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RESEARCH PAPER

Cuttings Transport Modeling in Wellbore Annulus in Oil Drilling Operation using Evolutionary Fuzzy System

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Abstract

A difficult problem in drilling operation that concerns the very drilling parameters is the cutting transport process. Correct calculation of the cuttings concentration (hole cleaning efficiency) in the wellbore annulus using drilling variables such as the geometry of wellbore, rheology, and density of drilling fluid, and pump rate is very important for optimizing these variables. In this study, a hybrid evolutionary fuzzy system (EFS) using artificial intelligent (AI) techniques is presented for estimation of the cuttings concentration in oil drilling operation using operational drilling parameters. A well-organized genetic learning algorithm that computes fitness values by symbiotic evolution is used for extraction of the Takagi–Sugeno–Kang (TSK) type fuzzy rule-based system for the EFS. A determination coefficient (R^2) of 0.877 together with a root mean square error (RMSE) of 1.4 between prediction and measured data for test data verified a very satisfactory model performance. Results confirmed that the estimation accuracy of the proposed EFS is better than other models such as Multiple Linear Regression (MLR), artificial neural network (ANN), and adaptive neuro-fuzzy inference system (ANFIS) for hole cleaning modeling.

Keywords:
Artificial Intelligent Methods,
Drilling,
EFS,
Hole Cleaning,
Wellbore

Introduction

In a rotational drilling method, the rock formation is crushed into minor pieces (cuttings) by the drill bit. To bring the cuttings to surface facilities such as shale shaker and mud pits, drilling fluid is pumped via pipe and bit nozzle and circulated back through the wellbore annulus. A major concern in directional well drilling is the efficiency of particle transportation (cuttings transport) by drilling fluid Fig. 1.

The main problem is settling of cuttings and forming a bed in the annulus. This issue may cause many drilling problems such as bit balling, pack-off, or stuck pipe. Hole cleaning efficiency affects the quality of oil/gas wells as well as time and costs. Estimation and field measuring of the cuttings concentration in wellbore annulus is a complicated, time-consuming, and costly problem because of the presence of numerous parameters, such as hole-pipe eccentricity, multiphase flow process, average fluid velocity, particle transport velocity, fluid flow regime, rheological properties of fluid, drill pipe rotation, rate of penetration, wellbore geometry and cuttings properties [1-8]. In underbalanced drilling, the fluid pressure is usually lower than the fluid pressure of the formation. Foam, as a drilling fluid, is usually used in

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underbalanced drilling. It is a combination of surfactants, liquids, compressed gases, and chemical additives. Foam quality, foam rheology, and foam density are among the foremost foam properties. Since foam has high viscosity (as a non-Newtonian drilling fluid), it significantly contributes to an efficient hole cleaning. Moreover, its low density establishes underbalanced conditions with minimal formation damage. In drilling with foams, effective cuttings transport is an important issue due to the multiphase flow and foam drilling hydraulic. Foam properties can be unfavorably affected by drilled particles. As a result, the downhole pressure control plan may be changed. Also, drilled particles bring about the same difficulties as in conventional drilling [7-12]. There are a few publications about cuttings transport with foam [7-9,13-22].

