Construction of fuzzy systems based on fuzzy c-means clustering and singular value decomposition for predicting rate of penetration in geothermal drilling

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ABSTRACT

The potential for geothermal energy is very abundant, but its utilization is still minimal. Therefore, the utilization of geothermal energy facility that has been installed must be optimized. This study aims to predict drilling rate of penetration using the first-order Sugeno's fuzzy system. Fuzzy c-mean and singular value decomposition were used to form the rules and determined the parameters respectively. This study used in total of 6738 data of geothermal wells drilling in Indonesia. The results show that the rate of penetration prediction has accuracy 85.76% for data training and 87.72% for data testing, and it is better than the radial basis function neural networks (RBFNN) and RBFNN-singular value decomposition (SVD) methods.

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1. INTRODUCTION

Geothermal energy, a renewable source of energy, is natural heat energy from within the earth which is transferred to the earth's surface by conduction and convection [1]. Indonesia has huge geothermal potential because it is one of the countries where the ring of fire passes through. About 40% of the world's total geothermal energy is in Indonesia because the country has high volcanic potential [2]. However, according to the data from the Directorate General of New Renewable Energy and Energy Conservation (EBTKE), Ministry of Energy and Mineral Resources, as of September 2018, of the 299 areas that have geothermal potential, the current installed capacity is around 11% of reserves or about 7% of all available geothermal potential [1], [2]. Since the number of utilizations that are still very minimal, the geothermal potential that has been installed must be optimized. Drilling optimization is important of a project as it takes 35% to 50% of the total project cost. The objective is to minimize the cost (it includes the time) of the project leading to the increase of profits derived from geothermal production in an efficient time. Most of studies considered the penetration rate as an objective function [3]. The velocity where the drill bit must break through the underlying formation to deepen the wellbore is called rate of penetration (ROP) [4].

Predicting the rate of penetration (ROP) in drilling activities has several significant benefits, including [5]-[8] operational efficiency (drilling operations can take place more quickly and efficiently), time and cost planning (the drilling team can plan time and costs more accurately), increased productivity (a good understanding of ROP allows drilling teams to identify factors that can improve productivity), rock formation assessment (variations in ROP can indicate changes in rock type, allowing the team to plan any special steps needed), real-time decision making (ROP information obtained in real-time can be used for immediate decision making. If the ROP indicates an obstacle or change in formation conditions, the team can change the drilling strategy quickly), and optimization of equipment and technology (companies can optimize the design of bits, mud motors, and other drilling equipments). It is important to remember that drilling operations can be very dynamic, and unexpected changes in geological conditions or equipment performance may occur. Therefore, continuous monitoring and adaptation of prediction models based on real-time data is essential for accurate ROP prediction. Additionally, collaboration between geologists, drilling engineers, and data scientists is critical to developing effective predictive models. ROP is affected by numerous parameters such as rock mechanics, subsurface conditions, drilling mud, drilling hydraulics, drill string mechanics, rock crushing model, bit types, mechanics of rock crushing in bits, and bit operating conditions. Five categories are used to classify them: formation properties, hydraulic parameters, drilling fluid properties, rig efficiency, and mechanical parameters [9]. These five categories can also be classified into two main factors, namely environmental factors, and controllable factors [10]. Because most drilling parameters depend on one another, it is challenging to determine the impact of each parameter [9]. Therefore, it is necessary to develop a logical relationship between parameters to assist the optimization of ROP.

Several models have been built to predict ROP with various parameters [11]-[16]. Preview study [12], it is provided a theoretical model for roller cone bits that is affected by drilling mechanical parameters like RPM, WOB, rock strength, and bit size. Later, Bingham [17] modified the model in [12] into a simple equation that ignores the threshold for the load on the drill bit. Weight exponential was introduced in this model [17]. Moreover, the model in [18] is a model for estimating the ROP value using multiple regression analysis with the original drilling data taken in short intervals. This model is a multivariable function such as formation strength, depth, pressure difference along the wellbore, drill bit diameter, drill bit load, rotation speed, bit wear, and drill bit hydraulics [18].

