation**

**Table 1: Statistical analysis of training and testing in the well A to predict the fracture gradient**

| Formation | $R^2$ | | RMSE | |
|---|---|---|---|---|
| Kangan | Training | Test-ing | Train-ing | Testing |
| | o.988 | 0.967 | 0.003 | 0.004 |
| upper Dalan | 0.975 | 0.995 | 0.005 | 0.002 |

Developed model from Well A for each formation:

Model of the Kangan formation (Eq. (1)):

$$G_f = \left(\frac{P_p^{4/3}}{\sigma_{ob}^2\left(\mu+\sigma_{ob}\right)}\right) + \left[\exp\left(-7/798\times\mu^{1/3}\right)\times\left(\sqrt{\mu}+\left(\sigma_{ob}+P_p\right)\right)\right]$$

$$-\left(\sigma_{ob}^3\times\left(P_p-\sigma_{ob}\right)^3\right)^3 + \mu \qquad (1)$$

Model upper Dalan formation (Eq. (2)):

$$G_f = \mu + \frac{\mu^2\times\left(\sigma_{ob}-\mu\right)}{\sigma_{ob}} + \sqrt{\left(\mu^3+6.09\right)\times\left(\sigma_{ob}\times P_p\right)} -$$

$$\left(\log\left(\sigma_{ob}\sqrt{P_p}\right)+1.66\times\sigma_{ob}\times\mu\right) \qquad (2)$$

## VERIFICATION OF THE MODELS

Developed models verified with using of 6000 data from well B. Figs. (6) and (7) show result of the models with using data from well B in compare with Eton's model.

In Kangan formation statistical parameters of difference between the mathematical models and Eton's model are R=0.898, RMSE=0.104 and std=0.037 and for Upper Dalan are and R=0.972, RMSE =0.107 and std =0.037.

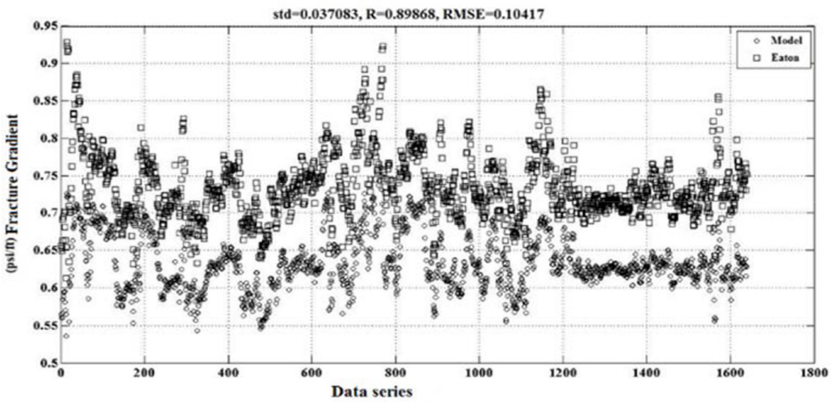


**Figure 6: Validation of the mathematical model of the Kangan formation using well B**

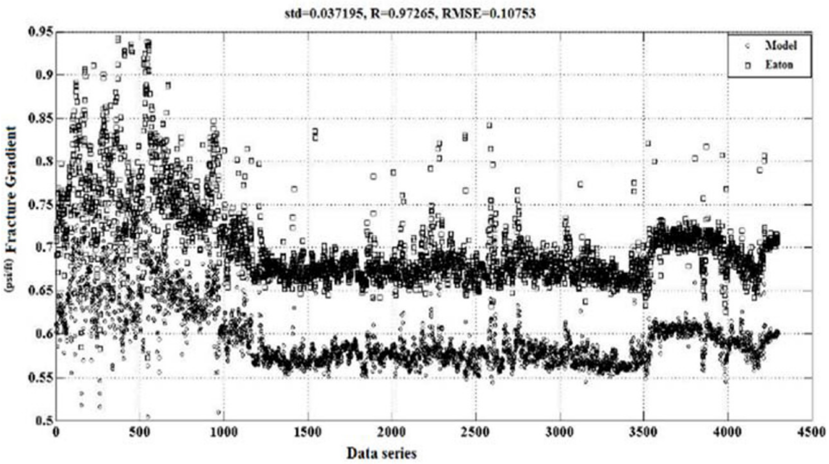


**Figure 7: Validation of the mathematical model of the upper Dalan formation using well B**

## CONCLUSION

1. With using the GEP method, determination coefficient in Kangan formation for train and test are 0.988 and 0.967, respectively, and 0.975 and 0.995 for the upper Dalan.

2. Verification did with using well B data in compare with Eton. Statistical analysis shows excellent results.

3. The results of this research can be used to plan and design oil and gas wells with the aim of field development.

4. In this study used new method (GEP) to predicting of fracture gradient with successfully so this method use in other area of oil and gas upstream industry.

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