PREDICTION OF ROTATIONAL TORQUE IN HORIZENTAL DRILLING USING ADAPTIVE NERO FUZZY INTERFERENCE SYSTEM (ANFIS)

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ABSTRACT

Horizontal directional drilling (HDD) is widely used in petroleum industry. In a variety of conditions it is necessary to predict the torque required for performing the reaming operation (near surface), However, there is presently no appropriate and convenient method to accomplish these tasks.

The objective of this study is to improve the prediction of the torque during drilling operations using adaptive Nero fuzzy interference systems (ANFIS) Although available information for drilling techniques does provide some means of predicting the torque, it is not sufficient for meeting the present needs. In this study, adaptive Nero fuzzy interference systems (ANFI) is used to predict the value of torque in horizontal drilling based on operational field data the parameters affecting on ANFIS changed to find optimum condition in prediction and finally better accurate prediction obtained, which is better than correlation which is presented to this aim before.

INTRODUCTION

Horizontal directional drilling (HDD) has been used widely throughout the world to construct underground pipeline systems. Most pipelines, including those employing HDD, are installed in soil formations for which engineers have accumulated a great amount of experience. Reasonable mechanical models and corresponding equations have therefore been developed for calculating various construction-related parameters [1].However; there is a lack of such a methodology in more difficult situations. In the absence of an appropriate model for such conditions, it is a challenge for engineers to determine and select a proper sequence of sizes of back-reamers to Achieve the ultimate required borehole diameter. it has been established that the required rotational torque at the drill rig depends on various factors, including geological conditions, drilling method, reamer cutter/bit size and type, rotary speed, axial force on bit, drilling mud properties, borehole diameter, length of drill string in the borehole, and borehole trajectory [2]. A general equation (Eq. (1)) has been presented to calculate the rotational torque in vertical boreholes.

$$M = c.P^{a_p}.n^b; \quad Nm \qquad (1)$$

Where c is a function of rock properties, drill string characteristics and hydraulic parameters of the mud, P the axial force on the cutter/bit, a_p the coefficient of influence of axial force, n rotational speed (revolutions per minute) of the bit, and b is the coefficient of influence of rotational speed. An alternate equation (Eq. (2)) is presented in which the borehole characteristics are explicitly considered (3).

$$\boldsymbol{M = c.P^{a_p}.n^b.L^d.\exp(p.k_l); \;\; \mathrm{Nm}} \qquad (2)$$

Where L is the length of drill string in the borehole, measured along the trajectory of the borehole's axis, d the coefficient of influence of the length of the drill string, k_l the total angular change of the borehole, and p is the coefficient of influence of the total angular change of the borehole.

Previous investigations have assumed constant values of axial force, rotational speed and drilling mud properties when drilling in macroscopically homogeneous rock [3]. The corresponding field results during construction agreed well with the resulting theoretical model, which may therefore be adopted as an initial basis for determining rotational torque during the back-reaming phase. Nevertheless, due to the variable nature of several factors during drilling, such as pull force and rotational speed of the reamer, as well as the absence of some important parameters, including reamer diameter, mud flow rate and mud viscosity, the model has deficiencies.

Haitao and et al present a model to predict the torque which contain more considerations [4], they assume that the rock strata are treated as macroscopically homogeneous, with uniform mechanical properties and past data of similar projects, as well as engineering experience and judgment, may be effectively used to select quantitative values of some specific factors using statistical methods. Based on the field data and Multiple Regression Analysis, they present a correlation to predict the torque value in HDD [4].

$$M = 202803.P^{0.4336}.n^{0.3626}.L^{0.2156}.e^{-0.0329}.D_i^{0.5430}.W^{0.3933}.V^{-0.2348} : kn\,m \qquad (3)$$

Where P the axial force on the cutter/bit, D_i is the diameter of the ith successive reamer, W the mud flow rate, V the mud viscosity and n is the rotational speed (revolutions per minute).this correlation could match with operational data with correlation coefficient of determination of $R^2 = 0.8051$.Today, Artificial intelligence provide some powerful method for scientists and engineer to modeling every complicated systems, more useable techniques which are widely used in numerical analysis are Artificial neural networks and fuzzy logic. the combination of fuzzy logic and artificial neural networks, Adaptive Neuro fuzzy interference system(ANFIS) is a very powerful method to predict the application of complicated systems Soft computing methods have been widely applied in many areas in the petroleum industry, such as reservoir description [5], well logging interpretation [6], production prediction [7] and treatment optimization].

in this research ANFIS is used to predict the torque in basis of data used to developed the Haitao and et al correlation(Eq. (3))

