Ferdowsi University Mashhad/ The second International Conference
Artificial Intelligence: Between Scientific Innovation and Human Responsibility

Pilot Project for Using Fog Computing in Drill Operations, Real-Time Penetration Rate Prediction & Optimization

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Article Info

ISSN (Online): 2582-7138
Impact Factor (RSIF): 7.98
Volume: 06
Issue: 06
November - December 2025
Received: 23-09-2025
Accepted: 25-10-2025
Published: 21-11-2025
Page No: 27-37

Abstract

It's one of the most essential and critical parameters influencing drilling efficiency is the rate of penetration. To increase the drilling efficiency, lower costs, and reduce NPT, necessary to predict ROP before drilling operations. Fog computing can deliver a strong response for applications through preprocessing and filtering the data. Trimmed data can then be transferred to the cloud for further analysis. The project's goal is to build a real-time framework for selecting the optimal penetration rate during the drilling operations.

Generally, two types of ROP prediction models can be classified into (1) traditional models (Maurer,

Bourgoyne & Young's, …) and (2) data-driven models (Neural Network, SVM, ...). In this work, to predict the penetration rate, Bourgoyne & Young's and Neural Network models are applied in terms of ROP modeling based on drilling data that has been taken from the fields of southern Iraq. The two models are then compared to see which one is the most accurate in predicting ROP. As a result, understanding the behavior of drilling data is a crucial part of developing an optimal ROP prediction model in real-time. Where the calculations were made and the results were presented using programming languages and the Spotfire software.

The Neural Network model and Bourgoyne & Young's Drilling model are applied to drilling parameters obtained from the fields of southern Iraq, which are used to predict the ROP. Then a comparison is made between the two models for the same data. The result proved the prediction of the ANN model is preferable than that of Burgoyne & Young's drilling model. The purpose of this project is to demonstrate how data models and learning methodologies can be applied to drilling calculations. ML algorithms are being developed to predict the penetration rate across the well. This model was expanded to maximize ROP for a given section by optimizing parameters such as (weight on bit, revolution per minute, pressure standpipe, and flow rate). Therefore, this model can be used for real-time on drilling rig surface but without using the down-hole parameters because such a model is easy to implement.

The use of fog computing can introduce Internet services such as cloud computing to advanced technology, providing control, computation, storage, communication, and service capacity. Prediction and optimization of ROP will be done in real-time data using machine learning algorithms in programming languages, then converted to a web page. So, we can monitor these results by using smart devices (watch, phone, and PC).

Keywords: ROP Prediction, Neural Networks, Drilling Optimization, Fog Computing

Introduction

Drilling process is an expensive factor for the oil industry while the time lost during the drilling operations causes an increase in the well cost. The simulation of drilling optimization is considered a common practice in the petroleum industry. So, the elimination of such challenges provides significant cost savings (Karnot *et al*., 2025; Hadi *et al*., 2019) [15, 13]. The main aim of the drilling processes is to improve the drilling speed while decreasing the budget.

Because of uncertainties in geology & uncontrolled factors, the optimization remains a difficult challenge for the petroleum industry. Scientists started searching for optimized ways for efficient and reduced costs of drilling since the late 1960s. The main idea of drilling optimization in industries depends on the previous data of wells. ROP is one of the parameters that can be analyzed to achieve this goal (Abbood *et al*., 2023; Alkamil *et al*., 2018) [1, 4].

There are models that were created to predict the penetration rate, while the accuracy differs from one to another depending on the changes in the parameters that are considered, so that each model has strengths and weaknesses. (Alkamil *et al*., 2024; Abughaban *et al*., 2019) [3, 2].

Generally, two types of penetration rate models can be classified:

(1) “Traditional models” are mathematical calculations that are depend on linear regression or inflexible equations related to the drilling parameters, and “empirical model coefficients” are calculated for each rock. Muarer (1962), Bingham, Bourgoyne, and Young (1986) [8] are all classified into these models (Bourgoyne & Young, 1974) [7].

(2) “Data-driven models” are models will use AI techniques to estimate the ROP, and this estimation is considered as a function of properties of the drilling fluid, formation characteristics, and the drilling parameters. Machine learning is classified into these models, as well as ANN (Karnot *et al*., 2025) [15].

ROP Models

A lot of models created to calculate the ROP, but the accuracy differs depending on the variation in the parameters of drilling, so that each model has strengths and weaknesses. We can summarize these models as shown below;

1. Maurer Model

It was created when drilling under the hole cleaning conditions, penetration rate directly affects the weight on bit squared. However, worst case scenarios experienced in the field can cause an increase in the penetration rate due to the hook load that generates more rock cuttings and more cleaning problems. The searcher explored that conditions are typically described by a linear relationship between the weight on bit and the rate of penetration (Bourgoyne *et al*., 1981) [9].

2. Bingham Model

Consider a simple model, an extension or modification of Maurer model. It represents a pilot model that used for low values of (WOB) and (RPM) or N. Because this neglects the drilling depth, the result will have less accuracy (Alum & Egbon***et al***., 2011) [6].

$$ROP = K\left(\frac{W}{d_b}\right)^{a_5} * RPM \quad (1)$$

3. Bourgoyne & Young’s Model

This model clarifies the penetration rate that the function of many parameters, e.g., sediment compaction, weight on bit, revolution per minute, etc. Bourgoyne & Young state eight main functions for varying drilling parameters that affect the ROP (Bourgoyne *et al*., 1981) [9] as shown below;

$$"ROP = (f1 * f2 * f3 * f4 * f5 * f6 * f7 * f8)" \quad (2)$$

This law remains one of the most commonly applied empirical methods in petroleum drilling optimization due to its simplicity and proven field performance (Alkamil *et al*., 2024) [3].

4. Warren Model

Presented as a perfect model for weak formation bits, ROP is not affected by the removal of cuttings. The Warren model relates the parameters by using the analysis for response.

$$"ROP = \left(\frac{a*s^2*d_b^3}{W*RPM^2} + \frac{c}{RPM*d_b}\right)^{-1}" \quad (3)$$

5. Artificial Neural Network (ANN) Model

It is the most familiar ML algorithm for ROP calculation and prediction. A neural network can learn in order to generalize & recognize the systems. A neural network is composed of three layers of neurons are called the input, output, and hidden layers. The neurons take the continuous neuron's input values, multiply them by the connection weights, combine them with a bias value, and feed them to their transmission function to create the outputs (Hadi *et al*., 2019; Karnot *et al*., 2025) [15, 13].

