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Selection of an Optimum Drilling Fluid Model to Enhance Mud Hydraulic System Using Neural Networks in Iraqi Oil Field

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Abstract

In drilling processes, the rheological properties pointed to the nature of the run-off and the composition of the drilling mud. Drilling mud performance can be assessed for solving the problems of the hole cleaning, fluid management, and hydraulics controls. The rheology factors are typically termed through the following parameters: Yield Point (Yp) and Plastic Viscosity (µp). The relation of (YP/ µp) is used for measuring of levelling for flow. High YP/ µp percentages are responsible for well cuttings transportation through laminar flow. The adequate values of (YP/ µp) are between 0 to 1 for the rheological models which used in drilling. This is what appeared in most of the models that were used in this study. The pressure loss is a gathering of numerous issues for example rheology of mud), flow regime and the well geometry. An artificial neural network (ANN) that used in this effort is an accurate or computational model stimulated by using JMP software. The aim of this study is to find out the effect of rheological models on the hydraulic system and to use the artificial neural network to simulate the parameters that were used as emotional parameters and then find an equation containing the parameters µp, Yp and P Yp/ µp to calculate the pressure losses in a hydraulic system. Data for 7 intermediate casing wells with 12.25" hole size and $9^{5/8}$" intermediate casing size are taken from the southern Iraq field used for the above purpose. Then compare the result with common equations used to calculate pressure losses in a hydraulic system. Also, we calculate the optimum flow by the maximum impact force method and then offset in Equation obtained by (Joint Marketing Program) JMP software. Finally, the equation that was found to calculate pressure losses instead of using common hydraulic equations with long calculations gave very close results with less calculation.

Key words: rheological properties, hydraulics, pressure losses, drilling mud.

Open Access
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1. Introduction

Drilling mud has a crucial part in the drilling processes for petrol wells. The Water base (WB) mud are desirable drilling fluid because of its character, the cheaper price, ecologically friendly, and equipped to justifying the well control difficulties [1]. A representative WB drilling mud comprises of water by way of a base and some additives to achieve aimed roles, for instance rheology controlling additive and density control additives [2]. The supreme public way for assessing and enhance the performance of mud is by inspecting their rheological properties for instance yield point and plastic viscosity [3]. Throughout circulations of the mud inside the well, the friction between mud and the wall of the annulus and drill pipe reason to pressure loss [4]. The launch of the JMP program was the beginning of the nineties, and then it developed little by little until it became as good as it is now to take benefit of the graphical border presented by the its operating systems [5]. This program has since been expressively revised and made obtainable also designed for the Windows system [6]. JMP program is used for applications for instance, quality regulator, and engineering, strategy of experiments, in addition to investigation in science and engineering. In supreme cases of an Artificial Neural Networks (ANN) is an updated system which make modifications in its construction based on exterior or interior instruction which flows inside the network throughout the learning stage information [7] , [8]. Current neural networks should be nonlinear numerical information demonstrating tools [9]. Nevertheless, at the moment, an excessive deal of determinations is attentive on the improvement of artificial neural networks for requests for instance information compression and optimization [10]. Artificial neural network contains of an organized collection of artificial neurons using a connectionist method for computation [11]. The main drilling problems for instance fluid loss, torque, wellbore strengthening, drag, well control, carrying capacity, and stuck pipe outcome from the inappropriate corresponding of drilling mud properties. Those problems happen because of differences in pressure, and temperature that have an excessive influence on the mud rheological properties. Mud properties may be improved for the effective drilling process [12]. The main goal of this study to identifying the effect of rheological parameters influence on the total pressure losses in the hydraulic system using experimental results such as the viscosity and yield point for the better understanding of the rheological model and pressure losses. This study is based on that the rheology model for pressure loss

Open Access
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prediction can be investigated to the desired level in an experimental laboratory facility and 111 drilling field data, which can be applied to reduce drilling problems in wells. This study presents a simplified procedure for selecting the rheological model of 25 samples which best fits the properties of a given hydraulic fluid to represent the shear-stress, shear-rate relationship for a given fluid. Throughout this particular study, an Artificial Neural Network model was implemented through the fitting tool of (Joint Marketing Program) JMP software. The study assumes that the model obtained by ANN technique which gives the lowest Absolute Average Percentage Error (AAPE) between the measured and calculated total pressure losses is the best one for a hydraulic system calculation. The results are of great importance for achieving the correct pressure drop and hydraulics calculations., in general, the best prediction of total pressure losses for the mud samples and drilling field data considered (AAPE = 8.7%) and (R=91.3%). The study also included optimum flowrate calculation for better hydraulic system.

2. Methodology

This study will be conducted with the input data sets of μp, Yp, (Yp /μp), Total Flow Area (TFA) and all drilling data provided. To maximize the accuracy and reliability of the model, the variables that been selected based on the importance toward the Pressure losses. The selection will be based on the R-Square (R) for each parameter. The variables with high R-square(R) will then selected. In order to minimize the randomness and increase the relevancy or the model, the data is then being simplified before being evaluated in Artificial Neural Network. Artificial Neural Network will be trained for the input of the selected variable with simplified data and the output of the target data, in this study, Pressure losses. With trainings and validations, the simulation for sample data will then be evaluated in order to find the matching between predicted and actual. An error analysis is then being observed in order to find the relevancy of the matching, and as shown in Figure (1).

