International Journal of Engineering
Journal Homepage: www.ije.ir

RESEARCH NOTE

Optimization of Cement Spacer Rheology Model Using Genetic Algorithm

S. Tabatabaee Moradi *, N.I. Nikolaev

Department of Wel Drilling, National Mineral Resources University (Mining University), Saint Petersburg, Russia

PAPER INFO

Paper history:
Received 11 October 2015
Received in revised form 24 December 2015
Accepted 10 January 2016

Keywords:
Cement Spacer
Genetic Algorithm
Rheology
High-Pressure
High-Temperature

ABSTRACT

The primary job of cement is a critical step in successful well completion. To achieve effective cementing job, complete mud removal from the annular space is recommended. Spacer and flushers are used widely to achieve this goal. This study is about weighted cement spacer systems containing a surfactant package, weighting agent and rheological modifiers. Weighted spacer systems are utilized when a high formation fluid pressure is expected inside the wellbore. A testing program is conducted in laboratory to determine the spacer fluid rheological properties at different temperatures. The measured rheological properties are estimated using the known rheological models. Each model is firstly optimized using genetic algorithm as an optimization tool and then the rheological properties are modeled. The performance of the genetic algorithm is then tested by comparing the real laboratory data and modeled data. The results show that the polymer based spacer systems are better described using Herschel Bulkley Model. Also, it is concluded that the genetic algorithm with a good formulation can be used as an effective optimization tool to predict the rheological properties of the spacer systems.

doi*: 10.5829/idosi.ije.2016.29.01a.17*

1. INTRODUCTION

Cementing a wellbore is a major stage in well completion and an initiation for production operations. An effective cementing job will reduce the future costs of work over operations. One of the primary objectives of the cementing operations is zonal isolation. For effective zonal isolation and optimum hydrocarbon production during the life of the well, the entire drilling fluid in the annular space should be removed. Over the years, several practices have been employed to help achieve mud removal and successful zonal isolation [1]:

- Conditioning the drilling fluid, chemically and physically.
- Using spacer and flushes capable of mud removal.
- Optimizing cement-slurry viscosity to maximize displacement and safe circulating pressures.
- Centralization of the pipe.
- Pipe movement: reciprocation, rotation, or both.
- Adjusting fluid displacement rates to provide optimum displacement efficiency.
- Using proper cementing systems.

From industry practices, efficient mud removal can be achieved, using spacers and flushes before cement is placed [2]. Except mud removal, spacers serve various other functions, including avoiding formation of drilling fluid and cement mixture and removal of gelled mud developed on the formation walls. A weighted spacer may contain a suitable surfactant package, a weighting agent to adjust the spacer's density and a rheological modification agent [3]. The proportions of these components in a spacer system will control the rheological properties of the final mixture, and thus, performance of the spacer. The weighted spacer systems are usually utilized in high-pressure, high-temperature (HPHT) conditions, where high formation fluid pressures (usually larger than 69 MPa) are expected and serious problems of sedimentation can occur in the case of low rheological properties of the systems. HPHT conditions exist in deep or thermal wells. Also, these conditions can be expected in shadow depths, where abnormally formation fluid pressure or temperature can be observed.

The spacer design can be changed based on different conditions including the geological condition of the well; however, it should be designed for a specific

*Corresponding Author's Email: *s.sh.tabatabaaee@gmail.com* (S.Tabatabae Moradi)

density, mud system, cement system and rheology. The efficiency of a spacer system is largely dependent on the rheological properties of both the fluid being displaced and the spacer itself, which emphasizes the importance of accurately modeling of rheological properties [4]. In this work rheological properties, i.e. shear stress versus shear rate of a spacer system have been measured at different temperatures (100, 140 and 190°F). The spacer is a weighted spacer, which is specially designed to meet the existing geological conditions of the well. Then, two rheological models, which are already optimized by genetic algorithm, are applied to predict the rheological parameters of the system. Genetic algorithm (GA) acts as a population search algorithm which is based on the principle of natural evolution ”survival of the fittest” presented by Charles Darwin. Over the last years, GAs have received more attention because of their potential application as optimization techniques for complex problems. Many researchers, including Romero et al. [5] have described the application of GA in hydrocarbon reservoir characterization. Gallagher and Sambridge [6] presented an excellent overview on the use of GAs in seismology. A new approach for modelling the dynamic process of Fluid flow in porous media is presented in the work of Yu and Lee [7]. The paper of Tupac et al. [8] presents a genetic algorithm application for selecting the best alternatives for oil field development.

