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Computational Analysis on the Selection of High Efficient Biodegradable-Polymer-Based Nanofluids for Drilling Mud

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Abstract
Proper and optimal selection of processing conditions in the production of nanofluids for drilling muds is critical. In this study, grey relational analysis (GRA) was employed as the computation analysis assisted by mathematical and graphical modeling to determine some optimal processing parameters to produce highly efficient biodegradable-polymer-based nanofluids for drilling muds. The multiple performance characteristics analyzed are consistency index (K), flow behavior index (n), yield point (YP), and plastic viscosity (YP). The obtained results revealed that 0.6 wt% starch, 1 wt% nanoparticles and 45 min. ultrasonic time are the optimal settings to be considered in the production of highly efficient nanofluids for drilling muds. The graphical modeling and ANOVA results also revealed that the experimental setups were influenced by some significant and unconsidered external factors in drilling fluids formulation. It is recommended that deeper study should be conducted to identify and employ some other unconsidered factors that may be responsible on the performance of drilling muds.

Keywords: Grey Relational Analysis, Drilling Muds, Rheological Properties, Optimization Modeling, ANOVA

Introduction
Drilling mud/fluid in drilling is an indispensable material in the recovery of underground minerals [1,2]. Originally, drilling fluid was being used to transport and remove rubbles from the front of drilling bit, but technology has made it in addition to its original use become useful in the suspension of cuttings and prevention of the cuttings to settle. Cutting fluids of course are used as coolants for drilling pipes and bit. It is used to mitigate friction between drilling equipment and drilling formation. It is used to stabilize wellbore and to avoid formation from being collapsed [3,4]. In oil well drilling, the cost of drilling mud is very high, hence it is important to minimize drilling mud cost and to produce a mud with high drilling efficiency and sustainable properties for continuous operation [5-7].

Drilling muds are producing from some materials with properties integral in drilling operation efficiency [8-10]. Additives in drilling muds are employed to enhance the quality and performance efficiency of the drilling muds, mitigating some underground pollutions on the landfills and the environment [11]. Hence, a proper production of drilling muds with better performance efficiency with lesser cost is essential. Several studies have been made in the production of drilling muds. Many of the researches are as follows: Salehnezhad et al employed response surface methodology (RSM) to investigate the rheological characteristics of water-based drilling muds when starch and ZnO nanoparticles are added [2]. Bayat & Shams investigated the effect of some different nanoparticles on shale inhibition and rheological properties of water-based drilling muds [12]. Pakdaman et al employed hydrophilic Gilsonite nanoparticles to improve the lubricity, rheology and differential sticking properties of water-based drilling muds at elevated temperature [13]. Hamad et al employed amphoteric polymer to improve the rheological properties and minimize the fluid loss of water-based drilling muds at high temperature [14]. Sulaimon et al improved drilling muds by adding starch for high-pressure high-temperature (HPHT) [15].

Mahmoud et al added ferric oxide nanoparticles to calcium bentonite-based drilling muds to improve the properties of filter cake formed in drilling muds [16]. In spite of these extensive studies, a challenge of selection of an optimum production conditions for better multiple performance characteristics is common as more than one performance characteristic is required for high quality and efficient drilling operation. It is not blurred that several optimization techniques only solve a problem of optimization of a singular performance characteristic, such as Taguchi design technique, response surface methodology (RSM), etc. However, Grey relational analysis (GRA) has been proven to be effective in singularizing as many performance characteristics as possible for multi-objective optimization [17-23]. Hence, in this study, RSM is assisted by GRA to conduct multi-objective optimization analysis on consistency index (K), flow behavior index (n), yield point (YP), and plastic viscosity (PV) of water-based drilling muds.

Data Curation

This study employed data from the work of Salehnezhad et al [2]. The RSM design model corresponding to the respective responses of different formulated drilling muds is shown in Table 1. The multiple performance characteristics analyzed on the water-based drilling muds are consistency index (K), flow behavior index (n), yield point (YP), and plastic viscosity (PV). Please see the work of Salehnezhad et al for-drilling fluids formulation [2].