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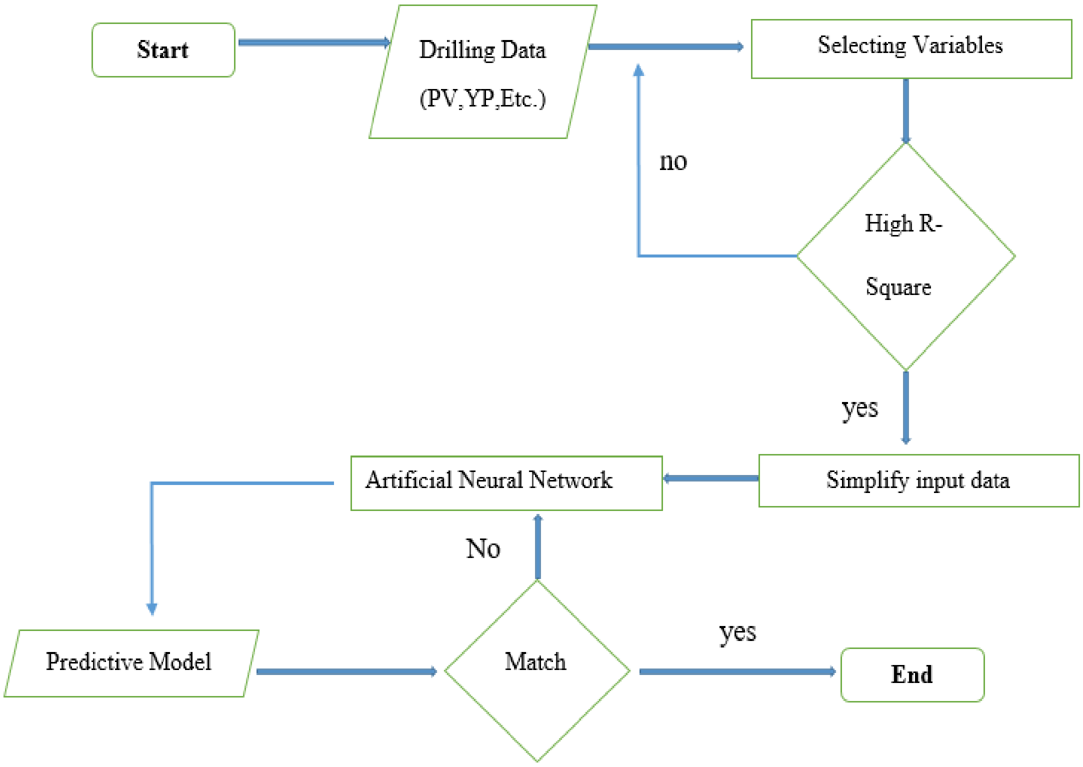

Fig. (1): Flow chart for the study.

3. Experimental Work:

Many Drilling fluid experiments have been carried out in the drilling laboratory and viscometer; Mud Balance and pressurized Mud Balance have been used, in order to get the data that used in the study like plastic viscosity and shear stress and the yield point. Various materials have been used in all experiments such as Bentonite, Barite, KCL, CMC, Starch, polyacrylamide, X-xanthan, Qubracho, PAC and Hematite, Table (1) shows the quantity of each used sample.

Open Access
No. 37, December 2022, pp. 50-67

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Table (1) Materials used in experiments and its quantities.

Samples	Water (cc)	Material and quantities
1	350	22.5 gm Bentonite + 10 gm Kcl
2	350	22.5 gm Bentonite + 1 gm PAC
3	350	11.5 gm Bentonite + 20 gm Hematite
4	350	22.5 gm Bentonite + 15 gm Corn starch
5	350	22.5 gm Bentonite + 3 gm CMC
6	350	33.75 gm Bentonite
7	350	22.5 gm Bentonite + 10 cc Qubracho
8	350	45 gm Bentonite + 10 gm Barite
9	350	22.5 gm Bentonite + 0.5 gm polyacrylamide
10	350	22.5 gm Bentonite + 1 gm xanthan
11	350	11.25 gm Bentonite + 10 cc Qubracho
12	350	11.25 gm Bentonite + 5 cc Qubracho
13	350	22.5 gm Bentonite + 15 cc Qubracho
14	350	22.5 gm Bentonite + 1 gm PAC+0.5 gm CMC
15	350	22.5 gm Bentonite + 2 gm xanthan
16	350	22.5 gm Bentonite + 1 gm polyacrylamide
17	350	22.5 gm Bentonite + 2 gm X-anthan+1 gm PAC
18	350	22.5 gm Bentonite + 2 gm palyacrylamide+1 gm CMC
19	350	22.5 gm Bentonite + 2 gm corn starch + 0.5 gm xanthan
20	350	22.5 gm Bent + 15 cc spersene +1 gm starch+ 5 gm Kcl
21	350	1.5 gm polyacrylamide+ 1 gm xanthan
22	350	11.5 gm Bentonite + 1.5 polyacrylamide + 20 cc xp-20
23	350	11.5 gm Bentonite + 15 cc spersene
24	350	22.5 gm Bentonite + 5 cc spersene+5 cc xp-20
25	350	22.5gm Bentonite + 5 gm Barite + 10 gm Hematite + 5 gm Galina