In recent years, artificial intelligent (AI) techniques such as artificial neural network (ANN) are widely applied in the application of drilling techniques. The most popular ROP prediction research using ANN is the research in [19]-[21]. They considered a wider range of parameters to predict ROP more accurately. Another study, however, used the ANN method with only six input variables but produced high accuracy [22]. Al-Abduljabbar *et al.* [22] has created a ROP model utilizing ANN in conjunction with self-adaptive differential evolution (SaDE), as well as a model for a horizontal carbonate reservoir. Six drilling parameters and rock attributes in the form of gamma rays, resistivity, and bulk density are used as input parameters. As a result, the model exhibited high accuracy [7], [23]. Hybrid ANN was used by Ashrafi *et al.* [23] to estimate ROP and this method is better than conventional ANN.

Researchers are continuously optimizing the drilling techniques of geothermal wells and fuzzy logic has been tested to predict the penetration rate. Fuzzy logic can explain and provide tolerance for fuzzy values that cannot be classified into 1 (true) or 0 (false) like firm logic. Therefore, the calculation of geothermal ROP is suitable to be solved by fuzzy logic. The fuzzy modeler goes through several processes such as fuzzification, fuzzy rules, fuzzy inference, and defuzzification [24], [25]. Basarir *et al.* [26] investigated the prediction of ROP using linear regression, nonlinear regression, and the ANFIS model. The results show the superiority of the ANFIS method over the regression method [26]. Ahmed *et al.* [4] used Sugeno's fuzzy logic built with fuzzy inference systems (FIS) to predict drilling ROP. This fuzzy model was developed using five drilling mechanical parameters and five drilling fluid attributes where the accuracy of ROP prediction is quite high ($r = 0.971$ and AAPE = 7.29%).

Drilling optimization using fuzzy logic is still in progress. The first-order Sugeno's method is one of the fuzzy modeling techniques in which the outcome of each fuzzy rule is a linear combination of the inputs [24], [25]. Furthermore, defuzzification in the first-order Sugeno's fuzzy system can be represented by a linear equations system. The singular value decomposition (SVD) can be used to obtain the optimal solution of a linear equations system. The number of fuzzy rules can be optimized by using fuzzy c-means clustering (FCM). Furthermore, the parameters on the consequence of the first-order Sugeno's fuzzy rules are discovered by the SVD method.

Based on the previous description, research on the prediction of ROP in geothermal drilling using the first-order Sugeno's fuzzy system with FCM and SVD methods has not been carried out. Therefore, in this paper, we discuss ROP predictions for optimizing geothermal drilling using a first-order Sugeno's fuzzy system by combining FCM and SVD methods. Moreover, we compare the accuracy of this models with two other models that are radial basis function neural networks (RBFNN) and the RBFNN-SVD models. In section 2, the proposed method of this research is explained in detail. It is about the geothermal data, including the geothermal concept and the data description, and the steps for executing this research. The results of this research and the discussion of them are explained in section 3. Last, the conclusion is in section 4.

2. METHOD

The displacement of rock per unit area (feet) per unit time (hours) is known as the penetration rate (ROP). In general, ROP measures the bit rate when drilling rock formation [15]. There are many parameters that affect the penetration rate. The important parameters used in this study are the drilling fluid and drilling mechanical parameters [27], [28].

The research's data from PT. Geotama Energi Yogyakarta are secondary data from a single drilling well with various data generated when the drill bit penetrates the rock. There are 6738 data from a depth of 60 ft to 6793 ft that are divided into 80% training data (5390 data) and 20% testing data (1348 data). To forecast the ROP for a geothermal drilling well X in an Indonesian area, nine variables were chosen to be used as inputs to the fuzzy model built from training data. The fuzzy model to estimate ROP is based on the depth (ft), four drilling mechanical parameters (load on drill bit or WOB (klbs), rotational speed or RPM (rpm), torque (ftlb), and standpipe pressure (psi), three drilling fluid (mudflow in (gpm), mud temperature in (°F), and mud weight in (ppg), and calculation of drilling parameters (drill exponent). Meanwhile, the output variable is ROP (ft/hrs). Table 1 presents the statistical analysis for the input and output variables.