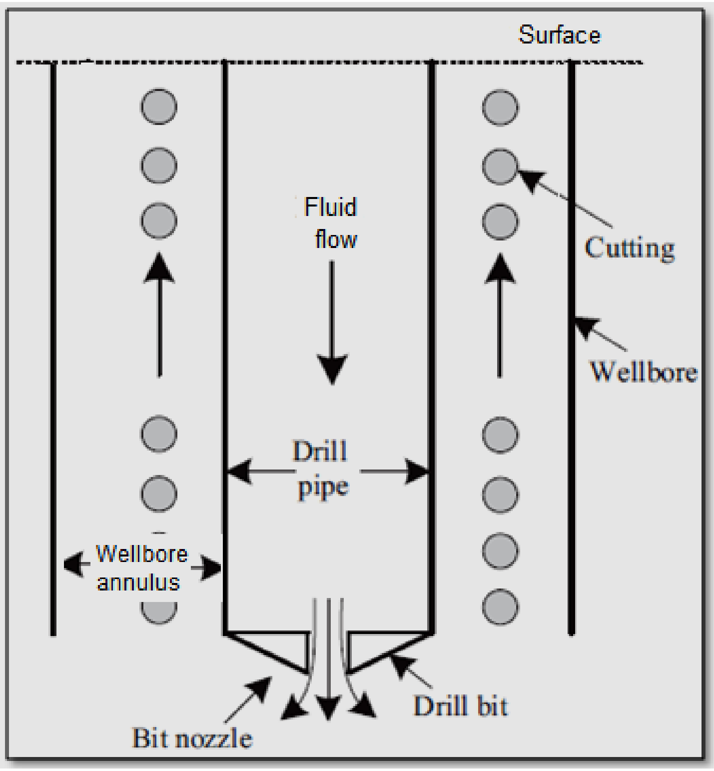

Fig. 1. Schematic of cuttings transport in a vertical-section

Accurate estimation of drilling particle transport efficiency by the effective drilling parameters using a simple and cost-effective method is necessary for the optimal design of a foam drilling program. In this regard, the application of artificial intelligence (AI) methods can be useful.

In computer science, the intelligence that is demonstrated by machines to mimic the operations of the human brain is called artificial intelligence (AI). AI methods including artificial neural networks (ANNs), fuzzy logic, and genetic algorithms (GAs) are prevalent models to cope with intricate problems in engineering optimization. Because of their flexibility, these models are capable of estimating non-linear relationships without the limitations of classical statistical models [23]. The AI techniques have been widely employed in engineering applications and the oil industry [5,24-29].

Every mentioned AI-based method has its advantages and disadvantages. To conquer the disadvantages and deal with difficult and complex problems, generating hybrid models by integrating several AI techniques is recommended. In this way, their strengths are combined and the impacts of their weaknesses are mitigated. It leads to achieving better results compared to those obtained by a single technique.

Fuzzy rule-based systems are popular intelligent models used for estimation problems. In more complicated problems, combining fuzzy logic systems with other intelligent techniques can yield hopeful results. In this regard, a widespread approach is using genetic fuzzy systems (GFSs) or evolutionary fuzzy systems (EFSs) which are a combination of GA and fuzzy logic [30,31]. An EFS is a learning process empowered by evolutionary computation. Applying GFSs to estimation problems can indicate a satisfactory performance because of its high precision in modeling complex and chaotic systems [32]. This study aims at using an EFS method to estimate the cuttings concentration with foam in the oil drilling operation.

Methodology

Developing EFS

Many real-world problems have been effectively handled using Fuzzy rule-based systems (FRBS). Designing an effective FRBS requires accomplishing several tasks. One thing to do is extracting a suitable knowledge base (KB) for the problem. The on-hand knowledge is stored in the KB in form of fuzzy linguistic IF–THEN rules. It includes a rule base (RB) and a database (DB). The RB is composed of the set of rules in their symbolic forms, and the DB is contained of the linguistic term sets and the membership functions describing their meanings [23].

GA can be effectively employed for deriving KB for an FRB. Particularly, the results of designing, learning, and tuning of KBs by GA have shown to be very promising. These approaches are generally entitled GFS [33]. The final output in TSK-type FRBS, is considered as a weighted mean of those of individual rules. A common rule for a first-order TSK-type FRBS is shown as the following:

If x_1 is A_1 and x_2 is A_2, THEN Y=b_0+b_1x_1+b_2x_2 where b_0,b_1,b_2 are linear parameters, x_1,x_2 are linguistic parameters and A_1, A_2 are the related fuzzy sets.