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P- ISSN: 2220-5381
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4. Data Preparation

Data used in program has been obtained from seven wells in x-oil field in south of Iraq and included flowrate, plastic viscosity, yield point and total flowrate as input data while the output data include total pressure losses in the hydraulics, In the critical operations, the ECD is used to control the formation pressure and prevent kicks without fracturing the drilled formations. When the mud pumps are switched off, the reduction of ECD may result in underbalanced conditions which require good knowledge of the ECD to avoid any drilling problems. At the same time, it is not possible to increase the mud weight due to fracture pressure limitations. the higher plastic viscosity generates higher resistance in mud which in turns will affect cutting lifting performance and increase pressure losses. The situation may be worsened by the increase of ultra-fine drill solids in the drilling fluid which causes incremental trend of plastic viscosity at constant mud weigh. The pressure losses & ECD have been calculated by using Excel program after analysis lab data and determine the type of model Table (2) illustrate the data used:

Table (2) The input data to JMP software

Type	Φ600	Φ300	Φ200	Φ100	Φ6	Φ3	μp	yp	p losses	ECD
Thick	69	53	45	36	23	20	16	37	1689.4	13.16
Intermediate	49	35	30	25	15	13	14	21	1597.7	13.08
Thin	24	16	13	10	3	3	8	8	1398.6	13.03
WBM	72	55	33	27	19	14	17	38	1711.7	13.16
Polymer Mud	47	34	29	24	14	11	13	21	1575.3	13.08
Gel Polymer Mud	37	29	20	17	15	12	8	21	1439.2	13.09
Thin	5	3	2	1.5	1	0.5	2	1	1050.8	13.01
Thin	7	4	3	2	1.5	1	3	1	1135.9	13.09
Thin	16	10	8	5	4	3.5	6	4	1327.5	13.04
Polymer Mud	40	26	20	15	13	10	14	12	1573.5	13.05
Polymer Mud	140	118	103	84	75	65	22	96	2007.4	13.48
Gel Polymer Mud.	197	167	149	112	92	76	30	137	2258.8	13.7
Gel Polymer Mud	276	235	190	165	122	97	41	194	2572.8	14.09
Gel Polymer Mud	318	269	221	191	143	101	49	220	2721.9	14.12

Open Access
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P- ISSN: 2220-5381
E- ISSN: 2710-1096

Gel Polymer Mud	104	82	65	53	44	29	22	60	1866.4	13.27
Gel Polymer Mud	169	143	113	87	71	57	26	117	2138.1	13.59
Gel Polymer Mud	223	195	129	94	78	64	28	167	2371.7	13.91
Thin	3	2.5	2	2	1.5	1.5	0.5	2	796.9	13.09
Thin	5.5	4	3	3	2	2	1.5	2.5	991.6	13.01
Thin	13	8	6	5.5	3	3	5	3	1274.8	13.03
WBM	35	22	17	12	9	7	13	9	1580.3	13.11
WBM	38	21	18	14	9	7	17	4	1680.3	12.11
WBM	48	31	19	17	11	8	17	14	1690.3	11.11
WBM	34	22	15	9	7	4	12	10	1580.3	13.11
WBM	38	24	19	16	9	7	14	10	1670.3	12.01

5. Results and Discussion:

The number of neurons in the input and output layers are fixed and can be determined from the number of input and output parameters. For example, in case I the number of output neurons is one, which are total pressure losses. The numbers of input neurons are five, representing the input parameters which were found to be most effective for predicting total pressure losses.

1. **µp (cp)**
2. **YP (lb/100 ft2)**
3. **YP/PV**
4. **TFA in2**
5. **Q gpm**

5.1 Hidden Layers:

TanH, Linear, and Gaussian are three types of node user can be selected to build the hidden Layer, and in JMP user can also select one or two hidden layers to build the model as shown in fig.2. The second layer is the layer closest to the input layer, and as shown in Figure 3 which contains more plates of neurons. Figure (4) which contains the smallest neurons between the input layers and the output layers

Open Access
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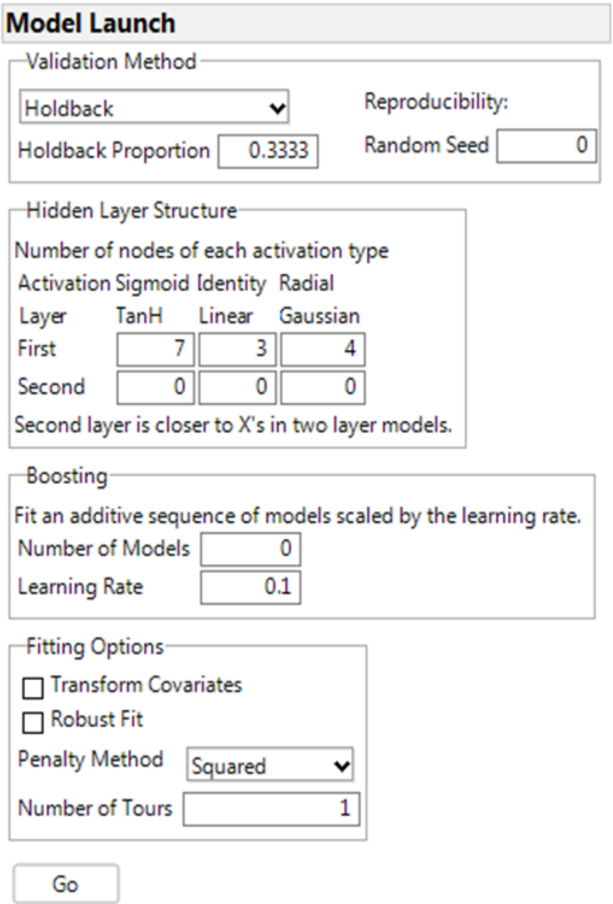