The steps are explained as follow, first, the data inputs in Table 1 will be clustered using fuzzy c-means (FCM) [29]. This FCM clustering are based on [30] that are inputting the data, determining the number of clusters, degree, maximum iteration, smallest error, initial objective function, generating random number as the elements of the initial partition matrix, calculating the summation of each column, calculating the center of each cluster, calculating the objective function of each iteration, calculating the matrix partition change, and last is checking the stop condition. Next, we generated the fuzzy system that is a knowledge-based system in the form of a set of IF-THEN fuzzy rules combined with the process of fuzzification, fuzzy inference, and defuzzification. We use the Gauss curve [30] as the membership function in the fuzzification process, the fuzzy rule base was built based on first order Sugeno's rules, and we use multiple fuzzy inference [25]. Singular value decomposition (SVD) is used to find the consequent part of each fuzzy rules [31], [32]. Last, for the accuracy test, we used mean absolute percentage error (MAPE) to validate the fuzzy model that we got [33]. Furthermore, the correlation coefficient was determined by Pearson's product-moment correlation coefficient [34]-[36]. To sum up, the methods of this research can be seen in Figure 1.

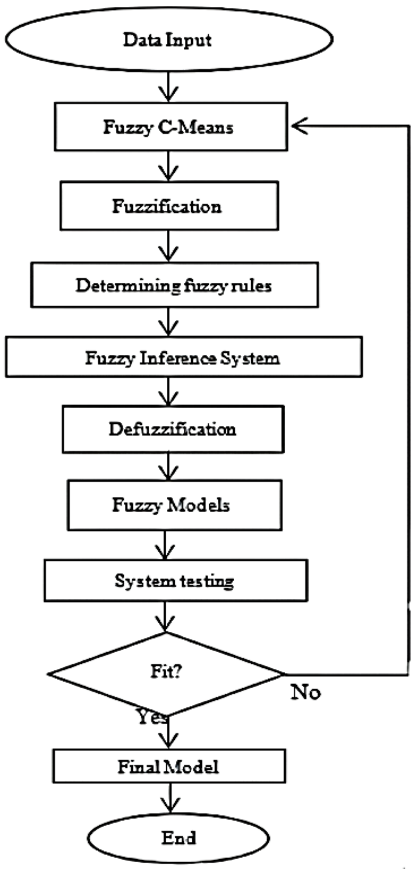

Figure 1. Research flowchart

Table 1. Statistical description for all parameters

Parameters	Depth	WOB	RPM	Torque	Mud flow	Mud temperature	SPP	Drill exponent	Mud weight	ROP
Minimum	60	0,0	0	1592.9	176	52.0	8	0.0000	8.474	2.125
Maximum	6793	38.7	263	13027.2	4266	197.2	3748	1.7827	194.000	277.645
Deviation standard	1943.1	4.0	41.4	2608.6	202.4	27.6	843.4	0.2	24.1	50.1
Mean	3425.337	4.757	148.029	5944.476	801.765	136.271	2128.223	0.695	13.360	86.962
Correlation coefficient	-0.272	-0.317	0.239	-0.069	0.235	-0.087	0.129	-0.600	-0.064	1

3. RESULTS AND DISCUSSION

This research used 9 input variables as shown in Table 1. The clustering was carried out to obtain the cluster center for each variable. The optimal number of clusters was determined by trial and error to provide the best accuracy value. The ideal number of clusters was 37. The cluster center obtained was then used to identify fuzzy sets in the input and to build fuzzy rules. Therefore, 37 fuzzy rules were obtained, of which parameters at each rule's consequent were determined by the SVD method.