Based on the work of Juang et al. [34], to create a TSK-type FRBS, a genetic learning algorithm is utilized. To do so, a fuzzy system is designed by incorporating symbiotic evolution where a fuzzy rule is represented by a chromosome. Finally, the ultimate fuzzy system is structured by amalgamating rules randomly chosen from the population. Noteworthy, the fitness allocation is carried out by symbiotic evolution. The following subsection delineates the proposed genetic learning algorithm and the procedure of constructing EFS.

The Proposed Genetic Learning Algorithm

The developed genetic learning algorithm is described as follow:

Step1- Encoding fuzzy rules

A Gaussian membership function with m and σ parameters as center and width of it, and a TSK-type fuzzy rule employed for encoding. The mentioned encoding method is shown in Fig. 2.

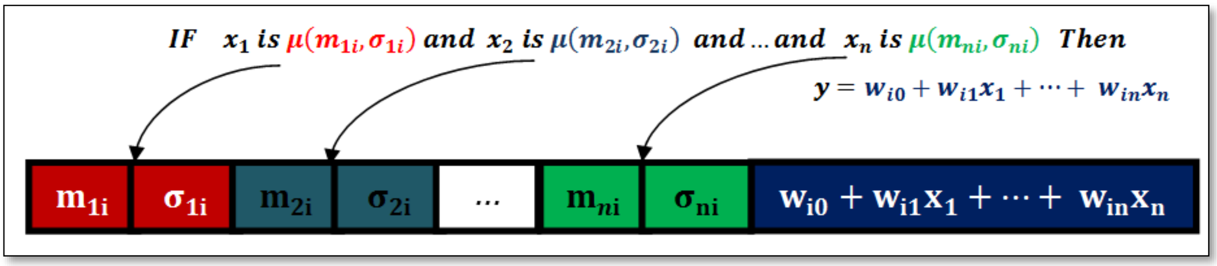

Fig. 2. Coding the ith fuzzy rule with n inputs in a chromosome

Step 2- Initialization

Several $\mathrm{N_c}$ initial chromosomes are randomly produced. If ith input variable (x_i) is in the range of $[\mathrm{min_i}, \mathrm{max_i}]$, the primary values of each m_{ji} are indiscriminately allotted to a floating-point number in $[\mathrm{min_i}, \mathrm{max_i}]$. For simplification, σ_{ji} is permitted to take value from $\{0.1\mathrm{k_i}, 0.2\mathrm{k_i}, 0.3\mathrm{k_i}, 0.4\mathrm{k_i}, 0.5\mathrm{k_i}, 0.6\mathrm{k_i}\}$ where $\mathrm{k_i}$ is defined as $\mathrm{k_i} = \mathrm{max_i} - \mathrm{min_i}$. Therefore, the value of σ_{ji} is coded as integer, with its value being "1", "2", "3", "4", "5", or "6" signifying the real normalized value of 0.2 $\mathrm{k_i}$ to 0.6 $\mathrm{k_i}$, respectively. Also, w_{ij} is randomly generated in$[-1,1]$.

In addition to the population size, the number of fuzzy systems to be constructed and assessed per generation ($\mathrm{N_f} \leq$ population size), the quantity of fuzzy rules constituting a fuzzy system ($\mathrm{N_r} < \mathrm{N_f}$), and the mutation probability ($\mathrm{P_m}$) should be specified.

Step 3- Fitness assignment

Each chromosome is evaluated by the fitness function presented below:

$$\text{Fitness Value}(\mathrm{S_k}) = \frac{1}{1 + \mathrm{E_k}(\mathrm{T}, \mathrm{Y})} \tag{1}$$

where, $\mathrm{E_k}(\mathrm{T}, \mathrm{Y}) = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{t_i} - \mathrm{y_i})^2}$, $\mathrm{t_i}$ is the real value and $\mathrm{y_i}$ is the estimated value of ith training data computed by kth fuzzy system and N is the number of training data. Accordingly, the performance of a rule is evaluated using the average fitness value acquired by the symbiotic evolution process. The fitness assignment procedure is elaborated in Algorithm 1 [35].