Fig. (2): Model preparation parameters

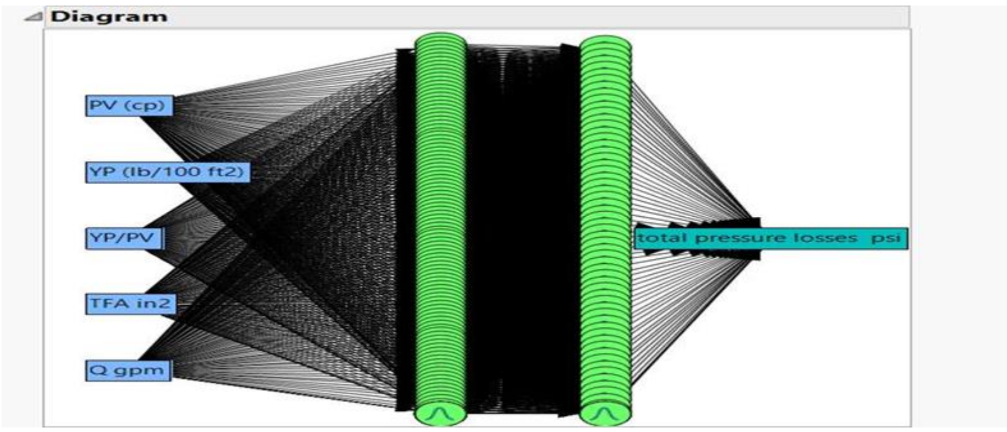

Fig. (3): A typical neural network training and operating process for Multi- Layer Perceptron (MLP)

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No. 37, December 2022, pp. 50-67

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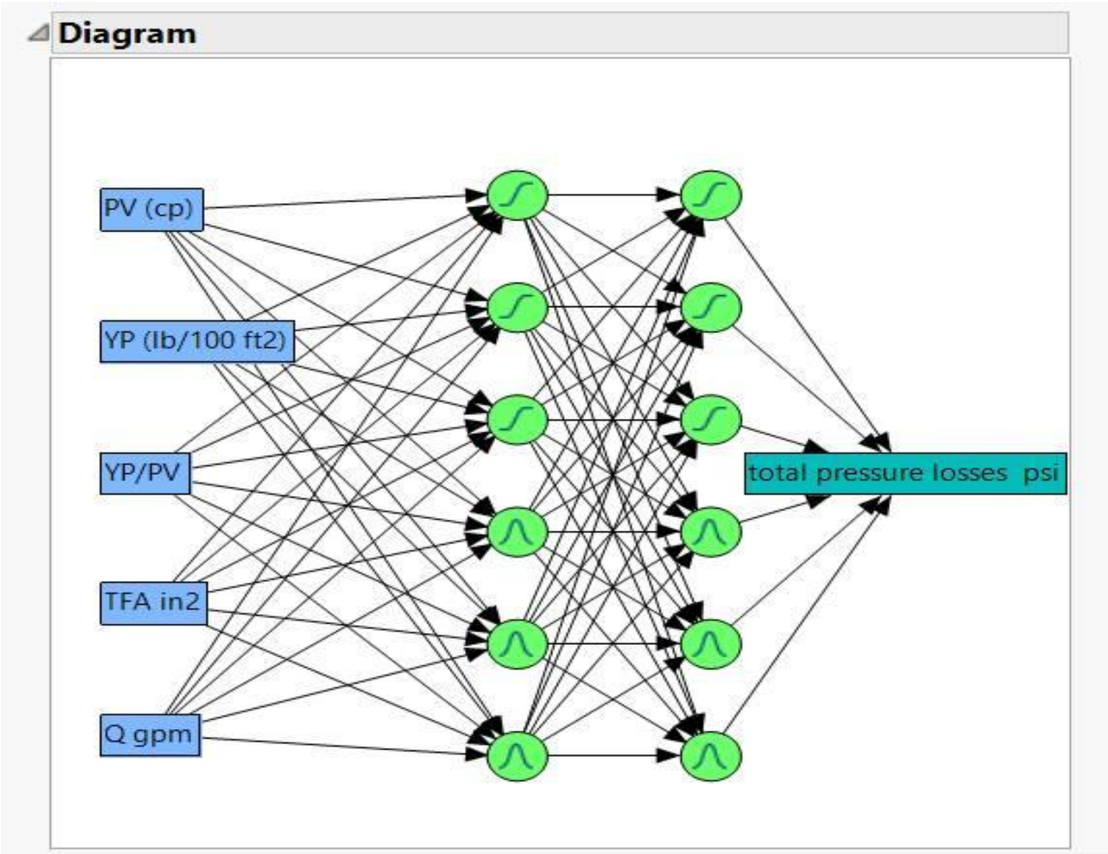

Fig. (4): Schematics of an Artificial Neuron for the building model.