However, this paper describes the implementation of a designed genetic algorithm to carry out spacer's rheological properties characterization.

2. MATERIALS AND METHODOLOGY

2. 1. Rheological Models and Designed Spacers

For accurate evaluation of fluid displacement, it is necessary to know the rheological behavior of the fluids [9]. Rheological measurements normally consist of imposing a strain and measuring a stress, or imposing a stress and measuring strain. Viscometers and rheometers are used to measure the rheological properties. In this work rheological measurements were carried out using RHEOTEST RN 4 rheometer on a specially designed weighted spacer system. The spacer is formulated as a water-based system, which contains hematite to adjust spacer density and surfactant to increase its cleaning ability. To control the rheological parameters, carboxyl methylcellulose (CMC) polymer is added to the system. CMC is an effective additive, which has a wide range of applications. In this work a high viscosity CMC is used to provide the sedimentation stability of the system. The detailed composition of the designed spacer is presented in Table 1. The spacer samples were prepared in accordance with standard procedures. Firstly, CMC has been solved in the water. Afterward the other additives have been added to the mixture.

TABLE 1. Composition of spacer

Composition of spacer	
Material	**Mass fraction (%)**
hematite	28-40
CMC	0.3-0.6
surfactant	0.5-1
water	60-70
Spacer density (g/cm^3)	
1.6-2	

Then, the prepared fluid was mixed for 3 min at a speed of 1500 rev./min. The rheological properties of the spacer fluid have been measured at different temperatures.

To mathematically model the measured rheological properties of the designed spacer two of the most common rheological models, Bingham plastic and Herschel Bulkley models are used (Equations 1 and 2). The given models should be optimized firstly by genetic algorithm.

Bingham plastic model:

$$\tau = YP + PV(\gamma) \tag{1}$$

where τ is the shear stress (Pa), γ shear rate (1/s), *YP* the yiled point of the fluid (Pa) and *PV* the plastic viscosity (Pa.s). Bingham plastic fluids exhibit a linear relationship between the shear stress and shear rate after an initial stress value (YP) has been reached.

Herschel Bulkley model:

$$\tau = \tau_0 + K(\gamma)^n \tag{2}$$

where τ is the shear stress (Pa), γ shear rate (1/s), τ_0 yield stress (Pa), *K* the consistency index and n the flow index. The Herschel Bulkley model can be described as a generalized model of non-Newtonian fluids, in which stress-strain relationship is characterized by three parameters.

2. 2. Genetic Algorithm

To use the proposed rheological models, firstly the constant parameters of two equations i.e. YP, PV, τ_0, K and n have been optimized using GA. Genetic algorithms were first presented in John Holland's book ”adoption in natural and artificial systems” [10]. GA is a random search technique, which abstracts the Darwin principle in natural evolution of biological organisms, into algorithms that may be used to find the optimal solution to a specific problem. The main difference between this algorithm and old traditional search algorithms is that it is a population-based algorithm, which means that it works with a group of candidate solutions while traditional search algorithms pick one solution from the search space at a time to find the optimal solution. GA also combines the solutions in a population to get the better solutions [11-13]. GA starts with an initial population of possible solutions to the problem being addressed. Solutions are then selected from the population according to a stochastic process that rewards to the solutions with better performance, and their genetic information is recombined and modified following genetic operators to form a new population. The process is repeated until a convergence is detected, or a specified maximum number of function evaluations or a generation is reached.