Algorithm 1: Fitness assignment in symbiotic evolution
1: choosing $\mathrm{N_r}$ fuzzy rules from a population of $\mathrm{N_c}$ rules randomly, and forming the fuzzy system using these $\mathrm{N_r}$ rules.
2: Obtaining a fitness value by the performance evaluation of the fuzzy system.
3: Divide the fitness value by $\mathrm{N_r}$ and accumulate the divided fitness value to the fitness record of $\mathrm{N_r}$ the selected rules with their fitness records set to zero initially.
4: Repeat $\mathrm{N_f}$ times of the above process until each rule has been selected for a sufficient number of times and record the number of the fuzzy system in which each individual has participated.
5: Divide the accumulated fitness value of each individual by the number of times it has been selected.
Output: Fitness value of each rule (chromosome)

Step 4- Reproduction

Firstly, all individuals are arranged based on their fitness values in descending order. Afterward, the top 50% of sorted chromosomes are moved to the next generation without any change. The remaining part of the new generation is produced by conducting crossover and mutation operations. The reproduction mechanism is similar to that of Juang et al. [34] showing outstanding performance in forecasting and control problems.

Step 5- Crossover

A binary racing selection is used to choose chromosomes for the crossover operation. In the selection method, two individuals are randomly selected, their fitness values are compared, and the superior one is chosen as one parent. The selection mechanism is reiterated to create the other parent. Afterward, a child is generated by exerting a one-point crossover method on the selected parents. It should be pointed out that after completing the crossover operation, an offspring with an undesired fitness value is replaced by a newly generated one.

Step 6- Mutation

The mutation operator used in this algorithm is of uniform type. Thus, a gene is randomly chosen and its value is replaced by a number generated using a uniform distribution in the allowable range of that gene.

Step 7 – Termination criterion

A maximum number of generations is specified. If the number of current generation equals the maximum number, the algorithm is terminated; otherwise, the consecutive steps from Step 3 to Step 7 are repeated.

Modeling of Cuttings Concentration using the EFS

In this paper, 77 experimental data of cuttings transport using foam in literature [7,8] were used to predict cuttings concentration (CC) using effective parameters including velocity (V), foam quality (Q), annulus eccentricity (e), pipe rotation (RPM), pressure (P), and temperature (T), similar to the work of Rooki et al. [5]. Test matrix of experiments has been shown in Table 1.

Table 1. Test matrix of experiments [7,8]

Testing Parameters	Values
Annular Size	5.76" by 3.5"
Pipe Rotation(rpm)	0, 40, 80, 120
Foam Velocity (ft/s)	2, 3, 4, 5, 6
Foam quality (%)	60, 70, 80, 90
Eccentricity (-)	0, 0.78
Temperature (^{0}F)	80, 120, 160, 170
Pressure (psi)	100, 200, 250, 400
Cuttings Size(mm)	3
Cuttings Density (kg/m^3)	2610

About 60 data from experimental data were used for the EFS design and 17 data were randomly used for testing the EFS. In this part, a fuzzy system is made by the proposed EFS to simulate and estimate cuttings concentration. Fig. 3 shows the architecture of the applied EFS, inputs, and output parameters. The employed system aims at modeling and data analysis hence deriving suitable knowledge for estimating cuttings concentration. According to Fig. 3, the EFS has six inputs and the cuttings concentration is its output. In this study, the modeling of EFS using the MATLAB simulation package was done.