The main purpose of ANNS solutions is training, where supervised. ANN's target is compared with the desired target. Learning function modifies the biases & weights, which were initially randomly set, so that the next repetition results in a good match with the targeted network result.

Digital Transformation 4.0

In the 18th century, the world witnessed the 1st revolution, the introduction of engines, and the manufacturing. In the 19th century, the hallmark of the 2nd industrial Revolution is the introduction use of electricity in both the domestic and industrial sectors. The third industrial revolution brought the automation of industrial processes in the 20th century. The 21st century is now witnessing the 4th revolution of the industry, highlighted by the use of digital networks for monitoring and controlling processes.

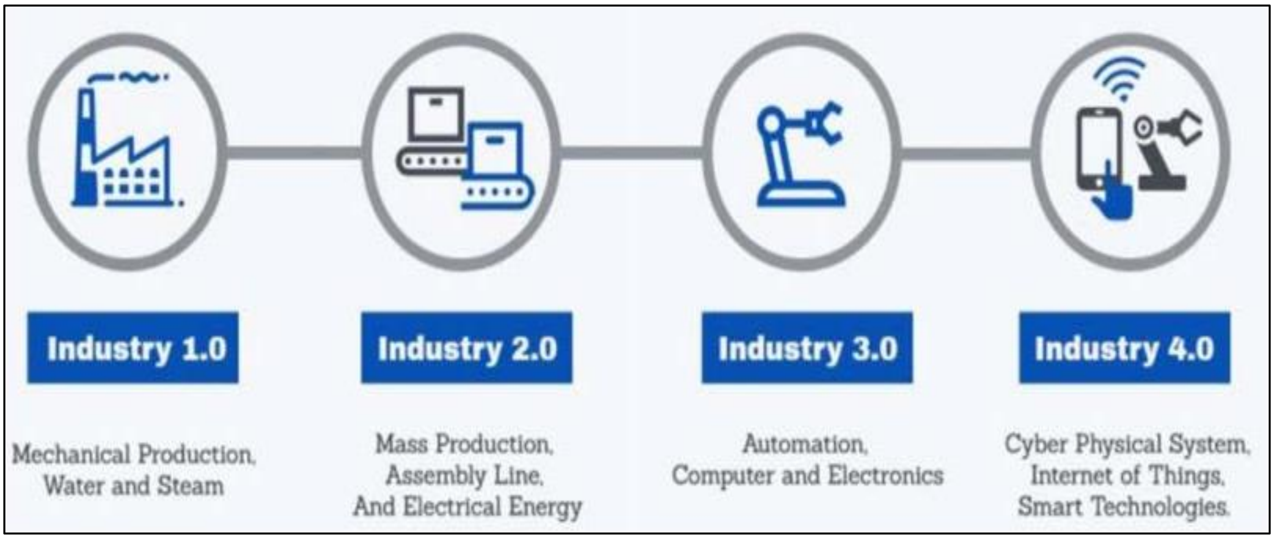

Fig 1: The four industrial revolutions

Digital transformation has strategies to increase energy efficiency and significantly decrease emissions. Digital transformation for oil and gas includes advanced imaging, such as using drones, machine/deep learning, advanced 3-D printing, smart personal protective equipment (PPE that connects to the internet to enhance safety), quantum sensors, cognitive computing, body-mounted sensors, power over WIFI, big data processing, IoT (edge computing), and cloud computing, as shown in Figure 1 (Alkamil *et al*., 2021; Kai Bai *et al*., 2024) [3].

Though the Industry 4th and the IoT's are complex, Figure 2 illustrates nine technologies that the oil and gas industry must invest in to create automated industrial simulations, horizontal and vertical system integration, robots, the cloud, cyber security, additive manufacturing, and big data are examples of the Industry 4.0 solutions (Alkamil *et al*., 2025; Zhe Huang *et al*., 2024) [15, 3].

Cloud & Fog Computing

Utilizing economies of scale to generate efficiencies, such as cloud computing, for big data management is necessary to maintain data security and almost complete accessibility (Pessier *et al*., 1992) The term "cloud" inspires images of vast, amorphous structures with a metaphysical, even mystical, connection to solid, three-dimensional stuff. This uncertainty is misleading, though. In reality, servers with a physical address are required to host all data and the internet. An important danger associated with cloud computing has been identified through a five-year case study of data storage for an oil and gas corporation (Ethar *et al*., 2020; Alkamil *et al*., 2021) [3].