- Rule (1): "If Depth is K_1 and Weight On Bit is WOB_8 and Rotary Speed is RPM_3 and Torque is TORQ_8 and Mud Flow In is MFI_{34} and Mud Temperature In is MTI_1 and Stand Pipe Pressure is SPP_4 and Drill Exponent is DXC_{15} and Mud Weight In is MWI_1 then $y_1 = 9047.881465 + (0.020346 * \mathrm{K}) + (-11.573161 * \mathrm{WOB}) + (-2.920472 * \mathrm{RPM}) + (-0.272039 * \mathrm{TORQ}) + (-4.254747 * \mathrm{MFI}) + (16.471228 * \mathrm{MTI}) + (0.312322 * \mathrm{SPP}) + (-2741.310137 * \mathrm{DXC}) + (-402.699134 * \mathrm{MWI})$."
- Rule (2): "If Depth is K_{22} and Weight On Bit is WOB_{29} and Rotary Speed is RPM_{25} and Torque is TORQ_{20} and Mud Flow In is MFI_{20} and Mud Temperature In is MTI_{27} and Stand Pipe Pressure is SPP_{25} and Drill Exponent is DXC_{32} and Mud Weight In is MWI_{25} then $y_2 = 69.136064 + (-0.246073 * \mathrm{K}) + (205.622024 * \mathrm{WOB}) + (18.530701 * \mathrm{RPM}) + (0.703450 * \mathrm{TORQ}) + (7.191648 * \mathrm{MFI}) + (-36.715351 * \mathrm{MTI}) + (-1.492256 * \mathrm{SPP}) + (-6784.951978 * \mathrm{DXC}) + (1194.382324 * \mathrm{MWI})$, and so on. Until
- Rule (37): "If Depth is K_{31} and Weight On Bit is WOB_{17} and Rotary Speed is RPM_{19} and Torque is TORQ_{34} and Mud Flow In is MFI_5 and Mud Temperature In is MTI_{34} and Stand Pipe Pressure is SPP_{30} and Drill Exponent is DXC_7 and Mud Weight In is MWI_{29} then $y_{37} = -28232.815283 + (1.005626 * \mathrm{K}) + (344.479020 * \mathrm{WOB}) + (30.782236 * \mathrm{RPM}) + (-1.024522 * \mathrm{TORQ}) + (8.809096 * \mathrm{MFI}) + (89.447724 * \mathrm{MTI}) + (4.217652 * \mathrm{SPP}) + (29319.964394 * \mathrm{DXC}) + (258.121158 * \mathrm{MWI})$.

These 37 fuzzy rules were used to build up the first order Sugeno's fuzzy system. Thereafter, the accuracy of the fuzzy system in predicting the ROP was compared with other models, namely radial basis function neural network (RBFNN) and radial basis function neural network-singular value decomposition (RBFNN-SVD). The accuracy level of the prediction results was decided by computing the MAPE value, accuracy, correlation coefficient (r), and coefficient of determination (R) on training and testing data. Table 2 reveals the comparison between the accuracy of ROP geothermal drilling prediction results using the first-order Sugeno's fuzzy system, RBFNN, and RBFNN-SVD. Figures 2-7 shows the accuracy graphs, and the correlation test plots for the first-order Sugeno's fuzzy system, RBFNN, and RBFNN-SVD models.

It can be seen in Figure 2 that the graph of the ROP prediction results follows the graph pattern of the actual ROP data on both the training data and testing data. Based on the correlation coefficient and determination coefficient in Table 2 and Figure 3, it can be concluded that the fuzzy model has high accuracy and high correlation between the actual and predicted data. Figures 4 and 5 on the training data shows that the prediction of the RBFNN model is very accurate with 100% accuracy and a correlation of 1, but when the model is validated on testing data, the prediction results are far from the actual data. In Figures 6 and 7, it can also be seen that the graph of the ROP prediction results follows the graph pattern of the actual ROP data on both the training data and the testing data. However, the accuracy of the RBFNN-SVD model is lower when compared to the first-order Sugeno's fuzzy model. Based on Table 2, the prediction of ROP with the fuzzy system provides better accuracy than that with the RBFNN and RBFNN-SVD models.

Table 2. Comparison of the accuracy of the first-order Sugeno, RBFNN, and RBFNN-SVD methods

Datasets	Method					
	First-order Sugeno		RBFNN		RBFNN-SVD	
	Training	Testing	Training	Testing	Training	Testing
MAPE	14.24%	12.28%	0%	128.039%	15.29%	25.33%
Accuracy	85.76%	87.72%	100%	-28.039%	84.71%	74.67%
Correlation coefficient (r)	0.960	0.940	1	0.340	0.950	0.920
Correlation of determination (R)	92.21%	88.41%	100%	11.57%	90.29%	84.64%