Neuro-fuzzy systems

Fuzzy logic (FL) and fuzzy inference systems (FIS), first proposed by Zadeh [5], provide a solution for making decisions based on vague, ambiguous, imprecise or missing data. FL represents models or knowledge using IF–THEN rules in the form of "if X and Y then Z". A fuzzy inference system mainly consists of fuzzy rules and membership functions and fuzzification and de-fuzzification operations. By applying the fuzzy inference, ordinary crisp input data produces ordinary crisp output, which is easy to be understood and interpreted. A more generalized description of fuzzy problems and uncertainty is provided in [6]. Broadly speaking, there are two categories of fuzzy inference systems, namely Mamdani [7] and Sugeno-Takagi(ST) FIS ,a mamdani FIS consist of simple rule such as: IF pressure is high and temperature is low, then volume is small, where pressure and volume and temperature are linguistic variables; high and small and low are linguistic values that are characterized by membership functions. ST type of fuzzy rules only involves fuzzy sets or membership functions in the premise part. A FIS has two inputs and two ST rules can be generally represented as follows:

R^1: if x_1 is A_1^1 and x_2 is A_2^1 then $f_1 = p_1x_1+q_1x_2+c_1$
R^2: if x_1 is A_1^2 and x_2 is A_2^2 then $f_2 = p_2x_1+q_2x_2+c_2$

Represents the first order ST type fuzzy rules. The output part can also be constants, named as Takagi–Sugeno–Kang fuzzy model [25], and represented as

R^1: if x_1 is A_1^1 and x_2 is A_2^1 then $f_1 = C_1$
R^2: if x_1 is A_1^2 and x_2 is A_2^2 then $f_2 = C_2$

For complicated problems as discussed in this paper, the first order ST FIS is widely employed to model the relationships of inputs and outputs.

FIS identification and refinement

Identification of the rule base is the key of a fuzzy inference system. The problems are: (1) there are no standard methods for transforming human knowledge or experience into the rule base; and (2) it is required to further tune the membership functions (MF) to minimize the output errors and to maximize the performance, as stated in [8]. There are many methods that can be applied to identify the MF and FIS. In this paper, sub clustering method is applied for FIS identification and refinement. ANFIS is a multi-layer adaptive network-based fuzzy inference system proposed by Jang [8]. An ANFIS consists of totally five layers to implement different node functions to learn and tune parameters in a FIS using a hybrid learning mode. In the forward pass, with fixed premise parameters, the least squared error estimate approach is employed to update the consequent parameters and to pass the errors to the backward pass. In the backward pass, the consequent parameters are fixed and the gradient descent method is applied to update the premise parameters. Premise and consequent parameters will be identified for MF and FIS by repeating the forward and backward passes. ANIFS has been widely used in automation control [9] and other areas.

ANFIS-SUB

The ANFIS-SUB fuzzy inference system combines the subtractive clustering method and ANFIS. The subtractive clustering method is proposed by Chiu [10] by extending the mountain clustering method [11]. It clusters data points in an unsupervised way by measuring the potential of data points in the feature space. When there is not a clear idea how many clusters there should be used for a given data set, it can be used for estimating the number of clusters and the cluster centers. Subtractive clustering assumes that each data point is a potential cluster center and calculates the potential for each data point based on the density of surrounding data points. Then data point with highest potential is selected as the first cluster center, and the potential of data points near the first cluster center (within the influential radius) is destroyed. Then data points with the highest remaining potential as the next cluster center and the potential of data points near the new cluster center is destroyed. The influential radius is critical for determining the number of clusters. A smaller radius leads to many smaller clusters in the data space, which results in more rules, and vice versa. Hence it is important to select proper influential radius for clustering the data space. After clustering the data space, the number of fuzzy rules and premise fuzzy MF are determined. Then the linear squares estimate is used to determine the consequent in the output MF, resulting in a valid FIS. As described above, ANFIS learns and refines the premise fuzzy MF and consequents using the least squares estimate and back propagation. Tuned by ANFIS, the resultant FIS achieves minimum training errors

ANALYSIS AND MODELLING

For generate the model data was normalized in the [0,1] interval, then the data set was divided into two part, 85 percent to train and 15 percent to test the application of our Nero fuzzy system(this data sets did not apply to the system before),the system is trained with the training data set and then it is tested with the test data .Data sets which are used in this research are the data Haitao and et all used (84 data sets) to generate a correlation to predict the torque [4].The modeling in this research is done in MATLAB ANFIS toolbox. Based on sub clustering method FIS were created, and the performance of the system was study to give best condition. Some important parameters which changing them is effective in the performance of the ANFIS (sub clustering FIS) which are squash factor, accept ratio, reject ratios and Range of influence, so the performance of ANFIS most be Studied with changing this parameters to obtain best condition.
Validation of performance in this study is in base of correlation coefficient square (R^2) and mean square error (MSE).

