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An Artificial Neural Network Approach for the Prediction of Water-Based Drilling Fluid Rheological Behaviour

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ABSTRACT

It is well known that high temperatures, which change the rheological properties of the drilling fluid and can frequently cause problems in deep wells, is a major problem during drilling. The importance of the estimation and control of the rheological parameters of the drilling fluid and the hydraulics of the well increases as the depth of the well drilled is being increased to explore new oil, gas or geothermal reserves. Since it is difficult to measure these parameters with standard field and laboratory viscometers, different conventional measurements and regression-analysis techniques are routinely used to approximate the true rheological parameters. In this study, water-based drilling fluid was initially prepared and rheological properties of the fluids were measured under elevated temperatures using high temperature rheometer (Fann Model 50 SL). Then, the shear stresses of drilling fluid are predicted using artificial neural network (ANN) method depending on the elevated temperature and shear rate. The results obtained from the high temperature rheometer and artificial neural network were compared with each other and analyzed. Consequently, it is observed that the artificial neural network could be used with good engineering accuracy to directly estimate the shear stress of drilling fluids without complex procedures. The testing process shows that the average percentage error was found to be approximately 2% for the prediction of shear stress values. Hence, rheological parameters of the drilling fluid could be determined quickly and controllability was facilitated using artificial neural network structure developed.

1. Introduction

Drilling fluid, also called drilling mud, is one of the most significant components in the drilling process. Drilling fluids perform several functions including controlling formation pressures, maintaining hole integrity and stability, cooling and lubricating the drill bit and the drill string, cleaning the bottom hole, and suspending cuttings in the annulus when circulation is stopped or carrying them to the surface during drilling [1], [2]. The rheological behavior of a drilling fluid directly affects all these functions and its knowledge enables better estimation of flow regimes, frictional pressure losses, equivalent circulating density under downhole conditions, hole-cleaning efficiency, swab/surge pressures, all of which have extreme importance to improve drilling efficiency [2]. As the depth of the drilled well increases, the drilling fluid is exposed to rising temperatures. Since the temperature changes during the drilling operation, proper planning and execution of drilling, especially for high pressure high temperature wells, takes precise and correct information of the behavior of the drilling fluid shear stress. This knowledge can only be obtained by measuring the shear stress of the drilling fluid at desired temperatures in real terms. Nevertheless, this takes specific material and laboratories to measure the rheological properties of the drilling fluid. These measurements take a lot of time and should be conducted frequently to ensure the quality of the drilling fluid. On the well site during the drilling operation, there is not enough time to conduct these tests [3]. A simple, reliable, and accurate methodology for predicting shear stress for flow of water-based drilling fluid is necessary and this is the aim of this paper. Prediction of the shear stresses of the drilling mud at various temperatures provides very

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useful and practical solutions for mud and drilling engineers in planning drilling operations.

Artificial neural networks (ANNs) are information processing systems, which are trained by using existing input/output data for obtaining the relationships between input/output of the process. The usage of ANN in engineering applications is rapidly increasing in recent years because of its processing capability when the process has complex and nonlinear input/output relationships. In petroleum engineering applications, the popularity of the neural-network models increases for estimation and classification of the process parameters [4], [5]. The studies about the usage of ANN in petroleum engineering show that artificial neural-networks have better performance against conventional approaches in a variety of problems [5], [6], [7]. However, it is observed that there are few studies in the literature about the estimation of the rheological parameters of drilling mud by ANN. Furthermore, it is seen that the studies have been done especially in recent years. Elkatatny [3] estimated the rheological properties of KCl polymer mud by using ANN and improved empirical correlations. It was concluded that the average absolute error of the rheological parameters was less than 6 % and the correlation coefficient was estimated at 90 %. Elkatatny et al. [8] developed new empirical correlations for estimating the rheological parameters of invert emulsion based drilling fluid using ANN. The model developed determined the rheological parameters of drilling fluid with average absolute error less than 5 %. Da Silva Bispo et al. [9] developed a soft-sensor based on an ANN to prediction the apparent viscosity of the water-based drilling fluids. In a present study, an artificial neural network model was developed to estimate the shear stress of water-based drilling fluids composed of xanthan gum, carboxy methyl cellulose and bentonite. To accomplish this task, a statistical study to define the impact of the shear rate and temperature on the shear stress of drilling fluids was carried out. Apparent viscosity, plastic viscosity, yield point, flow behavior index and consistency index values, which are used to determine hole cleaning efficiency, equivalent circulation density, hydraulic calculations, and surge and swab pressure calculations, are obtained by using shear stress values. Therefore, by estimating the shear stress values, the those parameters can be calculated using the estimated results obtained.