Table 1: Experimental Design Model and Data

Exp./No	Starch (wt%)	Nanoparticles (wt%)	Ultrasonic time (mins)	K (mPa.s)	N (unitless)	YP (mPa)	PV (mPa.s)
1	0.4	0.8	30	34.33	0.51	50.32	3.93
2	1	0.6	45	45.56	0.5	55.51	4.09
3	0.6	1	45	43.71	0.48	61.34	4.51
4	0.4	0.4	60	35.5	0.63	35.3	3.11
5	0.8	0.4	30	22.45	0.6	40.42	3.27
6	0.6	0.6	15	30.78	0.54	42.71	3.83
7	0.8	0.4	60	26.25	0.59	41.45	3.22
8	0.6	0.2	45	12.95	0.67	25.43	2.43
9	0.4	0.8	60	34.01	0.5	52.69	3.65
10	0.4	0.4	30	12.94	0.5	22.18	3.01
11	0.8	0.8	30	41.23	0.61	43.39	4.12
12	0.2	0.6	45	35.39	0.61	43.28	3.34
13	0.6	0.6	75	43.49	0.49	57.03	3.94
14	0.8	0.8	60	34.18	0.49	48.7	3.98
15	0.6	0.6	45	12.9	0.51	23.41	4.15
16	0.6	0.6	45	11.61	0.68	20.7	2.99
17	0.6	0.6	45	11.6	0.7	22.02	2.93

Computational Analysis

The four performance characteristics were analyzed for multiple performance optimization. GRA method was employed as the computational analysis but assisted my mathematical and graphical modeling. Consistency index, flow behavior index, and yield point were normalized using the higher-the-better consideration, which is shown in Equation 1. Consistency index is direct indicator of relative shear strength in a composite fluid. As it is increased the shear strength increases and the fluid becomes more stable, hence as much as possible consistency index is required in the formulation of high efficient drilling mud [24,25]. Flow behavior index is the degree of non-Newtonian characteristics of a fluid. It is a desirable property in drilling fluids [26]. Yield point shows the capacity of a drilling mud to lift or remove the cutting out of the annulus. When a drilling fluid has a higher yield point, it will have better cuttings carrying capacity compared to the one with a lower yield point [27]. The normalized data is shown in Table 2

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{max\ y_i(k) - \min y_i(k)} \tag{1}$$

However, as low as possible value is desired for the fourth performance characteristic in this study, which is plastic viscosity. When the plastic viscosity is low, drilling mud will the higher capability to drill [28,29]. Hence, to normalize the plastic viscosity data, Equation 2 is used as smaller-the-better consideration. Table 2 presents the normalized data.

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{max\ y_i(k) - \min y_i(k)} \tag{2}$$

x_i (k) is the normalized data for the ith experimental number, while y_i (k) is the actual experimental data.

Deviation sequence was then computed as shown in Equation 3. The deviation sequence data is presented in Table 2 also.

$\Delta_{oi}(k)=\|x_o(k)- x_i(k)\|$ (3)

Δ_{oi} (k) and x_o (k) represent deviation and reference data, respectively.

Table 2: Normalized and deviation data

Data normalization					Deviation data			
No	**K**	**n**	**YP**	**PV**	**K**	**n**	**YP**	**PV**
1	0.66932	0.13636	0.72884	0.27885	0.33068	0.86364	0.27116	0.72115
2	1	0.09091	0.85655	0.20192	0	0.90909	0.14345	0.79808
3	0.94552	0	1	0	0.05448	1	0	1
4	0.70377	0.68182	0.35925	0.67308	0.29623	0.31818	0.64075	0.32692
5	0.31949	0.54545	0.48524	0.59615	0.68051	0.45455	0.51476	0.40385
6	0.56478	0.27273	0.54158	0.32692	0.43522	0.72727	0.45842	0.67308
7	0.43139	0.5	0.51058	0.62019	0.56861	0.5	0.48942	0.37981
8	0.03975	0.86364	0.11639	1	0.96025	0.13636	0.88361	0
9	0.65989	0.09091	0.78716	0.41346	0.34011	0.90909	0.21284	0.58654
10	0.03946	0.09091	0.03642	0.72115	0.96054	0.90909	0.96358	0.27885
11	0.8725	0.59091	0.55832	0.1875	0.1275	0.40909	0.44168	0.8125
12	0.70053	0.59091	0.55561	0.5625	0.29947	0.40909	0.44439	0.4375
13	0.93905	0.04545	0.89395	0.27404	0.06095	0.95455	0.10605	0.72596
14	0.6649	0.04545	0.68898	0.25481	0.3351	0.95455	0.31102	0.74519
15	0.03828	0.13636	0.06668	0.17308	0.96172	0.86364	0.93332	0.82692
16	0.00029	0.90909	0	0.73077	0.99971	0.09091	1	0.26923
17	0	1	0.03248	0.75962	1	0	0.96752	0.24038

