



A Model to Predict the Performance of Drilling Operation Using SVM Approach in One of the Iranian Oilfields

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Abstract: Drilling operations in the oil and gas industry have a special place, and it is one of the leading and costly parts of this industry. No doubt there are many factors in the performance of drilling operations, including technical and economic factors. In this research, we will try to examine the critical parameters in the operation of drilling mast. The higher the rate of penetration, the faster the drilling speed and thus it reduces the time and will ultimately decrease the cost of the entire operation. Therefore, to gain the optimal drilling performance, there should be an assessment and proper prediction of the rate of drill penetration rate. Since the quality and properties of the formations and the depth of reservoir's layer are one of the most influential factors in the penetration rate of rock. Based on the results of the model, CSA LSSVM made in this study, the correlation coefficient the of total drill penetration rate recorded in the drilling reports and predicted value was 0.989, and the absolute error of the mean is also as low as 8.39%.

Keywords: Drilling Performance, Support Vector Machine (SVM), Penetration Rate

1. INTRODUCTION

Due to the problems in the automatic process of maintaining the proper lithology and maintaining well conditions parameters for drilling, the drilling industry needs a new method that the workers would observe the desired information at the desired time and control the drilling parameters. Thus, by analyzing field data, using the predictive model, and subsequently evaluating and correcting the useful parameters, a dramatic increase in the efficiency of the drilling operations and, reduction of costs can be achieved [1-7]. The higher the penetration rate, the higher the speed of drilling a well, resulting in a time reduction, which ultimately leads to a reduction in the total cost of the operation. Therefore, to become the optimal drilling operation, there should be an assessment and proper prediction of drill penetration rate. Thus, the structural properties and reservoir depth are the most influential factors in the rate of rock penetration; in respect of the way, as the depth increases, the formations become harder and the penetration rate decreases. Moreover, due to the depth of the wells in the oil fields of Iran, the assessment of the penetration rate is of importance [8-15].

1.1. Support Vector Machine (SVM)

Support vector machine is one of the supervisory learning methods that can be used for categorization and regression. A Support vector machine is mostly a two-class categorization that separates classes by a linear boundary. In this approach, the closest examples are called vector by vectors to the decision boundary. These vectors determine the boundary of decision-making equation. This method is due to the use of the structural risk minimization principle, which is applied by maximizing the distance between two superconducting transcoders from the support vectors of both classes. Contrary to the empirical risk minimization mode that attempts to minimize the training error, the performance is better on data which model is not made with them; For simplicity in understanding, the purpose of expressing the theory of a support vector machine, the most straightforward possible model for the two-class separation in a separable state begins linearly. In this method, it is assumed that the samples have the label $y_{i=[-1,+1]}$. Each sample is represented as a vector. The maximum margin method is used to find the optimal decision boundary. Therefore, the decision boundary, in addition to having to split all instances of both classes correctly into two categories, must also find the boundary of

decision, which has the greatest distance from all backward vectors. The mathematical expression of the decision boundary in vector space can be as follows [16-23].

$$f(x) = \text{sgn}(w \cdot x + b) \quad (1)$$

Where w is the normal vector of the hyperplane and b is the width from its origin. As stated, the decision boundary should correctly classify the samples, whose mathematical expression is as follows.

$$y_i(w \cdot x + b) \geq 1 \quad (2)$$

Considering the importance of the accuracy of the predictive models in this research, we will try to use new methods of modeling that will yield more accurate and reliable results, which will be used by the SVM technique [24-33]. It is worth noting that until now, comprehensive research on the use of this method for predicting drilling performance has not been reported. Regardless of the type of drilling rigs used in Iran and according to the data obtained from previous drilling operations, the objective of this paper is to provide a model for predicting the penetration rate. By comparing and studying the useful factors about the mud, the type of drilling, hydraulics, the rig power and, the study of the conditions can be achieved using modern modeling techniques [34-45].

2. PROPOSED COMPREHENSIVE MODEL

In this section, after defining common symbols, the limitations and functions of the model, we will model the comprehensive classification model geometrically and also in the form of mathematical programming. The Comprehensive Classification Model is designed to incorporate both SVM's advanced and improved models, as well as the linear and non-linear multi-objective, mathematical programming models that have been presented so far, as well as the creation of new particular situations. In real-time modeling, the Support vector machine is used, and the recorded drilling rig, as well as graphing operations, are used to predict the penetration rate. But for data to be applicable, some changes and corrections are required on the data [46-51]. In this chapter, we first discuss this issue and examine the data used, and then, the modeling is performed to achieve the desired goal, and the results are presented to express the status of the model. After the creation of the model, its weaknesses and strengths have been examined. In general, the factors affecting drilling speed can be divided into three main parts:

- Drill specifications and working conditions.
- Characteristics of the formation
- Characteristics of Drilling and Hydraulic Well Drilling

The bit specifications and operating conditions include bit type, hydraulic bit power, bit weight and bit speed. Also, the weight of the drill and the rotational speed is used as the input section. Naturally, to obtain a complete model, it is necessary to influence the factors and their individual effects on the formation. Factors affecting the impact of the formation of the penetration rate include porosity, formation pressure, hardening of the formation, tensile and compressive strength. Due to the available and available data in superior databases, there was not enough data to influence the above factors. But during discussions with expert's guides, the best way to affect the parameters was to change the size of the formation. These changes are noticeable in places where lithology improves 100%. But low torque variations can be attributed to low lithological mutations, in other words, close difficulty, and equal pressures [52-58]. As a result, the influence of the torque cannot be ignored on the penetration rate. This theory may later be taken into account by increasing the accuracy of the devices, and thus a better and more accurate correlation can be found for the rate of drilling permeation. To achieve the desired results, torque should be considered as one of the input parameters. The properties of drilling mud that are known to be efficient at drilling speed include plastic viscosity, bentonite content in mud, number of drilling bits and fluid viscosity. However, due to the available and independent parameters in the input section, the drilling mud weight is used.

Required information for modeling is provided in collaboration with a group of engineers in Iranian oil companies. The related information of Iran's oil field in Khangiran includes daily bit drilling data and some geological reports. In the data selection section, all data that affects the drilling speed has

been tried in various sections such as formation, drilling fluid and working conditions, to provide a comprehensive model. Due to the large volume of data, in this research, we tried to select parameters that have a significant impact on the rate of drilling permeation. With regard to the investigations concerning the drilling performance in the backup machine and the work done to improve the model in the past, it was concluded that the parameters entered the machine purely regardless of their effect on other parameters, this is a sign of weakness in their input parameters. Naturally, when the input parameters are not entered with the correct understanding, the accuracy of the answers cannot be guaranteed. For this purpose, the following parameters are selected in terms of the conditions stated as input parameters to the machine, namely the independent parameters, which is the number of about 400 data used in the machine.

Furthermore, the input and output parameters which is used in this model are statistically depicted in table 1.

Table1. *The Input and Output Parameters Which Is Used in This Model*

Depth (m)	Bit Size (inch)	Bit Type	Weight on Bit	Bit Rotation (RPM)	Mud Weight(pcf)	Flow Rate(gpm)	Pump Pressure (psia)	Rate of Penetration ROP (M/H)
18	26	1	3.5	35	65	100	0	0.2
20	26	1	3.5	35	65	100	200	2.5
1093	17 1/2	3	0	0	76	0	0	1.63
1163	17 1/2	1	0	0	80	0	0	1.77
3083	8.5	3	0	0	80	0	0	1.17
2896	12.25	3	0	0	92	0	0	0.68
2991	12 1/4	3	0	0	101.5	0	0	1.42
2792.6	12 1/4	2	30	0	89	550	2300	0.21
2792.6	12 1/4	2	27.5	0	89	550	2320	0.22
2796.3	12 1/4	2	27.5	0	89	550	2320	0.2
2800.25	12 1/4	2	30	0	89	550	2290	0.17
2801	12 1/4	2	30	0	89	550	2300	0.17
1900	12 1/4	3	0	0	91	670	1850	7.02
3333	8 1/2	3	7.5	32.5	85.5	385	2650	1.56
3366	8 1/2	3	7.5	32.5	87	385	2650	1.54
3387	8 1/2	3	7.5	32.5	87	385	2650	1.54
3389.5	8 1/2	3	7.5	32.5	87	385	2650	1.54
3290	8 1/2	3	7.5	32.5	84	395	2650	1.53
3570	6 1/8	2	5	35	62	200	1800	0.69
3696	6 1/8	3	15	35	62	200	1700	0.98

3. RESULTS AND DISCUSSION

3.1. Investigating the Regression and Statistical Analysis in SPSS

The factors affecting drilling speed, we deal with variables that are in some way related to several other variables. As a result, to better and more accurately answer the prediction of drilling speed, a multivariate linear regression method should be used to establish a relationship between these variables [45, 46]. Multiple linear regression is one of the most sophisticated statistical techniques that is usually used for data whose range of measurements is a distance. Linear regression is proposed in the form of simple linear regression and multivariate linear regression. Simple linear regression predicts the value of a dependent variable based on the amount of an independent variable. However, multivariate regression is a method for the collective and individual participation of two or more independent variables in the variation of a dependent variable. Since the task is the basis of science, the prediction and the explanation of phenomena, so in researches that are observing prediction and correlation, regression analysis can play a significant role. Linear regression models incorporate a broad and rich framework that meets and needs a lot of study. However, linear regression for all issues cannot be appropriate, because in some cases the response and regression variables are related to the unknown nonlinear function, but in this section, the highest correlation coefficient and the coefficient of determination according to Table 2 are related to linear regression, and other regression models are not applicable here.