2. Material and Method

2.1. Preparation of Drilling Fluid Samples

A water-based drilling fluid sample was prepared with xanthan gum, carboxy methyl cellulose and bentonite. Initially, bentonite was stirred with distilled water for 20 minutes, then xantam gum and carboxy methyl cellulose were added gradually and mixed for 10 minutes using five- spindle multi-mixer (model 9B) as shown in Figure 1(a). After homogenization, the bentonite dispersion was aged for 16 hours at ambient temperature conditions to ensure that the bentonite achieved the exact hydration. Table 1 shows the concentration of materials used in the formulated drilling muds and the temperature ranges studied.

Table 1. Composition of the drilling mud formulated and temperature ranges studied.

Temperature (°C)	Xantam Gum (g/350 ml H_2O)	Carboxy Methyl Cellulose (g/350 ml H_2O)	Bentonite (g/350 ml H_2O)
25	0.5	1	22.5
50	0.5	1	22.5
75	0.5	1	22.5
100	0.5	1	22.5
125	0.5	1	22.5
150	0.5	1	22.5

2.2. Determination of Rheological Properties

The rheological properties were measured using a High Temperature-High Pressure Rheometer (Fann-Model 50 SL, Houston, TX, USA) given in Figure 1(b). The equipment is a rotary viscometer and capable of measuring the shear stress depending on the shear rate over a wide range from 500 °F (260 °C) temperature to 1,000 psig (7,000 kPa) pressure. The shear stresses of the formulated mud were measured under 600, 300, 200, 100, 6 and 3 (rpm) shear rates and 25, 50, 75, 100, 125, 150 (°C) temperatures using high pressure-high temperature rheometer.

(a) (b)

Figure 1. Equipments used in the study a) Mud Mixer [10], b) Rheometer [11]

2.3. Artificial Neural Network

Artificial neural networks are computer systems that are designed to imitate the characteristics of the human brain and to automatically acquire new knowledge without any help by learning system behavior through existing data. In other words, artificial neural network systems are computer programs that mimic biological neural networks. They are able to solve problems that are too complicated for traditional techniques. Moreover, generalizations can be made in unexplored situations using familiar data through this learning ability. Therefore, artificial neural networks can be applied in many fields of our daily life such as financial issues, engineering and medical science applications and fault analysis and detection in production applications. Artificial neural network applications are generally used for prediction, classification, data association, data interpretation and data filtering [12,13]. There are basically three steps in the artificial neural network learning process; a-) to calculate the output, b-) compare outputs with target outputs and calculate the error, c-) repeat the process by changing weights. As a result of the training process, it is expected that the error calculated in artificial neural network reduces to an acceptable error rate. Artificial neural networks usually contain at least three layers such as input layer, hidden layer and output layer. All layers are composed of neurons, which are the most basic component of artificial neural networks. The input layer contains neurons that receive inputs from the outside. The output layer contains the neurons that transmit the results of the neural network. When the input and output layers are composed of a single layer, there can be more than one hidden layer between these two layers. These hidden layers contain a large number of neurons, which are all connected to other neurons in the network. In most network types, a neuron in the hidden layer only receives signals from all neurons of the previous layer. After neuron processing, it sends the output to all the neurons of the next layer. The output signal of each neuron is determined by applying activation function to its input data. The information flow takes place with the connection links from one neuron to the other neuron, and each link has a weight to create the desired input-output relationship. These weights are updated based on the error margin between the net output and the expected output [14], [15], [16].

Although there are differences in the structure of an artificial neural network and the number of neurons, there are no accepted rules for the formation of artificial neural networks. Artificial neural networks that have fewer hidden layers than the required number of layers may be inadequate for the resolution of complex functions. However, undesirable instabilities may be seen when artificial neural networks with many hidden layers are used. After the number of hidden layers is determined, the problem is how many neurons will be present in each layer. The input and output layers have specific neuron numbers depending on the number of inputs and outputs of the problem. However, there are no mathematical tests on how many neurons will be found most efficiently in the hidden layer. It should be decided by trials [13], [17].

The neural-network model was developed using 198 different experimental data sets for training, validation and testing of the network. These data sets are given in the Appendix. The network consists of two inputs and an output. The shear rate and temperature are determined as inputs and the output is shear stress. The network uses a back propagation algorithm which is the classical feed-forward artificial neural network and it uses this to calculate the error contribution of each neuron after a group of data is processed. ANN includes some parameters such as the number of hidden layers, number of neurons in each hidden layer in addition to applying different training algorithms which should be optimized in order to determine the most precise consequences. The optimal configuration of the artificial neural network is found out by a trial and error method. In this work, the number of neurons in the hidden layer is determined by an optimization procedure which minimizes some error indexes. The performance of training and testing of ANNs are appraised by the average absolute percent relative error (AAPE) and R^2, which are given as follows:

$$AAPE=\frac{1}{n}\sum_{i}^{n}\left|\frac{x-x_{\mathrm{i}}}{x}\right| \quad [18]$$

$$R^2=\frac{\sum_{i}^{n}(x-\bar{x})^2-\sum_{i}^{n}(x-x_{\mathrm{i}})^2}{\sum_{i}^{n}(x-\bar{x})^2} \quad [19]$$

Where n represents the number of data, x is experimental value, x_{i} denotes calculated value by ANN, and $\bar{x}$ is average value.