The optimization tool module of the MATLAB® computing language has been used in this work for genetic algorithm formulation. To start optimizing, the constant parameters of Equations 1 and 2 are binary encoded to one chromosome containing five sections (genes) each corresponding to one constant parameter of the models [5]. Then, the following steps are proceeded:

a) An initial population of chromosomes (solutions) is generated randomly, covering the entire search space. To this end, a creation function with uniform distribution has been used. The population size (N) is estimated by following formula (Equation (3)) [14]:

$$N \geq -2^{K-1} \ln(\alpha)\,(\sigma_{fitness}/d) \tag{3}$$

In which K is the minimum number of binary digits necessary to show each gene. For most problems its value is between 1 and 5, α the expected failing probability which should be less than 5%, $\sigma_{fitness}$ the standard deviation of the fitness of a set of chromosomes and d the expected fitness score difference between chromosomes. By selecting appropriate values of above parameters, N roughly lies between 50 and 400.

b) The fitness of each chromosome (how appropriate the solution is) is evaluated using a fitness function, which is defined by the programmer and is specific to the problem being solved. The fitness function has been defined in a root mean square sense as (Equation (4)):

$$fitness\ score = \sqrt{\textstyle\sum_1^n (\tau_r - \tau_m)^2/n} \tag{4}$$

In which n equals to the number of data points measured by rheometer, τ_r the measured shear stress and τ_m modeled shear stress. GA will find the parameters of the equations such that the fitness score become minimized. At the end of this step, each individual has a value corresponding to its fitness. If the average fitness of the population satisfies the convergence condition, the fittest solution in the population is picked up as the solution; nevertheless the following steps are taken.

c) Parent chromosomes are selected randomly from the initial population according to their fitness value to form a mating pool. After parents are selected, they undergo GA's operations like cross over and mutation to create offspring for new generation. There are many selection methods including roulette wheel selection, random selection, rank selection, tournament selection, Boltzmann selection and stochastic universal sampling. In this work the roulette wheel selection method is used with top 10% of each generation is passed to next generation without change.

After the offspring are generated, they replace the individuals in the old population. If the convergence or end condition is observed the searching process will be stopped and the best solution in the current population is returned as the optimum solution, otherwise the process is repeated from step (b) as a loop. Some of these end conditions are as follows:

- Maximum generation: the GA process stops when a specified number of generations are produced.
- Elapsed time: the GA process stops when a specified time is elapsed.
- Stall generation: if there is no change in the fitness functions of n successive generation the GA will stop. The value of n equals to stall generation.

2. 3. Result of GA Formulation

Different formulations of genetic algorithm are considered in this work. Three best formulations are presented in Table 2. The formulation a has been applied to optimize the parameters of the rheological models as it has the smallest fitness score value (2.451) among the other formulations.

At the end of this step, our rheological models are optimized. So the value of the constant parameters are known and the rheological models can be used in the spacer's rheological properties characterization, which is the overall contribution of this work. The GA optimized rheological models have been applied to precisely predict the spacer's rheological properties, which play a crucial role in the drilling fluid displacement process.

TABLE 2. Properties of designed GA

Formulation of GA	a	b	c
Population size	200	50	350
Selection method	Roulette wheel	Roulette wheel	Roulette wheel
Crossover strategy	Two point	Single point	Intermediate
Mutation function	Uniform (P_m=0.01)	Uniform (P_m=0.01)	Uniform (P_m=0.01)
Stopping criteria	Stall generation	Stall generation	Stall generation

3. DISCUSSION

In this work genetic algorithm, which is a powerful search and optimization method, is used to optimize two common rheological models. GA seems to be a good way for solving problems where normal algorithms are too slow or fall in the local solutions. It should be noted that genetic algorithms are not a solution for every kind of optimization problem. They give the best result if they are properly applied into the appropriate problem. The performance of the GA is significantly affected by population size, selection strategy, cross over strategy and encoding method. Designed genetic algorithm finds the constant parameters of the proposed rheological models (Bingham plastic and Herschel Bulkley model).

Figures 1 to 3 show the GA optimized rheological models and the measured shear stress of the designed spacer at different temperatures. As shown in the figures, the Herschel Bulkley model performance is far better than the Bingham plastic model, especially in the lower amounts of shear rates. The Bingham plastic model overestimates the yield points of the spacer systems.

The average coefficient of determination (R^2) for Herschel Bulkley model is 0.97, while Bingham plastic model has a coefficient of 0.75. The coefficient of determination is a statistical parameter, which shows the agreement between the real and modeled data.