RESULTS AND DISCUSSION

the performance of the ANFIS is studied and it was observed the best condition for the squash factor, accept ratio and reject ratio was the default values of ANFIS toolbox in MATLAB (1.15 , 0.5 , 0.15) and changing them from this values generate more errors, But the most important parameter which affect the accuracy of the ANFIS in this case is radius of influence, so this parameter is changed between its domain[0,1] and the following result for coefficient factor and MSE is generated for evaluation the performance of the model. for each stage value of correlation coefficient (R^2) and mean square error (MSE) were computed.
Result are presented in figures 3 and 4,as it is shown the performance of ANFIS is roughly dependent to radius of influence and by increasing in to high values ,MSE increase and R^2 decrease, which is not desirable.

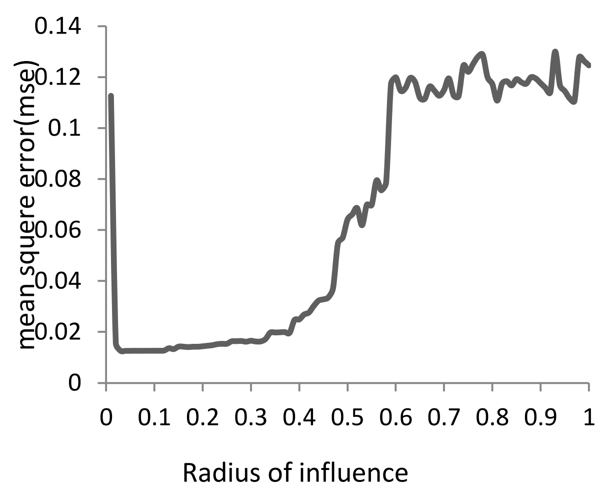

Figure 1

Trend of R-squered with changhing in radius of influence

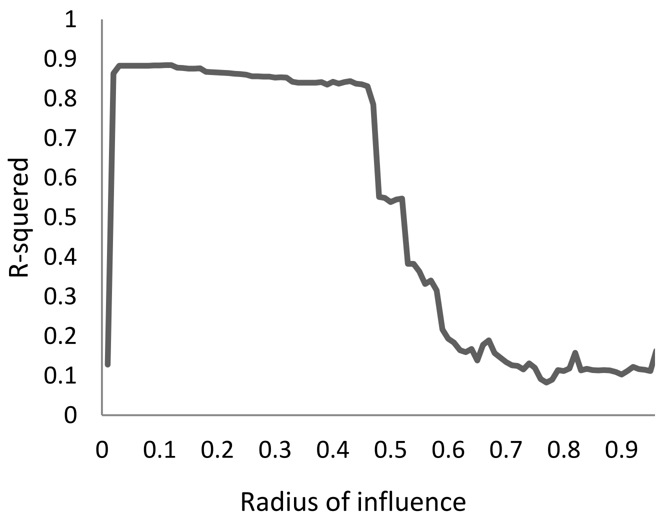

Figure 2
Trend of mean squared error with changing in radius of influence

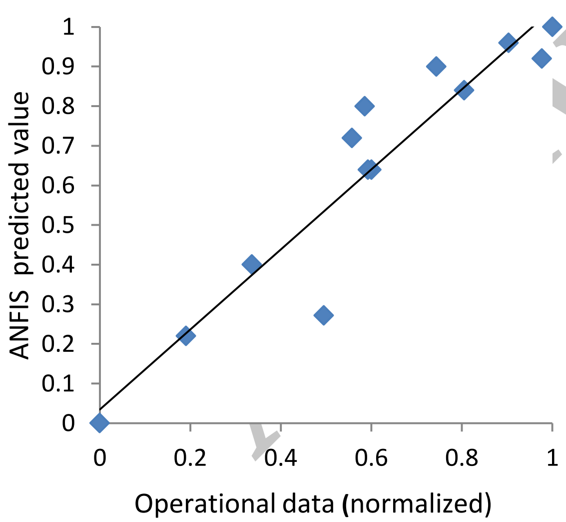

Figure 3
Correlation between ANFIS output and real data

Since increasing the influence ratio parameter reduces the corresponding number of membership functions the learning capability of ANFIS decreases as a result as can be concluded from figures 1 and 2.

The best condition occurs when radius of influence is between [0.7 0.13], In this situation maximum R^2 = 0.884 and minimum MSE = 0.012 where achieved.

Figure 3 show the correlation between operational data and data predicted by ANFIS when radius of influence factor is in optimum value (0.11), as observed the predicted data and test data are in good mach.

CONCLUSIONS

Soft computing is very help full to modeling complicated systems, in this effort rotational torque is predicted using ANFIS with only 84 data sets and a correlation factor of R^2 = 0.884 and minimum MSE near 0.012 was achieved for test data which is very better than correlations which are presented with other numerical and analytical methods. So soft computing could be used such a powerful method to predict the amount of rotational torque in field. Data used in this research was for a special formation therefore the result of it could be used for that formation, for other formation the training of ANFIS must be done with operational data from that formation. In this case, there was 8 dimension, because of high number of dimensions ,by using more data which could cover whole intervals ,more accuracy will be obtained.

KEYWORDS

Directional drilling, Rotational torque ,back reaming operation , ANFIS, sub clustering.

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