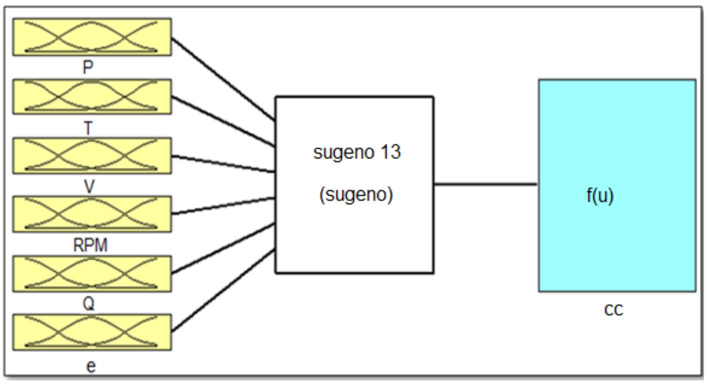

Fig. 3. Structure of the EFS

Implementing the Proposed Method to Construct the EFS

Parameters tuning is an important task in developing metaheuristic algorithms, since it can significantly affect their performance [36]. In the beginning, an initial set of parameters is used; it is preferable to use the starting values that their performance over several numerical tests has shown to be satisfactory. The architecture (parameter values) of the model is improved by sampling in parameter space, considering a stream of instances, successively assessing candidates by minimum mean-square error statistic, rejecting statistically inferior ones, and picking the winner architecture. Accordingly, to achieve the optimum architecture yielding the fewest errors for estimation cuttings concentration, different modes of variables (i.e. different numeric values) were tested to obtain suitable settings. The appropriate parameter settings of the EFS are provided in Table 2.

Table 2. The appropriate parameters settings of the EFS

Proposed EFS-suitable features	value
Population Size (N_C)	80
Generations Number	200
Fuzzy rules (N_r)	13
Number of evaluated Fuzzy system per generation (N_f)	40
Mutation probability (P_m)	0.02

As shown in Table 2 an accurate model was obtained with 13 fuzzy rules for the EFS to simulate cuttings concentration according to effective parameters given in Fig. 3. The simulated fuzzy inference system formulates the mapping from the input space to the output space. Therefore, a foundation for simulating cuttings concentration behavior as a function of the influencing factors is provided by the mapping. Fig. 4 shows the tuned membership functions of inputs and rule base of the system in the designed EFS.