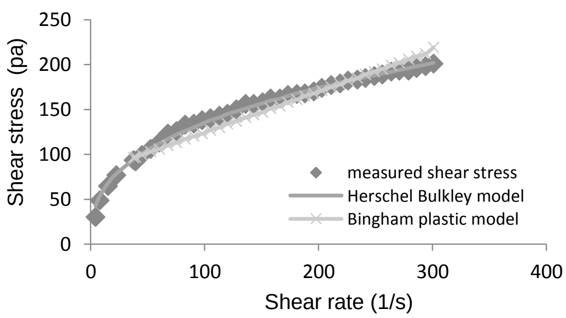

Figure 1. Spacer rheological properties at 100°F

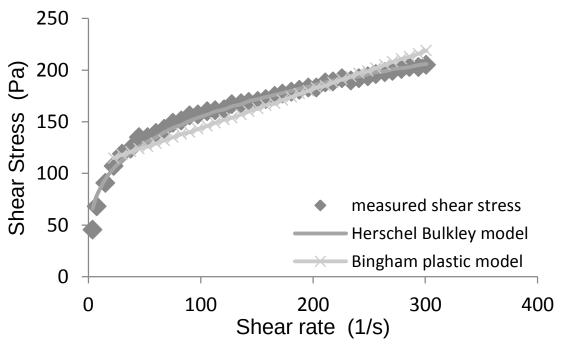

Figure 2. Spacer rheological properties at 140° F

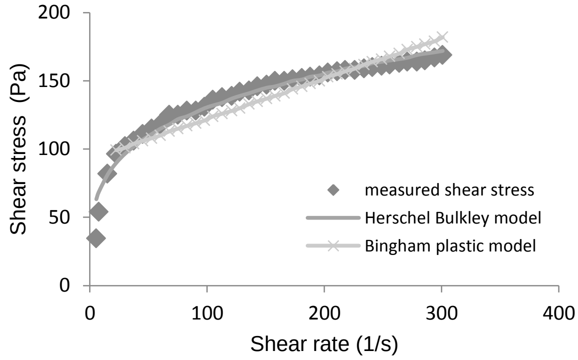

Figure 3. Spacer rheological properties at 190°F

4. CONCLUSION

The following conclusions can be made according to the results of this work:

- The polymer based spacer systems of this study are better described using Herschel Bulkley Model. As this model gives more accurate prediction of the spacer rheological behavior at different temperatures, compared to Bingham plastic model.
- Polymer based weighted spacer systems, containing CMC show reliable performance at elevated temperatures.
- The genetic algorithm as a search algorithm, finds the parameters of each model far better than the old traditional technique, however the design of the GA play a critical role in its performance.
- The reliability of optimized rheological model depends on the knowledge of uncertainty, which implies the validity of the specified models.

5. REFERENCES

1. Crook, R.J., Benge, G., Faul, R. and Jones, R.R., "Eight steps ensure successful cement jobs", ***Oil & Gas Journal***, Vol. 99, No. 27, (2001), 37-43.
2. Olowolagba, K.O. and Yerubandi, K.B., "Improved spacer rheology model for cement operations", in SPE Production and Operations Symposium, Society of Petroleum Engineers., (2011).
3. Brandl, A., Bray, S., Magelky, C., Lant, K., Martin, R. and St-Clergy, J., "An innovative cement spacer with biodegradable components effectively sealing severe lost circulation zones", in Offshore Mediterranean Conference and Exhibition, Offshore Mediterranean Conference., (2011).
4. Gordon, C., Lewis, S. and Tonmukayakul, P., "Rheological properties of cement spacer: Mixture effects", ***Paper AADE***, (2008).
5. Romero, C., Carter, J., Gringarten, A. and Zimmerman, R., "A modified genetic algorithm for reservoir characterisation", in International Oil and Gas Conference and Exhibition in China, Society of Petroleum Engineers., (2000).