5.2. Network Architecture Design & Analysis Of Data Base:

The neural network model was tested to predict total pressure losses in a new well for the same formation. Although tested for the same formation, the new well test was carried out in a different field and area. Testing in a different area has been carried out in order to enhance the generalization of the model developed. The neural network model that was previously trained and developed from the field located in one of the fields in southern Iraq. The result showed that the model was able to generalize and to predict the pressure losses in the new wells, producing a correlation coefficient value of 0.913 for training an 0.924 for validation.

Actual versus Predicted pressure losses Plot Figures (5) and (6) show the actual vs. predicted total pressure losses in the training and validation sets for the results obtained from the ANN analysis of One of the fields in southern Iraq. The results show increasing in number of neurons

Open Access
No. 37, December 2022, pp. 50-67

P- ISSN: 2220-5381
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effects on error value but an increasing in number of hidden layers has no effect on decreasing error and performance of network. In this study activation function and different number of neurons has been used to achieve this job and considered the fastest method for training moderate-sized feed-forward neural networks reach to several hundred weights.

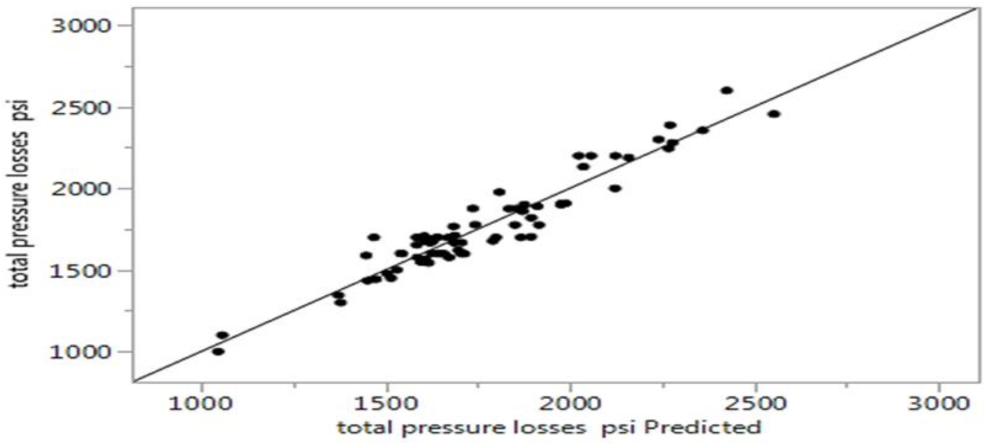

Fig. (5): Total measured pressure losses vs. total Predicted pressure losses (Validation test)

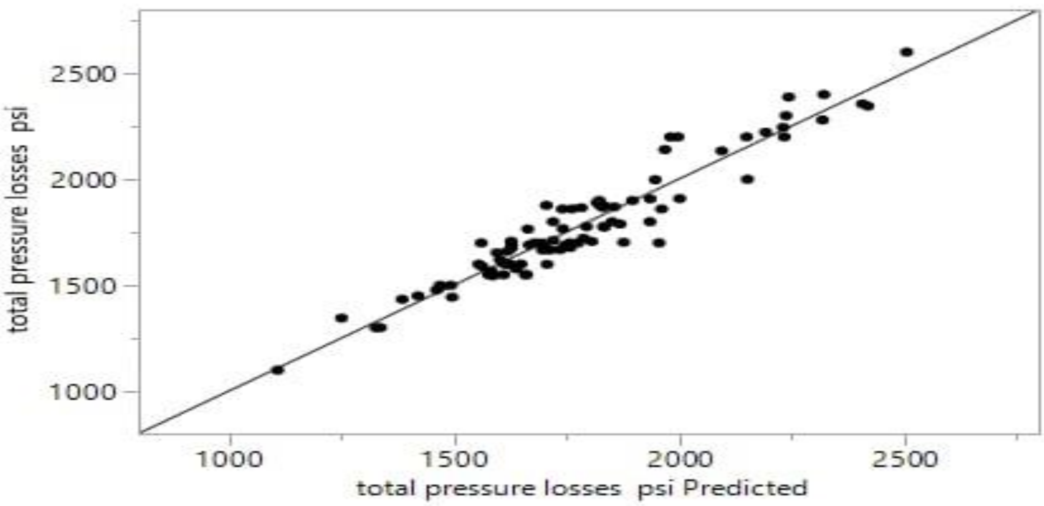

Fig. (6): Total pressure losses (Measured)vs. total pressure losses (Predicted), Training test

Open Access
No. 37, December 2022, pp. 50-67

P- ISSN: 2220-5381
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5.3. Prediction of Pressure Losses Equation Based on Ann:

The results are extracted and discussed here from training and testing regression with BPNN technique. The BPNN has been implemented for carried out non-linear regression to obtain predicted pressure losses in hydraulic system. The values of (R), (R2) and (AAPE) represent an assessment of all stages of the regression, where the high correlation coefficient was observed in all stages with the maximum value in the validation stage and an acceptable AAPE value. This is indicating the model performance is a satisfactory. Empirical model in this study based on weights and biases associated with the input layer/hidden layer and hidden layer/output layer has been lead to give us equation that predicted the pressure losses in new wells as shown in Equation 1.

$$p = 1977.89991 - 0.770735 * \mu p - 0.994336 * Yp - 143.9694 * \frac{Yp}{\mu p} + 254.063 * TFA - 0.126952 * Q \quad \ldots\ldots\ldots\ldots\ldots..(1)$$

5.4. Calculation of Optimum Flow Rate:

Depending on the data in Tables (3) and (4) and equations (2 and 3), the optimum flowrate is founded by using maximum impact force method. Table (5) illustrates the results of the previous method.