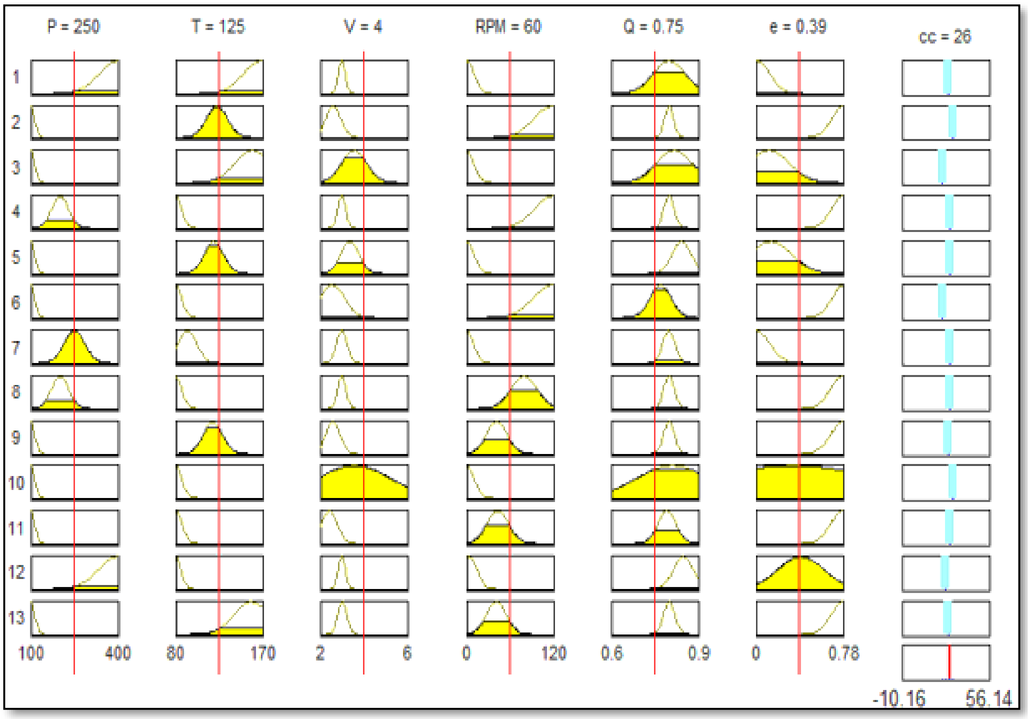

Fig.4. The rule base of the EFS for cuttings concentration estimation

Performance Analysis of EFS

For evaluating the performance of the designed EFS, the EFS results were compared with three other models including multiple linear regression (MLR), artificial neural network (ANN) [5], and adaptive neuro-fuzzy inference system (ANFIS). The comparison was done using common evaluation statistics including root mean square error (RMSE) and determination coefficient (R^2) for the test data (17 data records from 77 experimental data records):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - Y_i)^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_i - \bar{T})^2}{\sum_{i=1}^{N}(T_i - \bar{T})^2} \tag{3}$$

where T_i is the measured value and Y_i is the estimated value of cuttings concentration for ith test data obtained from the models, $\bar{T}$ is the mean of cuttings concentration variable, and N is the number of test data. Fig. 5 shows the estimation results of the proposed models versus measured cutting concentration (%) for the test data. Also, Fig. 6 shows the RMSE of all models for the test data. A determination coefficient (R^2) of 0.877 together with an RMSE of 1.4 indicated a very satisfactory model performance. As it's shown in Figs. 5 and 6, the proposed EFS provided more accurate results compared to the other three models. Table 3 illustrates the results (R^2 and RMSE) of ANN, MLR, ANFIS, and EFS models for the test data records. Higher R^2 and lower RMSE denote better estimation. As can be inferred from the obtained results, the proposed EFS model is capable of providing high-quality solutions and can be fittingly used as an appropriate tool for solving the cutting concentration estimation problem in oil drilling.