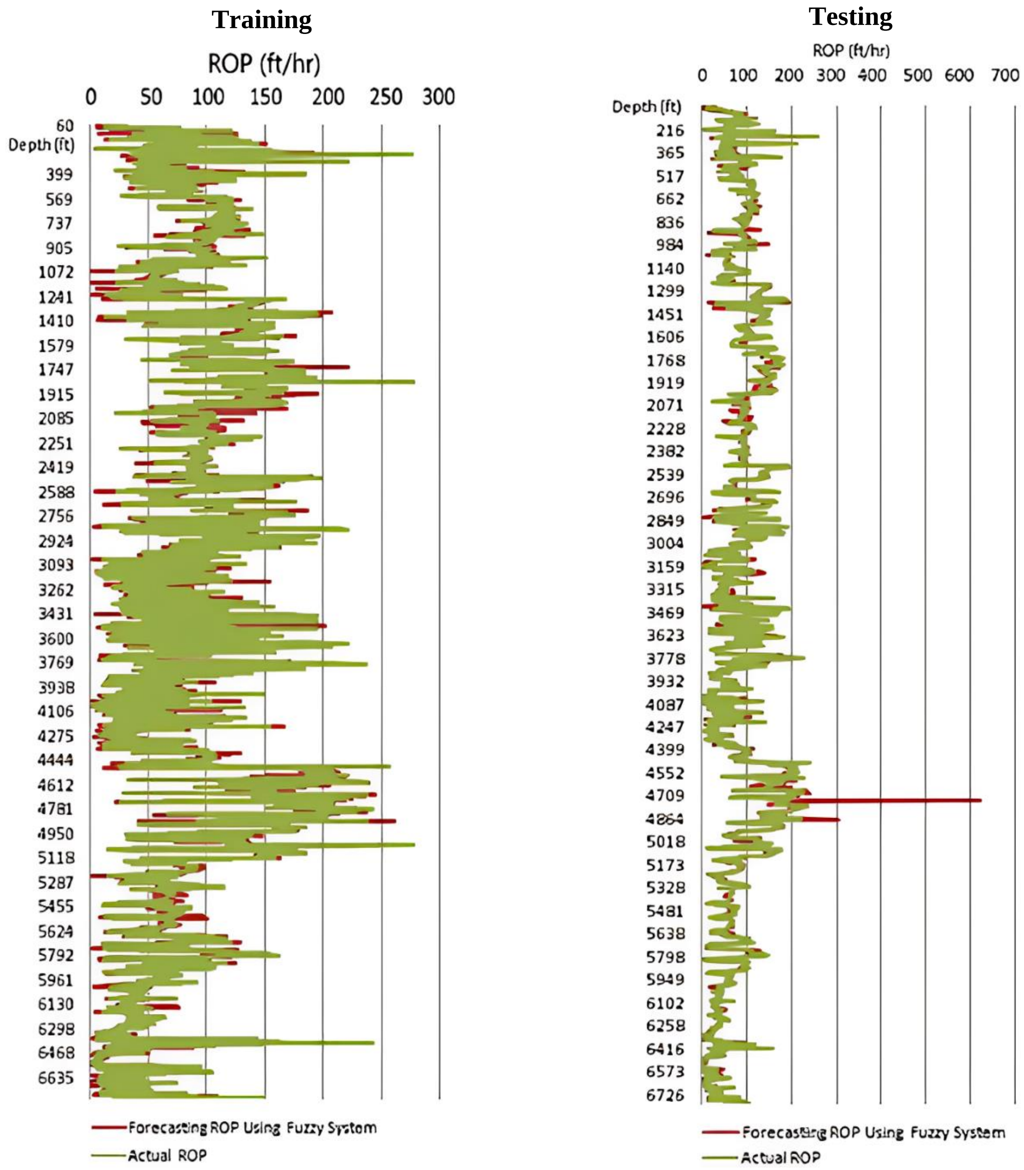

Figure 2. Comparison of ROP prediction results with the actual data on training and testing data using a fuzzy system