Table (3) flowrate for intermediate casing vs. circulation pressure.

Q gpm	259	310	444	498	577	610	644	798	800	810	844	866	888	899	910
P_s psi	498	632	965	1300	1600	1850	2000	2800	2900	3100	3400	3600	3800	3976	4100

Table (4) Other important data

P stand pipe psi	=	**4500**
density (ppg)	=	9.5
hole size inch	=	12.25
nozzle size	=	3*(15/32)
area of three nozzles ($in^{2)}$	=	0.517456

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No. 37, December 2022, pp. 50-67

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$$P_b = \frac{9.22*10^{-5}*\rho*Q^2}{AT^2} \quad \text{.......... (2)}$$

$$pc = ps - pb \quad \text{.......... (3)}$$

Where P_b= bit pressure psi, Q= flowrate gpm,ρ= mud density ppg ,AT=nozzle area in^2,P_c= circulating pressure psi,P_s = stand pipe pressure psi

Table (5) Results of maximum impact force method.

Q gpm	Ps psi	Pb psi	pc psi
259	498	219.43	278.56
310	632	314.36	317.63
444	965	644.87	320.12
498	1300	811.27	488.72
577	1600	1089.07	510.92
610	1850	1217.21	632.76
644	2000	1356.68	643.31
798	2800	2083.11	716.88
800	2900	2093.57	806.42
810	3100	2146.23	953.76
844	3400	2330.19	1069.80
866	3600	2453.25	1146.74
888	3800	2579.48	1220.51
899	3976	2643.79	1332.20
910	4100	2708.83	1391.11

5.5. Calculating – n - Index:

The optimal bit pressure drop is associated to the factor “n” that is a distinguishing of a specific system. The slope of the pressure loss curvature for the whole system (Pcirc), not including of the bit, designed on a log-log chart. The entire pressure losses of the system, that should be corresponding to standpipe pressure (Psurf), possibly will also be designed by way of the sum of the bit pressure loss (Pbit), and also the circulating pressure loss of the system (Pcirc). It

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No. 37, December 2022, pp. 50-67

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should be Note that the comprehensive relations for the pressures drop by means of a function of mud flowrate. The slope is 1.447 from Fig.(7), that value of n, is used in the equation 4 in order to get $P_{b\ optimum}$ value .

(Pb)opt $=\frac{n}{n+2} * Ps$ ………………………………………………………………….(4)

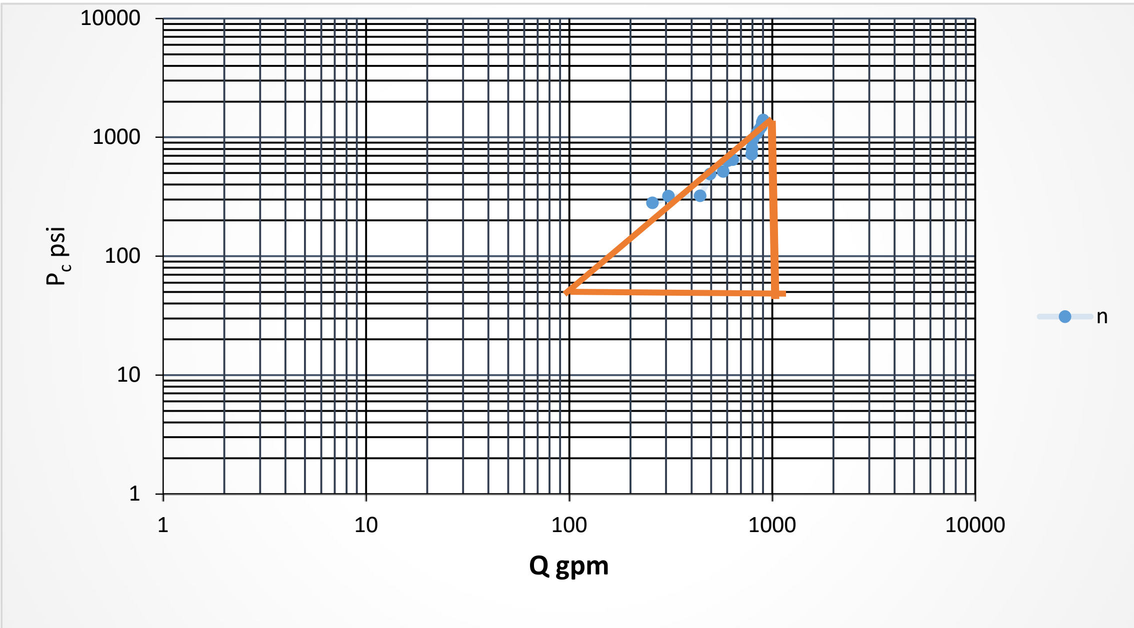

Fig. (7): Measure the slope of the circulating pressure line.