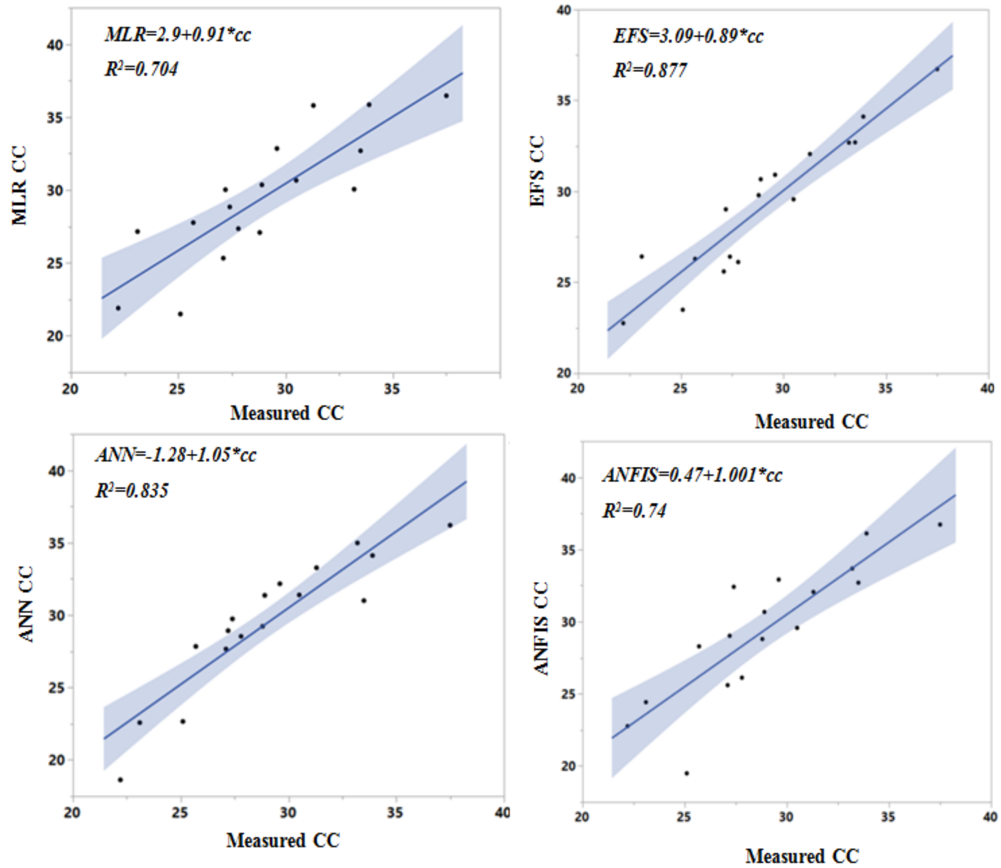

Fig. 5. The results of the different models versus measured cutting concentration (%) for the test data

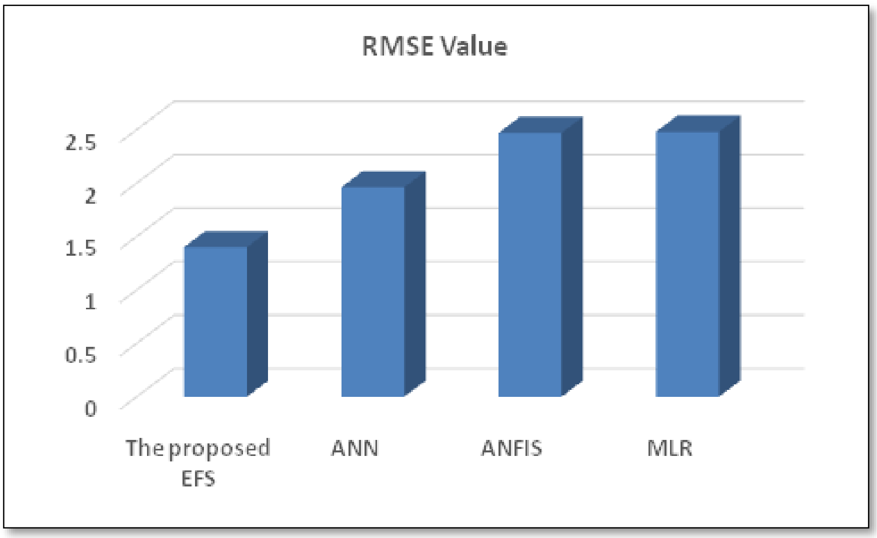

Fig. 6. Estimation error of the models for test data

Table 3. Comparison of the results obtained from different methods for the test data

Method	**R^2**	**RMSE**
The proposed EFS	0.877	1.4
ANN [5]	0.835	1.96
MLR [5]	0.704	2.48
ANFIS	0.74	2.47

Response surface methodology (RSM) represents the relation between a response variable (output) and one or more explanatory inputs. The proposed EFS model can be used as a cutting concentration simulator to simulate the effects of the influencing factors by using RSM. The sensitivity analysis of cuttings concentration for effective parameters was done using RSM for some variables Figs. 7 and 8. For example, Fig. 7 depicts the simulated response surface of foam quality (Q), pressure (P), and cutting concentration (CC) for a state where T=125, V=4, RPM=60, and e=0.39. As it can be observed, cutting concentration increases with increasing P and decreasing Q.