6. Gallagher, K. and Sambridge, M., "Genetic algorithms: A powerful tool for large-scale nonlinear optimization problems", ***Computers & Geosciences***, Vol. 20, No. 7, (1994), 1229-1236.
7. Yu, T. and Lee, S., "Evolving cellular automata to model fluid flow in porous media", in Evolvable Hardware. Proceedings. NASA/DoD Conference on, IEEE., (2002), 210-217.
8. Túpac, Y.J., Vellasco, M.M.B. and Pacheco, M.A.C., "Selection of alternatives for oil field development by genetic algorithms", ***Revista de Engenharia Térmica***, Vol. 1, No. 2, (2002).
9. Becker, T., Morgan, R., Chin, W. and Griffith, J., "Improved rheology model and hydraulics analysis for tomorrow's wellbore fluid applications", in SPE Production and Operations Symposium, Society of Petroleum Engineers., (2003).
10. Holland, J.H., "Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence, MIT press, (1992).
11. Golberg, D.E., "Genetic algorithms in search, optimization, and machine learning", ***Addion Wesley***, (1989).
12. Mahdizadeh, M. and Eftekhari, M., "Proposing a novel cost sensitive imbalanced classification method based on hybrid of new fuzzy cost assigning approaches, fuzzy clustering and evolutionary algorithms", ***International Journal of Engineering-Transactions B: Applications***, Vol. 28, No. 8, (2015), 1160-1168.
13. Mahmoudzadeh, S., Mojallali, H. and Pourjafari, N., "An optimized pid for capsubots using modified chaotic genetic algorithm (research note)", ***International Journal of Engineering-Transactions C: Aspects***, Vol. 27, No. 9, (2014), 1377-1384.
14. Harik, G., Cantu-Paz, E., Goldberg, D.E. and Miller, B.L., "The gambler's ruin problem, genetic algorithms, and the sizing of populations", ***Evolutionary Computation***, Vol. 7, No. 3, (1999), 231-253.

Optimization of Cement Spacer Rheology Model Using Genetic Algorithm

RESEARCH NOTE

S. Tabatabaee Moradi, N.I. Nikolaev

Department of Wel Drilling, National Mineral Resources University (Mining University), Saint Petersburg, Russia

P A P E R I N F O

Paper history:
Received 11 October 2015
Received in revised form 24 December 2015
Accepted 10 January 2016

Keywords:
Cement Spacer
Genetic Algorithm
Rheology
High-Pressure
High-Temperature

چکیده

عملیات سیمان کاری اولیه یک مرحله اساسی در تکمیل موفقیت آمیز چاه به شمار می رود. دست‌یابی به عملیات موثر سیمان کاری نیازمند تخلیه کامل فضای حلقوی از گل حفاری می‌باشد. سیالات جداساز به طور گسترده‌ای برای رسیدن به این هدف مورد استفاده قرار می‌گیرند. این پژوهش درباره سیستم‌های جداساز با چگالی بالا می‌باشد که از یک بسته فعال سطحی، عوامل وزنی و عوامل بهبود دهنده خواص رئولوژیکی تشکیل شده‌اند. این سیالات در شرایطی به کار می‌روند که در درون چاه فشار بالای سیال سازندی قابل انتظار باشد. در این پژوهش یک برنامه آزمایشگاهی بر روی سیال جداساز به منظور بررسی خواص رئولوژیکی آن در دماهای مختلف انجام گردیده است. خواص رئولوژیکی اندازه‌گیری شده به وسیله مدل‌های رئولوژیکی شناخته شده تخمین زده می‌شوند. هر کدام از این مدل‌ها ابتدا به وسیله ابزار بهینه سازی kالگوریتم ژنتیک بهینه شده و سپس در تخمین خواص رئولوژیکی به کار می‌روند. عملکرد الگوریتم ژنتیک از طریق مقایسه داده‌های آزمایشگاهی و داده‌های تخمین زده شده مورد ارزیابی قرار می‌شوند. نتایج نشان می‌دهند که سیستم های جداساز بر پایه پلیمر به وسیله مدل هرشل ـ بالکلی بهتر توصیف می‌شوند. در ضمن، الگوریتم ژنتیک می‌تواند به عنوان یک ابزار موثر بهینه سازی در جهت پیش بینی خواص رئولوژیکی سیستم‌های جداساز استفاده گردد.

doi*: 10.5829/idosi.ije.2016.29.01a.17*