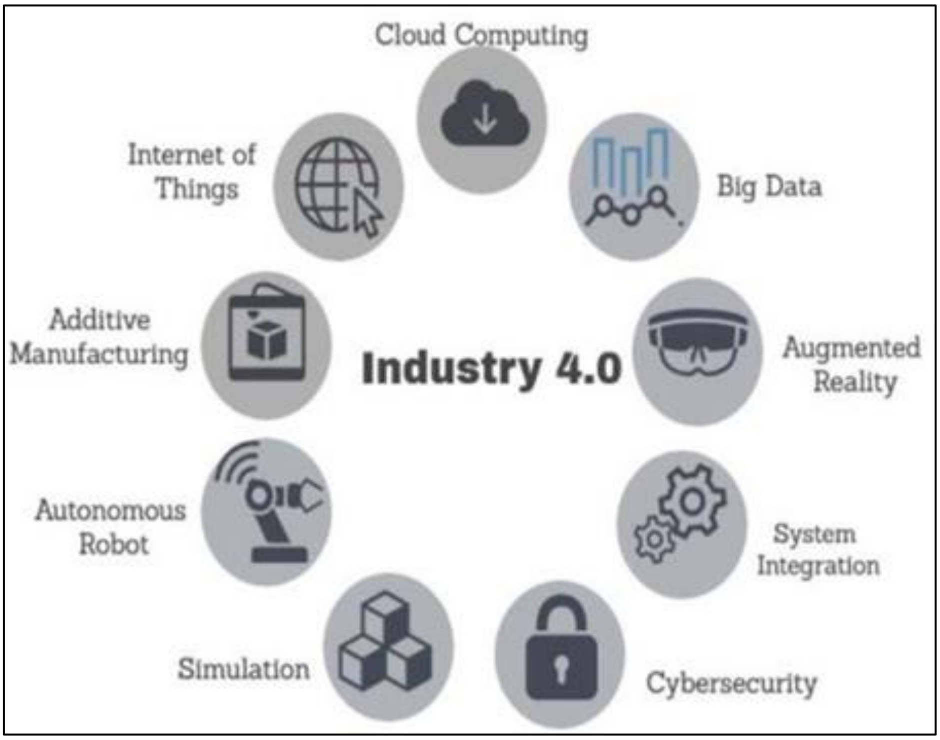

Fig 2: Nine components of Industry 4.0

Cloud to Fog Computing Model

Fog pattern has a lot of advantages over the cloud pattern, including closeness to endpoints (e.g., parameters' sensors, required actuators, smart devices, and IoTs). The capacity of such end devices is often relatively restricted. As a result, end-user applications usually need more powerful devices. One possibility for such applications is to use cloud computing to that end. However, this strategy results in excessive latency due to the lengthy network connection between end devices and cloud paradigm centers. Furthermore, the bandwidth of cloud data center network connections may cause serious bottlenecks (Alkamil *et al*., 2021) [3].

Cloud computing is a centralized information technology infrastructure that enables industrial cyber-physical-social systems (CPSSs); cost-effective, on-demand access to huge resources, and flexible services. The fog connects CPSSs to cloud pattern centers and has the possibility to lower the bandwidth (Feng *et al*. 2020). Cloud computing is a critical model for managing and performing all types of calculations. When the mission or task must be completed in a real-time with a low hiding, the cloud can become inactive (Feng *et al*., 2020; Mutlag *et al*., 2020).

Fog computing pattern is considered to be more costly than cloud computing pattern in time applications, such as care, health because of its low hiding and latency (Mutlag *et al*. 2020). Cloud computing provides several IoT services, including storage capacities, resources for computation, processing, heterogeneity, and others. At many levels, the cloud allows for the virtualization of computational resources (Mutlag *et al*., 2020).

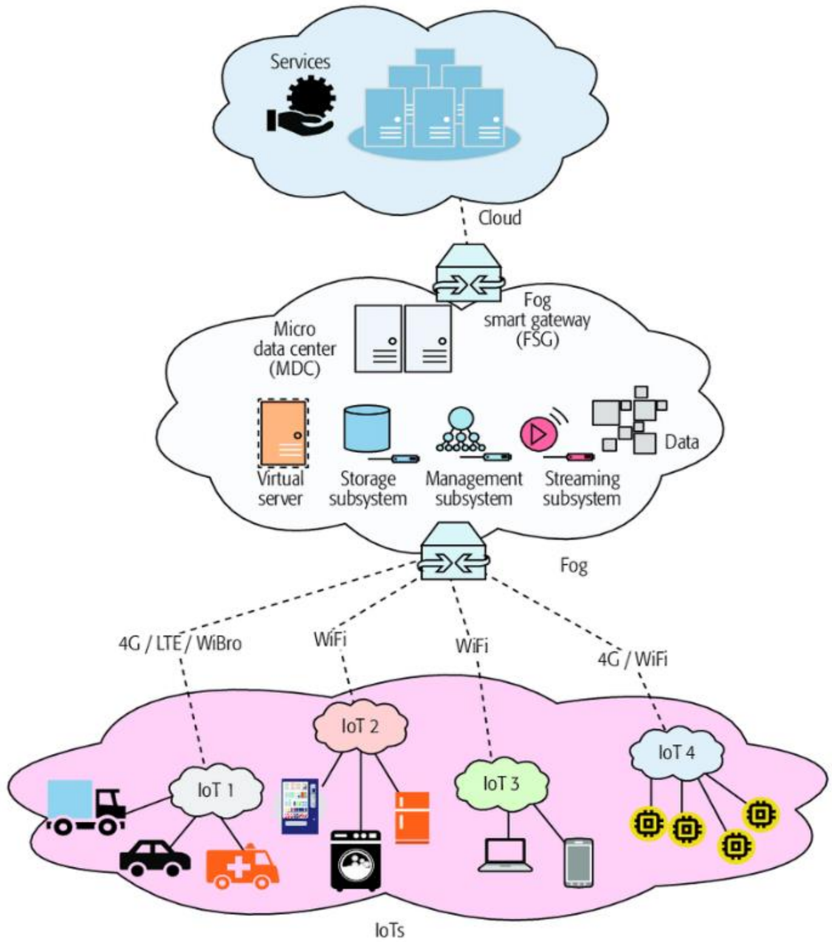

Fig 3: Overall architecture and positioning of the fog (Hall and Miller 2018)

Machine Learning in ROP Prediction

The statistics to uncover the relationships between any described inputs weather features or predictors and the response. The most important advantage of machine learning systems in analysis is their flexibility in forming the model. Without setting the equation, Machine Learning models provide segmentation of the drilling parameter. However, when the complexity of the model will be increased this will diminish the interpretability, and that's mean the adjustment to the inputs will change the output. There isn't single rate of penetration (ROP) model we can apply it in every case or situation (Hadi *et al*., 2019; Alkamil *et al*., 2024) [13, 3].

Model Training and Validation

As shown below in Figure 4, the training and testing data are considered important steps in evaluating the performance. When we use all the data just in the training stage, the root mean square will be high and which indicates a strong compatibility for the model. However, this may cause overfitting. The model suggests a high performance on known data. To decrease this problem, the data is split, for example, 70% for training and 30% for testing, which will provide a more balanced model. Gradual changes in the training and test ratios would also lead to a similar change in R^2 values.

Conversely, higher RMSE values suggest deviations that may arise from data noise or model underfitting.

Thus, careful calibration of training data proportions and continuous evaluation of performance metrics such as R^2 and RMSE are essential in developing reliable, field-specific ROP prediction models using machine learning techniques.