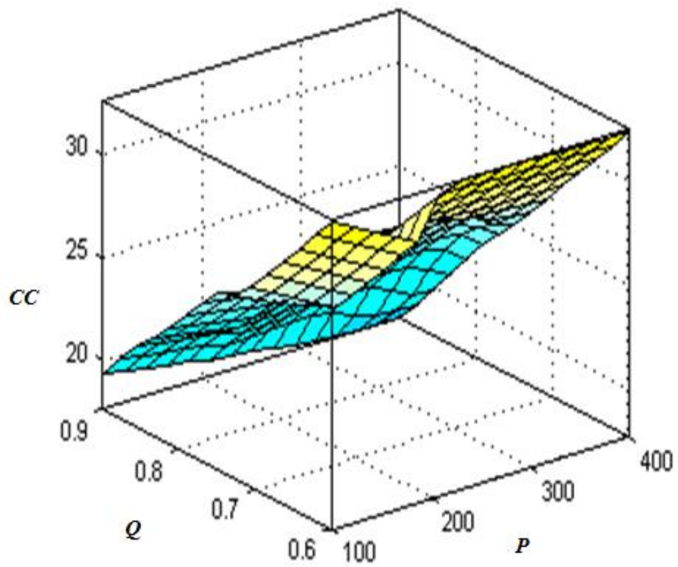

Fig. 7. Simulated response surface of Q, P, and cutting concentration for a state that T=125, V=4, RPM=60, e=0.39

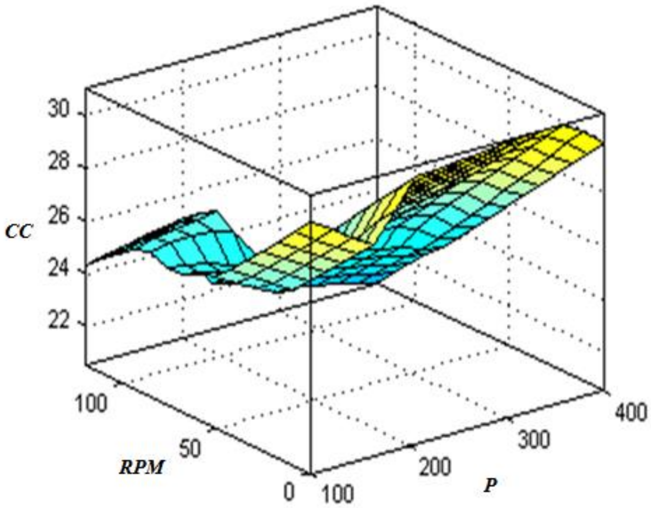

Fig. 8. Simulated response surface of P, RPM, and cuttings concentration

Fig. 8 shows the simulated response surface of pressure (P), pipe rotation (RPM), and cuttings concentration for a state where T=125, V=4, Q=0.75, and e=0.39. As it can be seen, cuttings concentration increases with an increase of pressure and decrease of pipe rotation in wellbore annulus

Conclusions

A difficult problem in drilling operation that concerns the drilling parameters is the cutting transport process. This study developed an evolutionary fuzzy system (EFS) based on the genetic learning algorithm using MATLAB software for cuttings concentration estimation in the oil drilling operation. A determination coefficient (R^2) of 0.877 together with an RMSE of 1.4 for the test data extracted from literature, indicated a very satisfactory model performance. Also, the obtained results (R^2 and RMSE) showed that the estimation accuracy of EFS was better than its counterparts, including ANFIS, ANN, and MLR models. Thus, it can be concluded that the proposed EFS model is capable of providing high-quality solutions and can be fittingly used as a proper tool for solving cutting concentration estimation problems in oil drilling. Also, it can be used as an intelligent simulator to estimate and control cuttings concentration in drilling operations with different operational parameters.

Nomenclature

ANN	Artificial neural network
EFS	Evolutionary fuzzy system
ANFIS	Adaptive neuro-fuzzy inference system
MLR	Multiple linear regression
RMSE	Root mean square error
R^2	Determination coefficient
CC	Cutting concentration
V	Velocity (ft/s)
Q	Foam quality
e	Eccentricity of annulus
P	Pressure (psi)
T	Temperature (^{0}F)

RPM Pipe rotation (rpm)

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