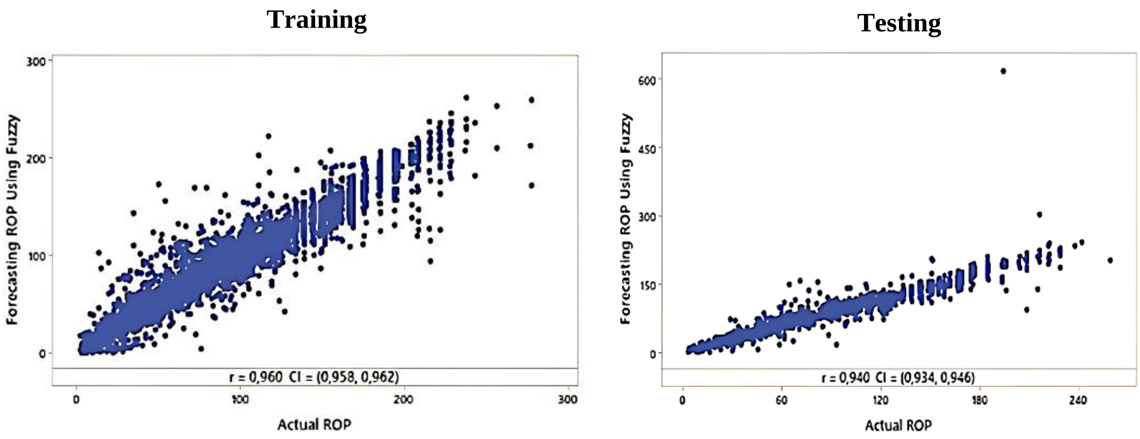

Figure 3. Pearson's correlation test between ROP prediction results and the actual data on training and testing data using a fuzzy system