As shown in Fig.3, if all datasets are trained, the R^2 for the actual ROP and predicted ROP will be high, while if 70% of the dataset is trained and 30% tested, the value of R^2 will be very high and represents optimal training and testing data. So, by decreasing or increasing the training and test of the dataset gradually, the R^2 will gradually decrease or increase, as shown in Table 1**.**

Table 1: The performance signals for the ANN model

Training data %	Testing data %	*R*2 Training	RMSE Training %	*R*2 Testing	RMSE Testing %
70	30	0.566	15.627	0.529	16.472
75	25	0.689	13.332	0.593	15.495
80	20	0.643	14.063	0.611	15.970
85	15	0.656	14.027	0.654	14.312

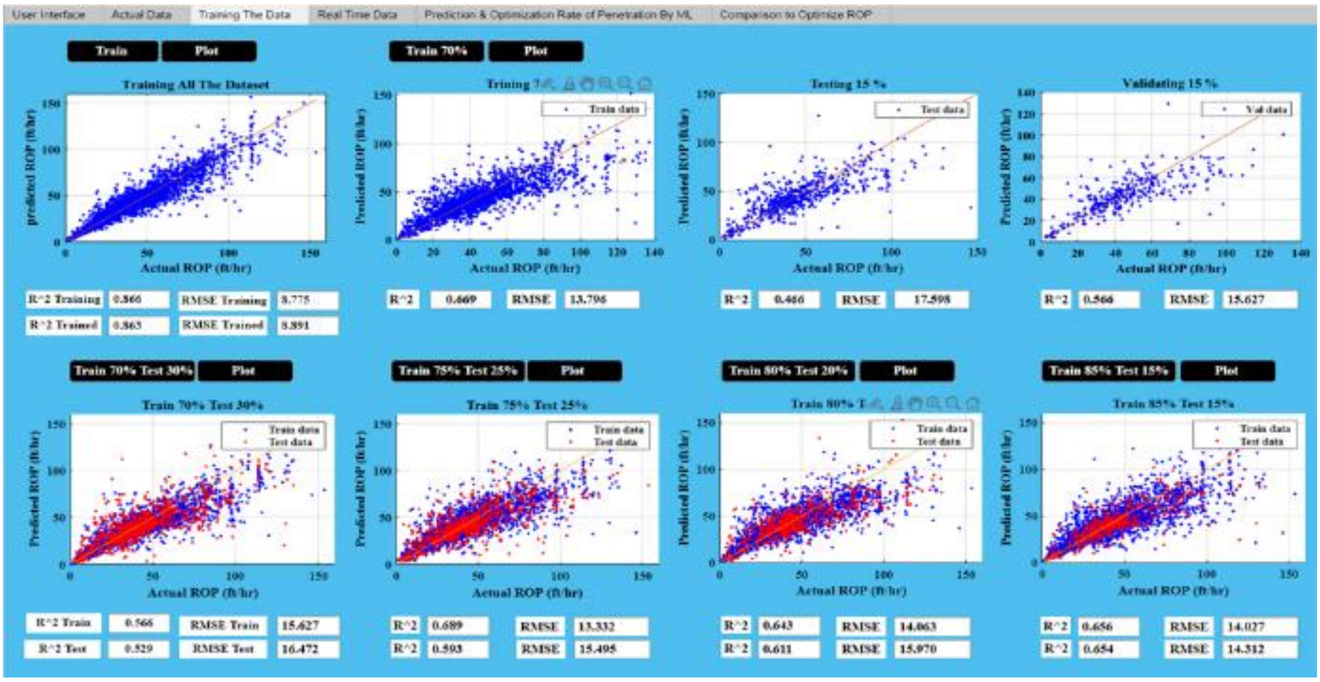

Fig 4: Training and Testing results are plotted with Machine Learning

As for the RMSE, the smaller its value, the better, which indicates a high accuracy of the dataset used for the field to be studied, and this can be clarified in Table 1.

Spotfire Analytics Platform

Spotfire is a sophisticated enterprise-grade analytics platform for extracting useful business information. It's a smart, safe, versatile, and scalable platform for data visualization, exploration, and wrangling, as well as predictive analytics. Spotfire also comes with a powerful dashboard and interactive analytics programs (H. Almomen *et al*., 2023).