Next, grey relational coefficient (GRC) was computed using Equation 4 and the computed data is as shown in Table 3

$$\xi_i(k) = \frac{\Delta_{min}+\zeta\Delta_{max}}{\Delta_{oi}(k)+\zeta\Delta_{max}} \quad (4)$$

ξ_i (k) is the grey relational coefficient (GRC) of a response data, which is in terms of the minimum deviation (Δ_{min}) and maximum deviation (Δ_{max}). ζ represents the differentiating coefficient ranging from 0 to 1 (0~1), however equal coefficient of 0.5 is often assigned to each response data.

Lastly, the grey relational grade (GRG) was computed using Equation 5, and the data is presented in Table 3.

$$\gamma_i = \frac{1}{n}\sum_{i=1}^{n} \xi_i(k) \quad (5)$$

γ_i represents GRGvalue for the i^{th} experimental number and n is the total number of responses

Table 3: GRC, GRG and ranking

Exp./No.	GRC				GRG	Rank
	K	**n**	**YP**	**PV**		
1	0.60191	0.36667	0.64837	0.40945	0.5066	12
2	1	0.35484	0.77706	0.38519	0.62927	2
3	0.90175	0.33333	1	0.33333	0.6421	1
4	0.62796	0.61111	0.43831	0.60465	0.57051	6
5	0.42355	0.52381	0.49273	0.55319	0.49832	13
6	0.53463	0.40741	0.52169	0.42623	0.47249	15
7	0.4679	0.5	0.50535	0.56831	0.51039	11
8	0.34241	0.78571	0.36137	1	0.62237	3
9	0.59516	0.35484	0.70142	0.46018	0.5279	10

10	0.34234	0.35484	0.34163	0.64198	0.4202	16
11	0.79681	0.55	0.53096	0.38095	0.56468	7
12	0.62541	0.55	0.52944	0.53333	0.55955	8
13	0.89134	0.34375	0.82501	0.40784	0.61699	4
14	0.59873	0.34375	0.6165	0.40154	0.49013	14
15	0.34206	0.36667	0.34884	0.37681	0.3586	17
16	0.3334	0.84615	0.33333	0.65	0.54072	9
17	0.33333	1	0.34071	0.67532	0.58734	5

From the analyzed data, the ranking revealed the order of significance of the various developed drilling muds based on their GRG values. The findings showed that the 3rd experimental number is the best performance fluid. Its processing conditions as displayed in Table 1 are 0.6 wt% starch, 1 wt% nanoparticles and 45 min. ultrasonic time. It can be concluded that to produce an efficient drilling fluid, the mentioned processing conditions are expedient to be considered.

Analysis of variance (ANOVA) was used to examine the contribution of each processing condition on GRG value of the drilling muds. The result shows that nanoparticles is the most significant factor, followed by ultrasonic time, then starch. However, it is important to note that error or noise had a very great impact on the GRG value. This shows that there were some influencing factors that have not been accounted for or possible. Hence, an in-depth study should be considered to identify and incorporate some other essential factors necessary in the formulation of drilling muds.

Table 4: ANOVA of GRG

Source	DF	SS	MS	Contribution (%)
Starch (wt%)	4	0.0155	0.0039	13.78091873
Nanoparticles (wt%)	4	0.0208	0.0052	18.3745583
Ultrasonic time (mins)	6	0.0277	0.0046	16.25441696
Error	2	0.0292	0.0146	51.59010601
Total	16	0.0932	0.0283	

Mathematical and Graphical Modeling

The mathematical modeling was done using regression analysis. The mathematical model of the drilling mud GRG based on the considered parameter is shown in Equation 6. The modeled versus the experimental GRG is displayed in Figure 1. The patterns of the two parameters showed haphazardly against each other. Their patterns did not align with each other. This shows some imperfections in the experimental setups. This observation is supported by the ANOVA findings, highlighting that there was much and very significant noise within the experiment. Graphical modeling or interaction plot model of the processing conditions versus the GRG values is presented in Figure 2. This shows the generality of the processing parameters interactions relative to GRG values. Different settings with different GRG values are seen clearly in the Figure.