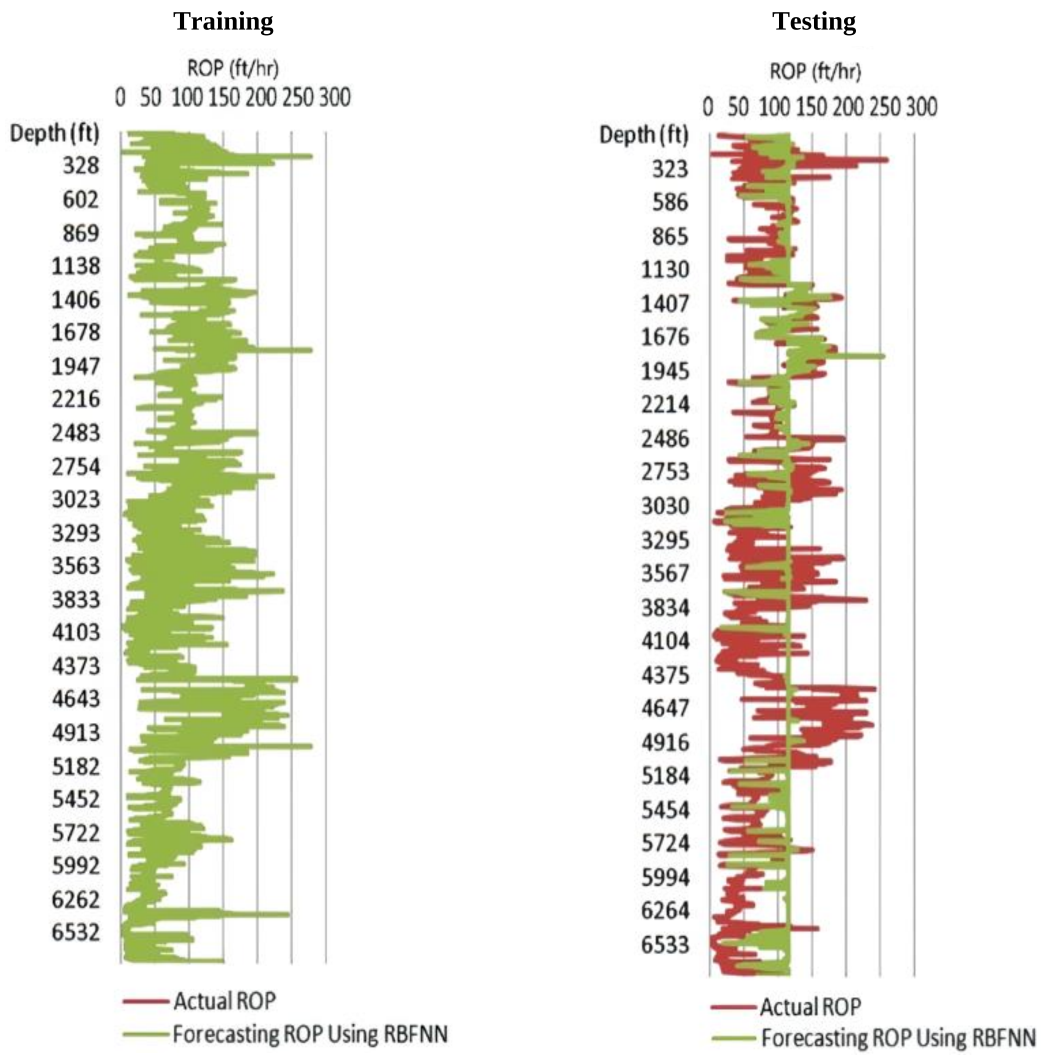

Figure 4. Comparison of ROP prediction results with the actual data on training and testing data using RBFNN

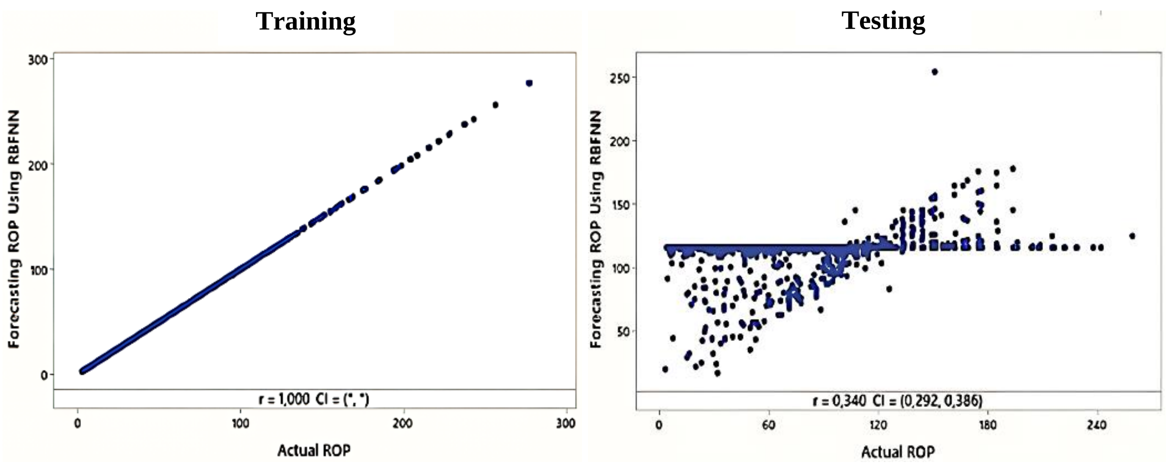

Figure 5. Pearson's correlation test between ROP prediction results and the actual data on training and testing data using RBFNN