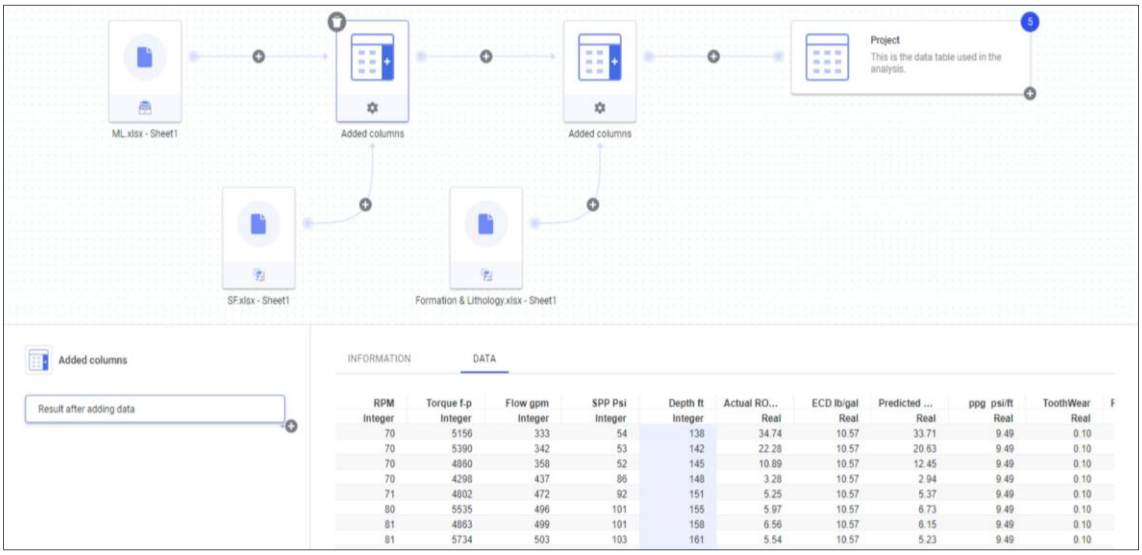

Fig 5: Data Canvas in Spotfire

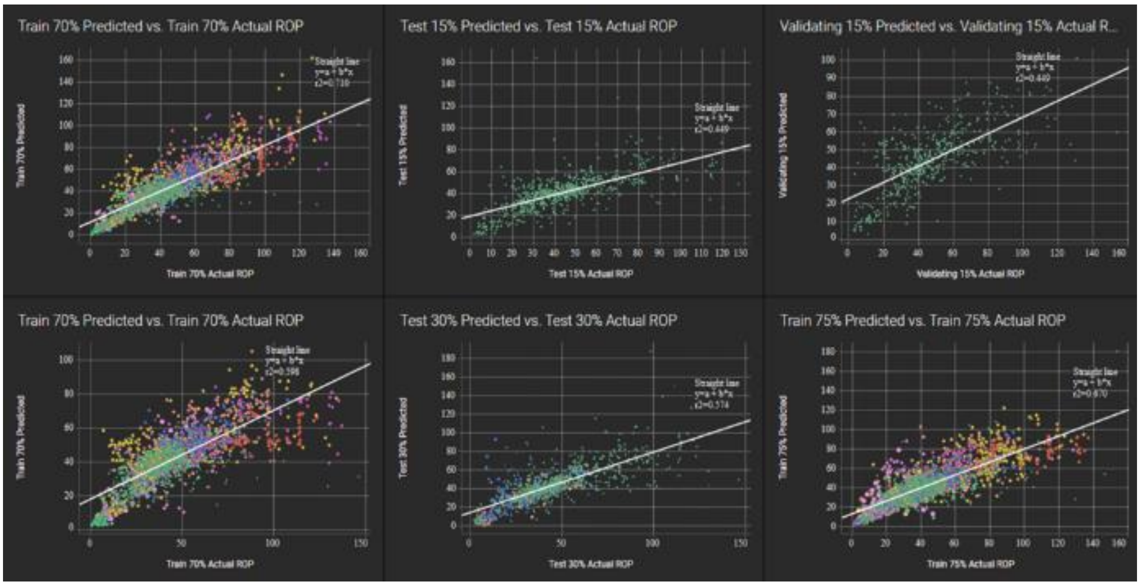

Fig 6: Training data and Testing data results were plotted with Spotfire

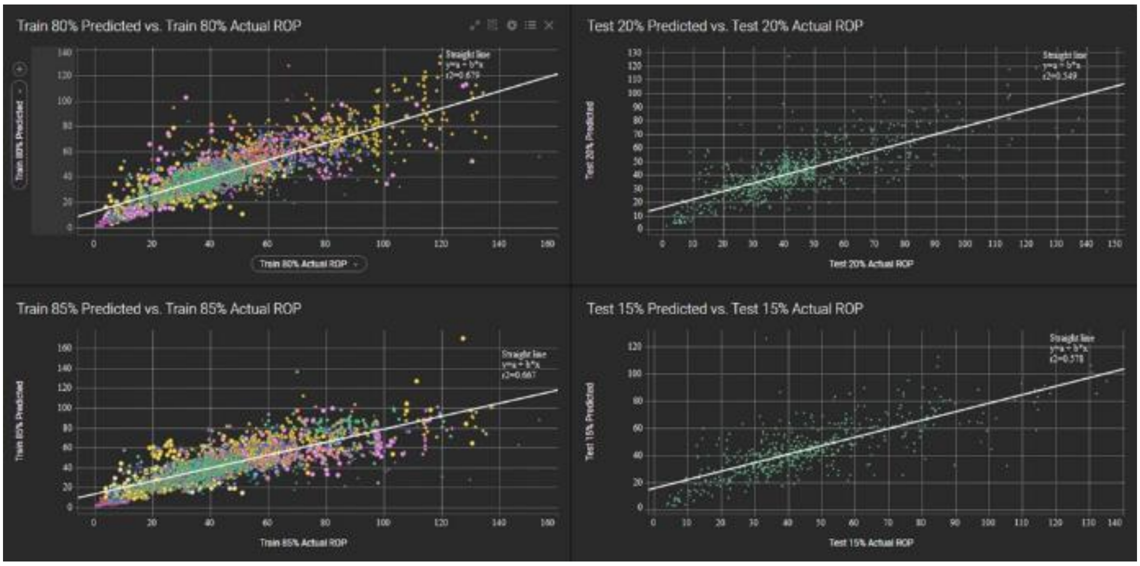

Fig 7: Data results were plotted with Spotfire

Shown below in Figures 3 and 4, the same training and testing results that appeared with the ML appeared in the Spotfire, and the same precision.

Real-Time Data Analysis in Drilling Operations

It could be defined as data that would exist as soon as it's built, created, or acquired. without delay, rather than store it, which is important for supporting live seen, and making decisions instantly. real-time streamed to end users, the drilling penetration rate can be independent of drilling variables such as speed of the rotation, weight on bit of the string, the characteristics of the formation, and the flow rate (Mutlag *et al*., 2020).

This process is specific for the formation, and in real-time, to have a penetration rate plotted against the depth, with a specific parameters, can give a new model to the nature optimization of drilling. Also, in real-time, any noticeable difference between the actual ROP trend and the predicted ROP can give a hint that will be recognized early. This strategy could be used in future drilling processes on a wide range, where it will reduce the drilling costs and probability of finding problems (Chen, X *et al*., 2016) [10].

Processing of real time data involves capturing input and analyzing input from surface systems, which including parameters such as standpipe pressure, torque, hook load, bit depth, and flow rate. These inputs or parameters feed into algorithms such as artificial neural network-based penetration rate models to predict the drilling performance dynamically. In comparison with traditional methods or batch processing where real time systems provide close analytical results as instantly.

In this moment, however, a lot of data processing is done by artificial intelligence (AI) and machine learning (ML) algorithms. The nature of processing noticed at least some time delay; the speed of processing provides a faster and quicker, as well as more complex analysis. There are six steps to actionable insights for training the data, and those steps are repeated looks like a cycle (Mutlag *et al*., 2020; Alkamil *et al*., 2024) [3].

On the rig's surface, drilling data acquisition systems receive real-time data. The weight on bit, revolution per minute, torque, standpipe pressure, the differential pressure, hook height, bit depth, and flow measurements are all part of the process.

After drilling a specific section of a hole, the user can monitor the results of that section. You can also see the changes that have occurred in the previous parameters. In addition to the type of stratigraphy, lithology, and final duration for the drilled section. The artificial neural network model built in this search is trained to utilize a variety of data sets as input parameters to predict the penetration rate as an output parameter, including RPM, T, WOB, and DP.