Based on the relationship between share rate and share stress that have been obtained from the lab tests, it is possible to know the type of rheological model if the relationship is linear, this means the model type is Bingham, but if the relationship is non-linear, this means the model type is power low. The type of model can also be known through the materials included in its composition Drilling mud is composed of materials that increase viscosity such as polymers, this means that the type of model is low in solids, it tends to follow the Power model, but if it contains light materials that do not contain polymer and heavy materials, it will follow the Bingham model. Figure (8) for sample 20 which gave the optimum pressure losses for Bingham model and Figure (9) for sample 5 which gave the optimum pressure losses for power law model.

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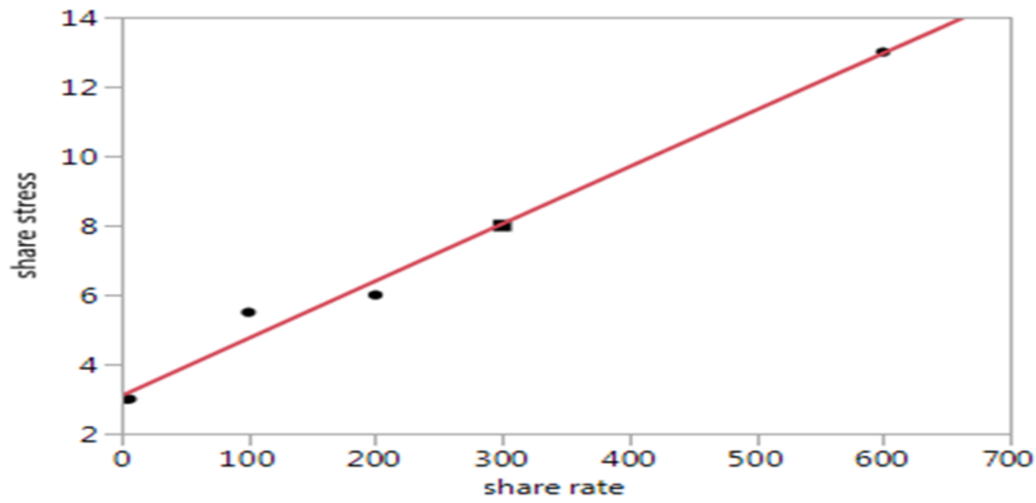

Fig. (8): Relationship between share rate and share stress for sample 20

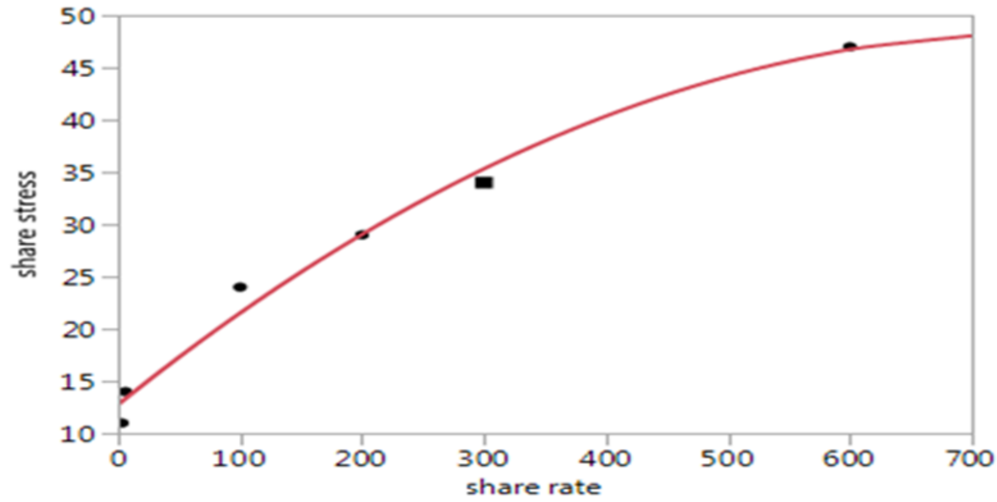

Fig. (9): Relationship between share rate and share stress for sample 5

The result of tests shows that the samples (1, 2, 3, 4, 5, 6, 8, 11, 12, 13, 14, 15, 16, 18, 22, 23, 24, 25) are represent power low model but samples (7, 9, 10, 19, 20, 21) are represent Bingham model. Figure (10) shows the relationship of viscosity, yield point and pressure loss, as it is clear that increasing viscosity and yield point leads to an increase in pressure loss. Because this leads to fatigue of the mud pump in order to pump high viscosity drilling fluids, and thus leads to additional pressure loss. Figure (11) shows the relationship between the equivalent density and pressure loss, as it is clear that increasing the equivalent density leads to an increase in

Open Access
No. 37, December 2022, pp. 50-67

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pressure loss. That led to bad effect on mud circulating pressure because of increasing in annulus pressure losses.