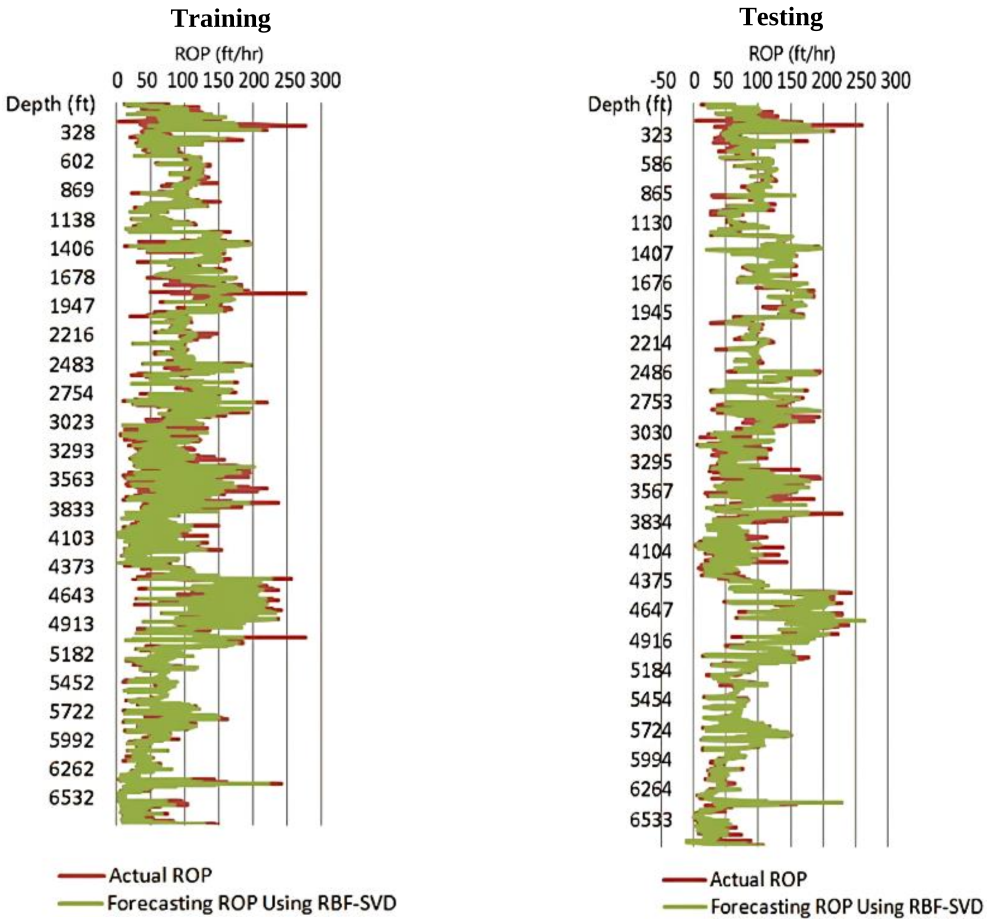

Figure 6. Comparison of ROP prediction results with the actual data on training and testing data using RBF-SVD

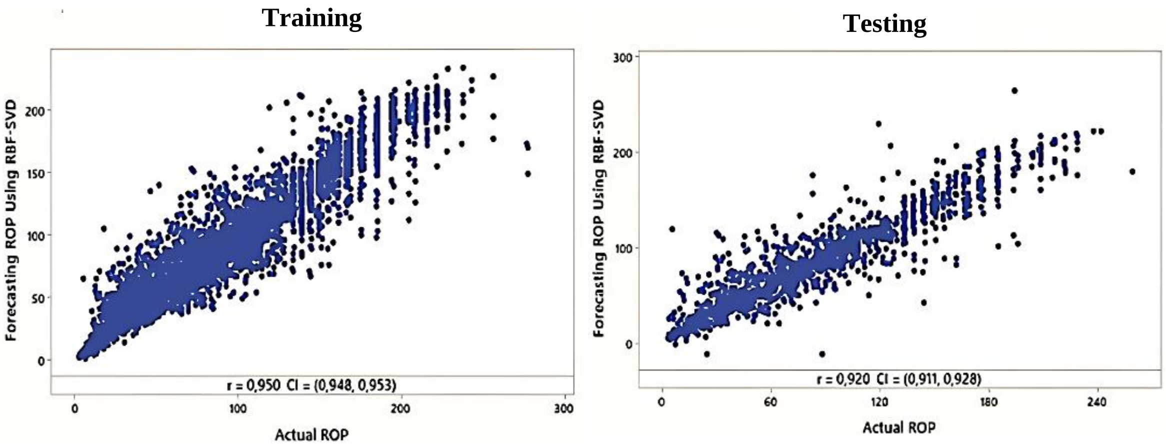

Figure 7. Pearson’s correlation test between ROP prediction results and the actual data on training and testing data using RBFNN-SVD

4. CONCLUSION

Drilling optimization through ROP prediction depends on the availability of drilling data used to build mathematical models. In drilling projects, the available data is limited, making the prediction of ROP difficult. Determination of ROP with a fuzzy system was based on depth, drilling mechanical parameters, drilling fluid, and calculation of drilling parameters. The results show that the fuzzy system is useful to predict ROP with high accuracy and correlation.

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