Fig 8: Input parameters, the Actual and Predicted Penetration Rate in Spotfire

Table 2: Part of the Drilling Data for calculating the ROP model

Data Number	Depth (FT)	WOB (Pounds)	torque (lb x ft)	N (RPM)	Pressure (PSI)	Flow (GPM)	ROP (ft/min)
1	86	11	2747	62	35	278	38.16
2	89	11	1221	62	35	280	35.17
3	92	11	1181	62	32	276	49.31
4	96	11	1127	62	35	279	39.37
5	99	11	1127	62	35	279	39.37
6	102	11	1108	62	35	279	38.19
7	105	11	1096	62	35	279	38.16
8	109	11	1062	62	34	280	38.12
9	112	11	1091	62	35	280	41.01
10	115	4	1002	62	35	279	41.37
11	119	5	1002	62	35	279	35.27
12	122	10	1150	62	35	305	36.91

13	125	12	1135	62	34	301	32.22
14	128	5	1050	62	34	299	7.94
15	132	5	1050	62	34	299	7.94
16	135	2	1461	63	38	285	18.47
17	138	12	5156	70	54	333	34.74
18	142	11	5390	70	53	342	22.28
19	145	10	4860	70	52	358	10.89
20	148	6	4298	70	86	437	3.28
21	151	6	4802	71	92	472	5.25
22	155	18	5535	80	101	496	5.97
23	158	18	4863	81	101	499	6.56
24	161	20	5734	81	103	503	5.54
25	165	21	4518	80	103	508	4.99
26	168	19	4239	89	108	504	4.59
27	171	21	4490	84	106	502	8.04
28	194	6	3516	86	104	506	32.97
29	197	5	2077	86	114	503	34.45
30	201	6	1897	86	110	502	34.45

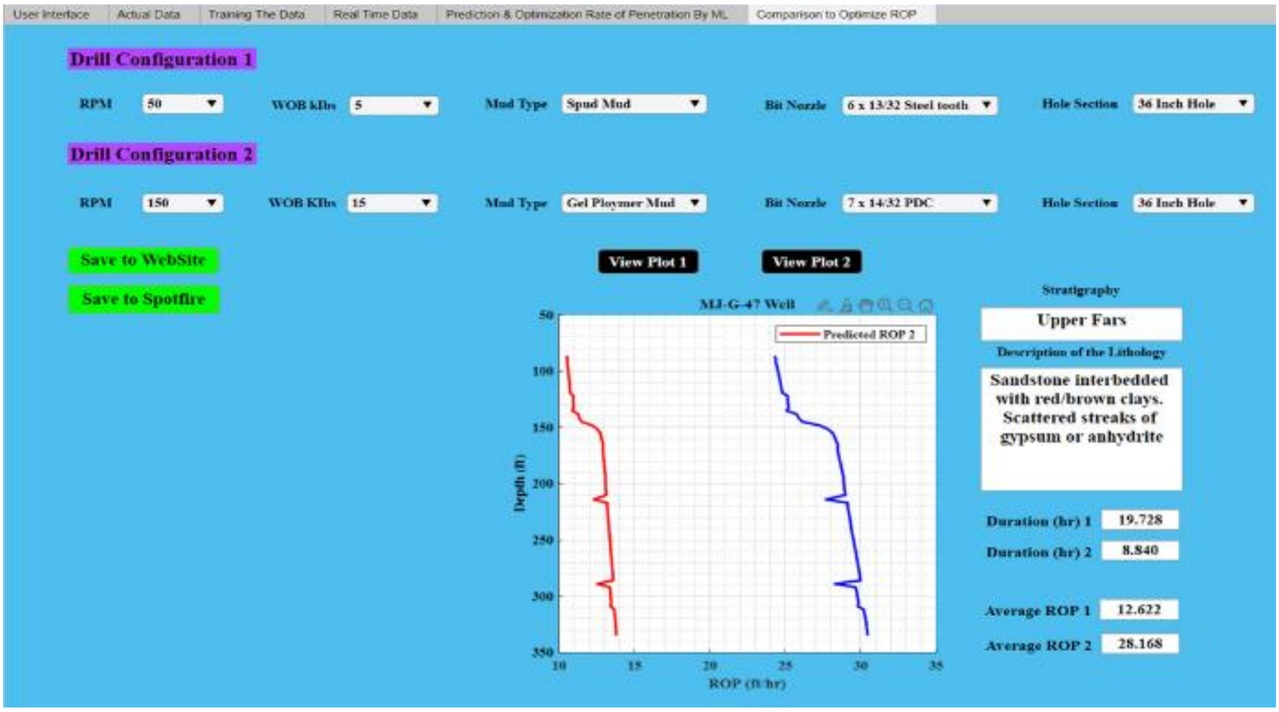

Fig 9: Comparison between drill configurations to optimize ROP

Results and Discussion

The Neural Network model, Bourgoyne-Young's Drilling models are applied to drilling parameters obtained from the Southern Iraqi field, where used to predict the ROP. Then a comparison is made between the two models for the same data. In this part, the calculation performance is made between the artificial neural network and Bourgoyne-Young's Drilling models, where the time of training is recorded.

The accuracy of the model can be evaluated by comparing the R^2 and RMSE performance signals for the data sets presented in Tables 3 and 4.

Table 3: The performance signals for the ANN model

Indicator	*R2*	*RMSE*%
Predicted	0.878	8.394
Optimized	0.961	4.737

Table 4: The performance signals for Bourgoyne & Young's model

R2	**0.321**
RMSE (%)	36.420

As shown in the tables above, the result proves that the calculation of the Neural Network pattern is preferable to that of Burgoyne & Young's drilling model.

After drilling a specific section of a hole, the user can monitor the results of that section. You can also see the changes that have occurred in Weight on Bit, Revolutions per minute, Torque, Pressure Standpipe, and Flow Rate. On the other hand, the type of stratigraphy, lithology, and final duration of the drilled section.