Table2. Results of regression types

Regression Type	Relevant factor	Determination Factor
Non- Linear Exponential	0.29	0.41
Non- Linear Cubic	0.47	0.62
Non- Linear Quadratic	0.46	0.61
Non- Linear Inverse	0.26	0.53
Non- Linear Logarithmic	0.30	0.41
Non- Linear Multiple linear	0.89	0.94

Available data were gathered to obtain regression and evaluate its performance with the help of the **SPSS** software. Of course, in **SPSS** software, according to the number of input samples, the numbers were varied, the more the number of samples was, the lower the correlation coefficient, which indicates the weakness of the software in the statistical society. The results for the sample number are shown in Table 3.

Table3. The coefficients obtained from different statistical population

Sample Numbers	Relevant factor
300	0.89
107	0.968
59	0.99

According to the table 2 and the results obtained, it shows that the higher the number of samples, the lower the correlation coefficient, and given the fact that the statistical population of the data in the oil field is high, the accuracy of using **SPSS** software is low. And it cannot be used as a computational reference.

3.2. Modeling

After the previous steps, the data is ready for modeling. At this stage, the proper equipment is selected according to its advantages and disadvantages, and our goal is to do the job. At this stage, the model of the equipment, its structure, and its components are chosen. After selecting the equipment, the structure must be specified. The condition for the end of the training period is also determined for the car at this stage. In addition, we use support vector machines and optimization algorithms to create the appropriate model.

3.3. Operational Criteria

In order to evaluate the performance of the models and compare the results, criteria are needed to be used in the research. Among the standard criteria, regression coefficient, the coefficient of determination and, mean square error (MSE) were used. The value indicates the relationship between the actual data and the model, the value between negative one and one; the negative value of one represents an inverse relationship, and the relation 1 describes the direct relationship, and the zero value indicates the absence of a connection between the data. The value of this variable is obtained from equation 3. The magnitude of the regression coefficient is two. If there is a substantial difference between the actual data and the model, the regression coefficient alone cannot indicate a strong relationship between the data. Therefore, another criterion that shows the difference between the actual data and the model is used. For this purpose, the MSE criterion was used. The lower this criterion, the higher the accuracy of the model. The MSE value is calculated using the relationship 3.

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (3)$$

In the equation 3, x_i and y_i , and, are the total average of the predicted and actual data.

$$\varepsilon(n) = MSE = \frac{\sum_{i=1}^n (y_{pi} - y_{ti})^2}{n} \quad (4)$$

Initially, the information about the excavation of the formation was collected from the daily excavation reports of Khangiran field and entered into Excel. The factors influencing drilling penetration rates (ROPs) included in these statements are: drilling area (m), drill type, drill size (inches), drilling depth (m), drill operation time (h), weight On the drill (WOB), drill rotational speed (RPM), flower weight (MW), pump injection rate (Q) (gallons per minute), and pump strain pressure (P) (PAM). These parameters were considered as input and drill penetration rate (ROP) as the output of CSA-LSSVM model. The ordered data were divided into two groups of training (80%) and a test (20%) using a random permutation. These data were also normalized to 0 to 1 before entering the machine learning process.

4. CONCLUSION

In this study, the primary objective is to determine the relationship between mechanical parameters, hydraulic parameters and environmental parameters to predict and achieve the highest rate of drilling. To achieve the objective of operational data in Iran, this research is based on the capabilities of a support machine to provide a model for predicting drilling speed with different parameters. Not to mention the model that has been introduced, depending on the laboratory or operational conditions, only some of the factors affecting the drilling rate are used in the model. The results show that it is possible to obtain a reasonable and reliable relationship between these parameters using the least squares method. Based on the results of the CSA-LSSVM model in this study, the total correlation coefficient between the total drill penetration rate recorded in the drilling reports and its predicted value is 989. And the absolute error of the mean also shows a low value of 839. This very strong overlap between data predicted by machine learning algorithms and laboratory data can be attributed to the very strong relationship between the input and output parameters that came from the daily drilling reports. According to the obtained results, the model made in this study can be used with a high degree of confidence in prediction of drill penetration rate in Khangiran field Formations. Moreover, in this research, by interfering the following factors, a model for forecasting the rate of bit penetration in various rock formations and structures will be presented.

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