$$GRG = 0.404 + 0.0556\ Starch + 0.0404\ Nanoparticles + 0.00166\ Ultrasonic\ time \quad (6)$$

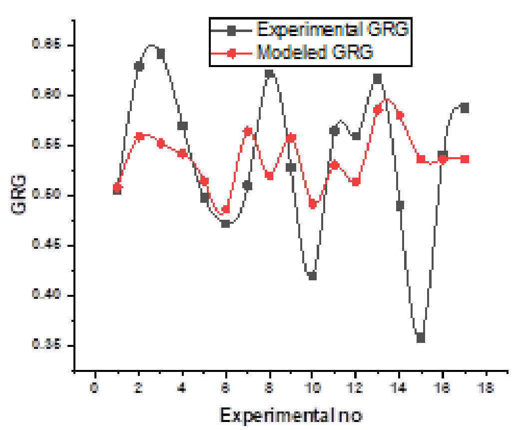

Figure 1: Modeled and Experimental GRG of Drilling Muds

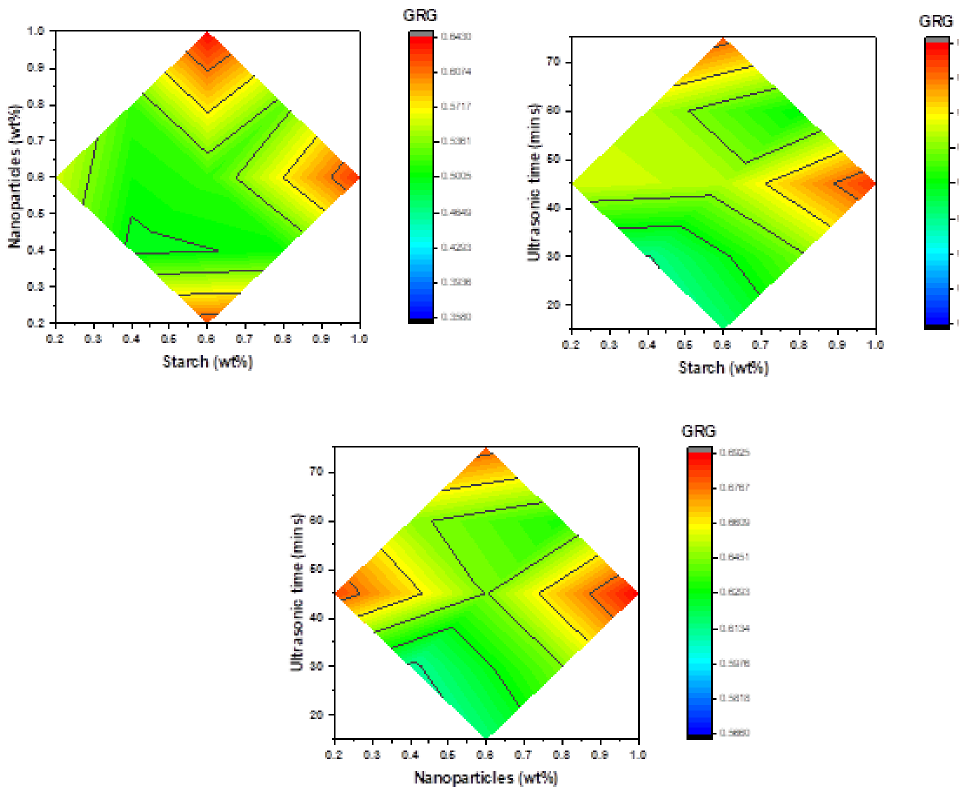

Figure 2: Interaction plots of processing parameters with GRG values of drilling muds

Conclusion

This study has successfully employed GRA as the computation analysis assisted by mathematical and graphical modeling in the optimization of multiple performance characteristics of a drilling mud. The obtained results showed that 0.6 wt% starch, 1 wt% nanoparticles and 45 min. ultrasonic time are the optimal settings to be considered in the production of highly efficient nanofluids for drilling muds. The graphical modeling and ANOVA results revealed that the experimental setups were influenced by some significant unconsidered external factors that were not considered to influence. It is recommended that deeper study should be conducted to identify and employ some other unconsidered factors that may be responsible for drilling muds performance.

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