Table 5: Monitoring for real-time data

Depth (ft)	WOB (Ib)	RPM (rpm)	Torque (Ib*ft)	Q (gpm)	SPP (Psi)	Actual ROP (ft/min)	Predicted ROP (ft/min)
299	6	85	2010	477	167	36.45	33.38
496	10	72	1471	811	1253	51.57	44.24
604	13	72	2226	811	1398	38.98	43.66
703	19	70	3045	805	1420	47.21	42.13
758	2	69	2509	812	1475	49.9	43.4

Figures following (10,11,12, and 13) illustrate actual ROP vs. predicted ROP, for the same section, as determined by the two models:

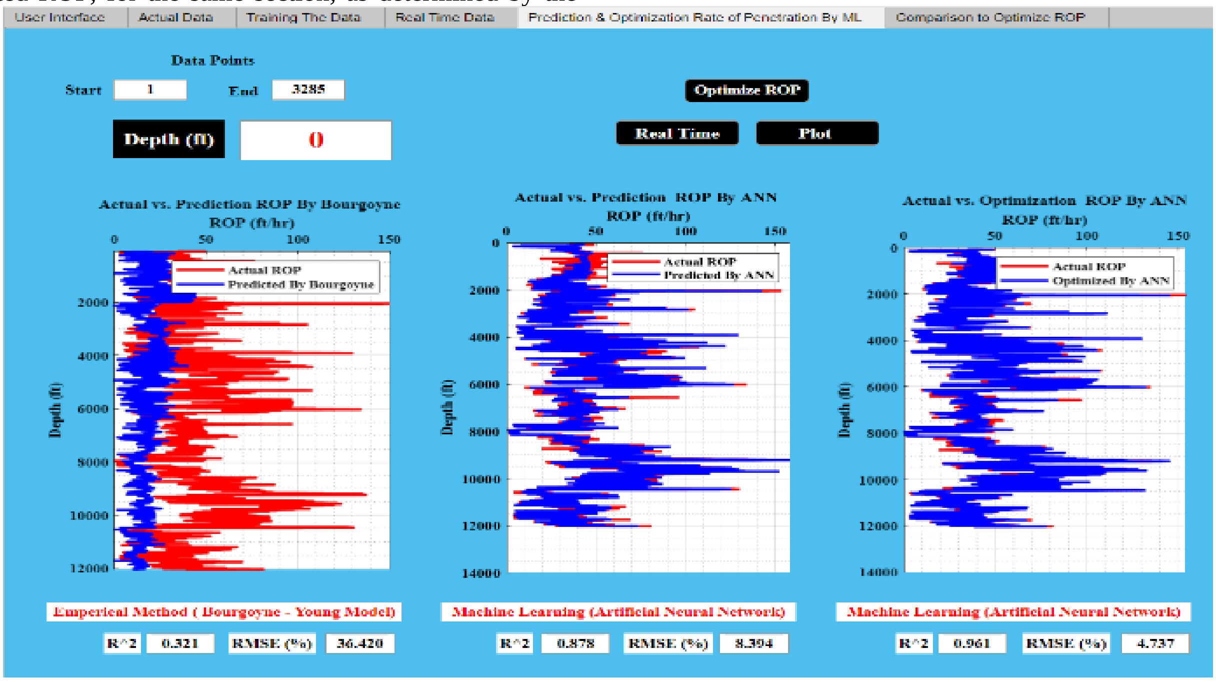

Fig 10: ROP prediction by ANN and Bourgoyne-Young's Models with ML

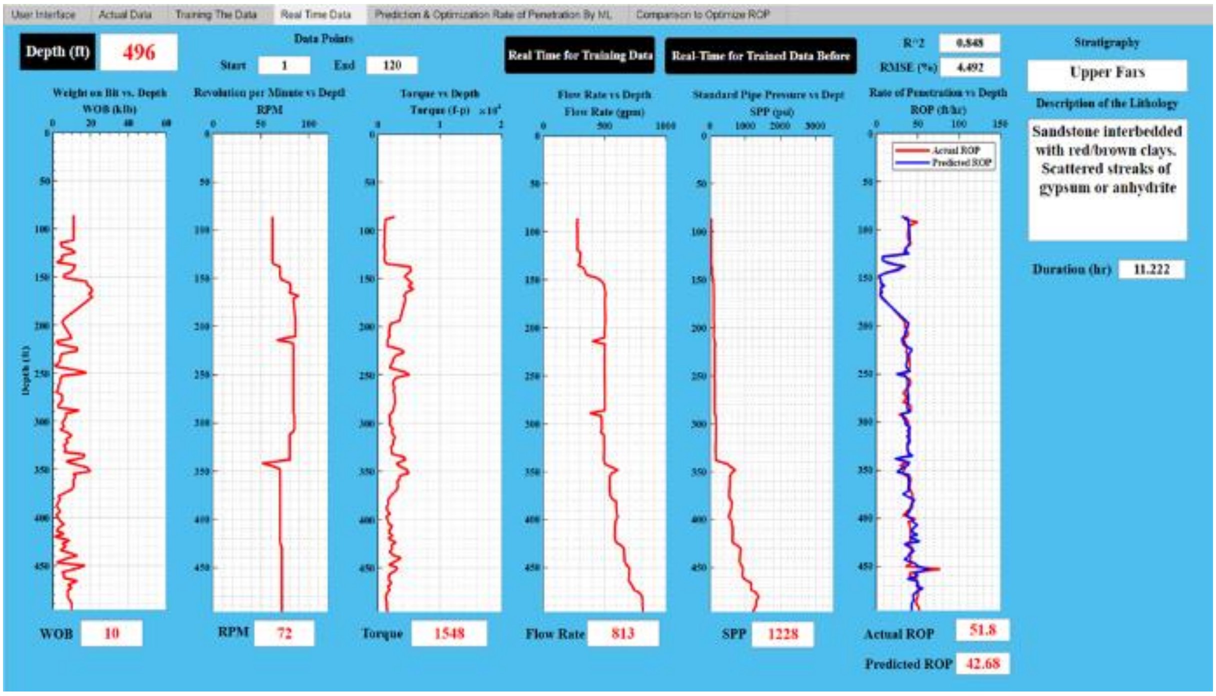

Fig 11: Monitoring for real-time data

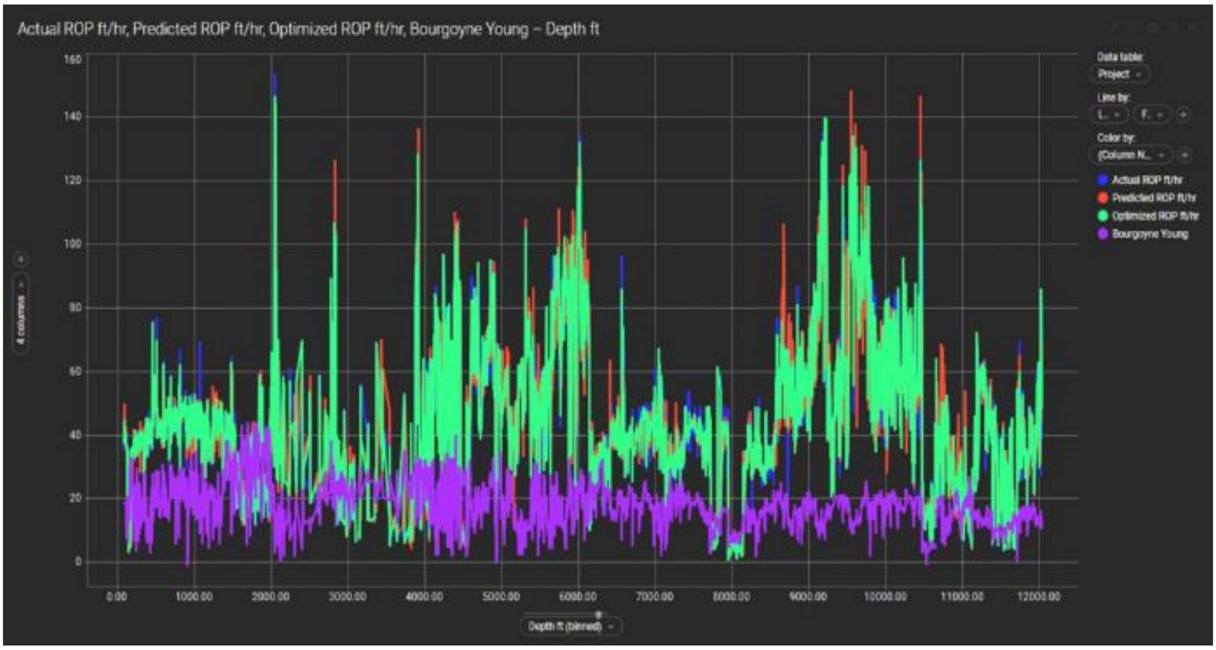

Fig 12: Actual, Predicted, and Optimized ROP vs. Bourgoyne-Young's Model i n Spotfire

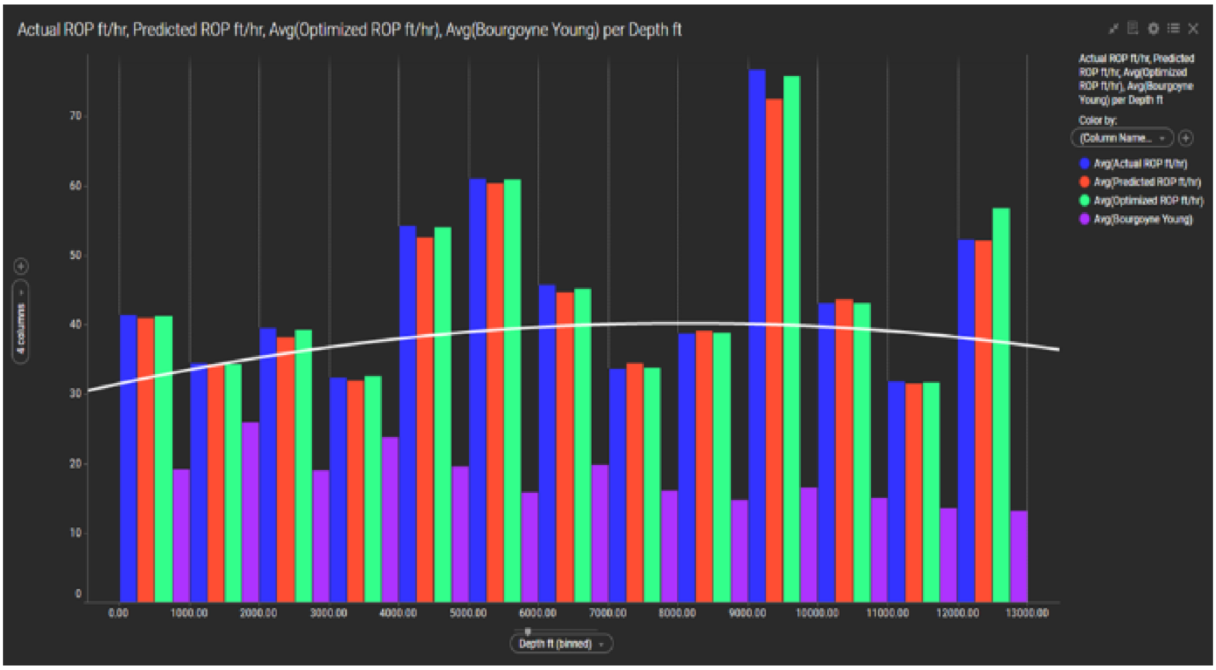

Fig 13: Actual, Predicted, and Optimized ROP vs. Bourgoyne-Young's Model in Spotfire

Conclusion

The purpose of this project is to demonstrate how data models and learning methodologies can be applied to drilling calculations. ML algorithms are being built to calculate the penetration rate across the well.

This model was expanded to maximize ROP for a given section by optimizing parameters (Weight on Bit, Revolution per Minute, Pressure Standpipe, and Flow Rate).

Therefore, this model can be used for real-time calculations on the drilling rig surface, but without using down-hole parameters, because such a model is easy to implement.

This strategy saves time and effort since all data and outcomes can be accessed remotely, much more efficiently and simply than before.

The use of the intended ROP App in this project, which provides remote access to real-time data, can assist the oil and gas sector in dealing with difficulties such as the COVID-19 pandemic and the global emergency circumstances.

Nomenclature

S=Compressive Strength
a=Bit Constant
c=Bit Constant
b=Bit Constant
d_b=Bit Diameter
W=Weight on Bit
RPM=Rotation Per Minute
F_{jm}=Modified Jet Impact Force
γ_f=Fluid Specific Gravity
K=Constant
μ=Coefficient of Sliding Friction
W/d_b=Threshold Value
f_1=The Formation Strength

f_2=The Exponent of Compaction Trend
f_3=The Exponent of Compaction
f_4= The Exponent of Differential Pressure
f_5=WOB Exponent
f_6=The Torque Exponent
f_7=The Tooth Wear Exponent
f_8=The Hydraulic Exponent

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