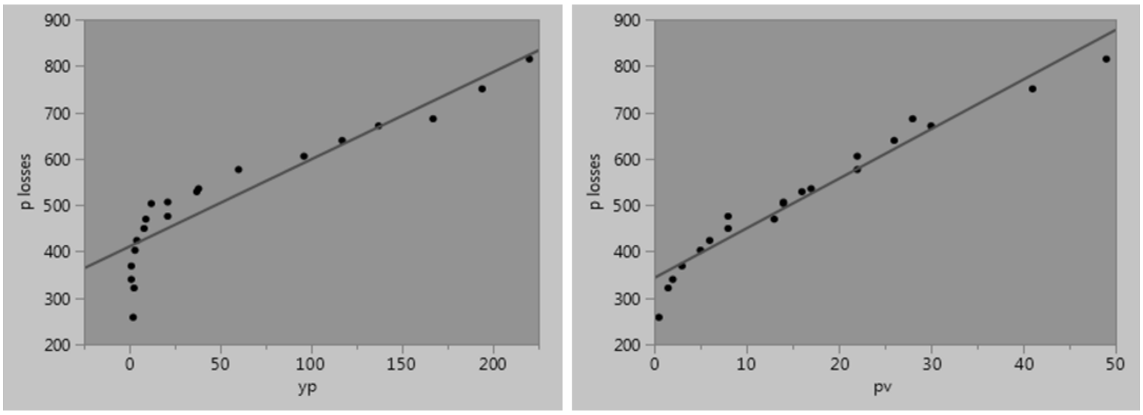

Fig. (10): Relationship between, P_v and pressure losses by using JMP program

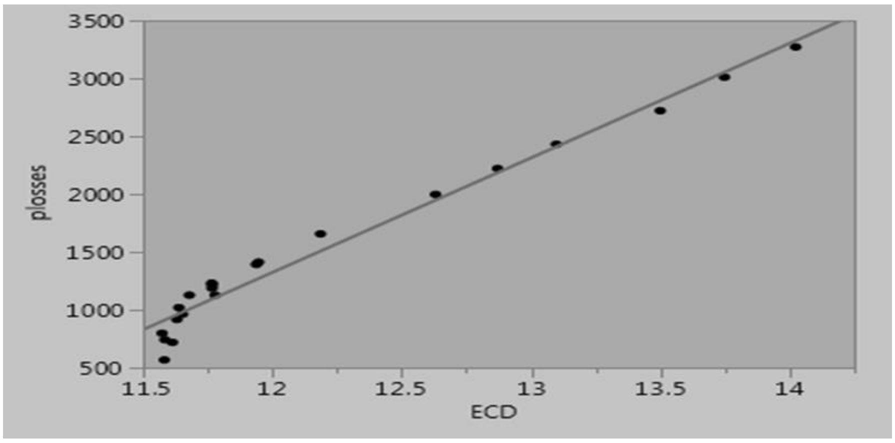

Fig. (11): Relationship between ECD and pressure losses by using jmp program

6. Conclusions:

1- Blending the experimental and program work based on ANN technique includes . 25samples have been used to identifying the model of drilling fluid. The result of tests shows that the samples (1, 2, 3, 4, 5 ,6 ,8, 11, 12, 13, 14, 15, 16, 18,22.23,24,25) are power low model but (7, 9, 10, 19, 20,21) are Bingham model.

2- The pressure losses & ECD have been calculated by using Excel program after Lab analysis and determine the type of model. For the high viscosities samples, the pressure losses become very high and this lead to some problems such as collapse, kick, sticking and blowout but at low viscosities samples ECD would decrease.

Open Access
No. 37, December 2022, pp. 50-67

P- ISSN: 2220-5381
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3- In order to set up model the number of output neurons is one target, which is the total pressure losses. The numbers of input neurons are five, representing the input parameters which were found to be most effective for predicting total pressure losses. The effective parameters that have been choose is µp, YP, YP/ µp, TFA, Q as input data.

4- The neural network model was tested to predict total pressure losses in a new well for the same casing sections; analysis in an altered formation has been done for enhancing the simplification of the developed model.

5- The result showed that the model was able to generalize and to predict the pressure losses in the new wells, producing a correlation coefficient value of 0.913 for training an 0.924 for validation.

6- The results of Equation 1 deduced from the model based on artificial intelligence gave approximate values for the total pressure loss of Power's equation with fewer steps. That's mean equation 1, It could be a successful alternative to using Power's equation in our southern fields to find the total pressure loss during drilling

7- Depending on the results of impact force method, the optimum Q Value was 1450 LPM While the optimum flow area and nozzle size was0.987145 in2, 1*13/32 and 2*12/32. The optimum bit pressure losses were 1889.034 psi.

Nomenclatures:

τ	Shear stress	**ANN**	Artificial neural network
τ_0	Shear stress at shear rate of 0(γ=0)	**CMC**	Carboxy methyl hydroxyl ethyl cellulose
μ_p	Plastic viscosity (c.p)	**TFA**	Total flow area
γ	Shear rate	**PAC**	Polyanionic Cellulose
Q	Flowrate (gpm)	**XP-20**	chrome lignite
P_m	Mud density (ppg)	**PAC**	Polyanionic Cellulose
D_h	Hole diameter (in)		
D_e	Effective diameter (in)		
P_s	Stand pipe pressure (psi)		
Q_{opt}	Optimum flowrate		
D_n	Nozzles diameter		
An	Nozzles area		
$P_{crit.}$	Critical pressure		

Open Access
No. 37, December 2022, pp. 50-67

P- ISSN: 2220-5381
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