In this study, one hidden layer with twelve neurons is used in the developed network. The neuron number of hidden layers is obtained at the end of several trials to maximize the correlation coefficient R. Figure 2 shows the structure of the neural network architecture used for estimating the shear stress depending on the shear rate and temperature.

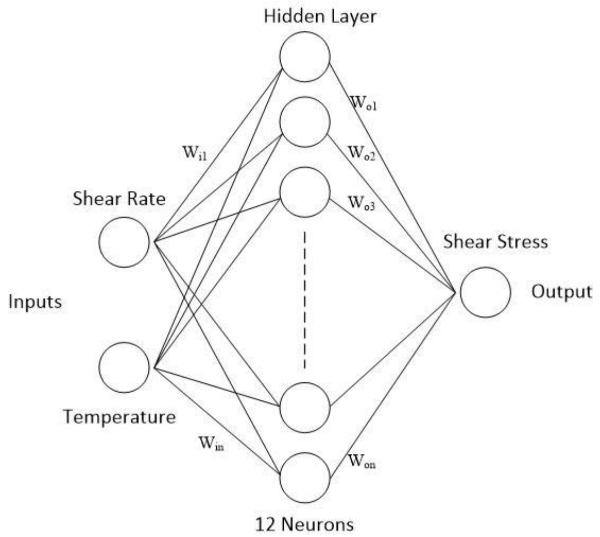

Figure 2. The structure of the Neural Network

W_{ij} and W_{oj} denote the weights of the synapse of the network. The desired input/output relationship of the network during the training process with these 198 data sets is provided by adjusting the weight of the connections. After the training process, the neural network architecture developed was tested with 20 experimental data points which were not used in the training process of the network due to validation of its estimation performance.

3. Results and Discussion

The main goal of this study is the estimation of the drilling mud shear stresses without the need for long-running experiments. For this reason a neural network architecture was developed. The performance and accuracy of the developed neural network model was checked by comparing the predicted shear stress values with actual shear stress values. The neural network was designed with ANN Toolbox of MATLAB. The efficiency of the network was evaluated using statistical parameters such as the correlation coeeficient (R) for training and mean absolute error (MAE) for testing with different data. Figure 3 shows the performance results of the ANN toolbox depending on the 198 training sets. The training, validation and testing performances were evaluated depending on the R correlation error. The large value of R means that the mean square error value of the estimator is much smaller than the average target variance and this shows that modeling of most of the variation in the input-target transformation is managed successfully by the net. In other words, the closer R is to 1.00 then the better the regression model is able to reproduce the target data.

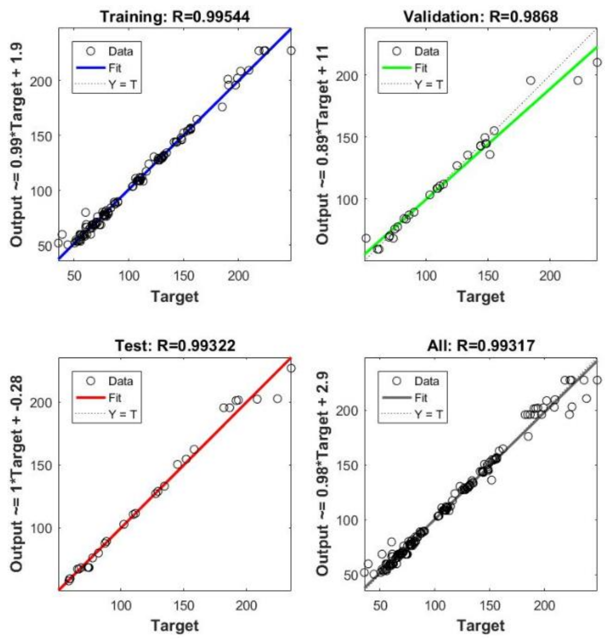

Figure 3. Results of ANN Toolbox for training, validation and test

The training data, validation data and test data sets are used for adjusting the weights of connections, validate the input-output relationship, finding the best configuration and testing the generated network to evalute the trained neural network parameters, respectively.

Neural network used about 70 % of these sets for training, 15 % for validation and 15 % for testing. The results show that the correlation coefficient value R of training, validation and testing subsets shown in the diagram is 0.99544, 0.98688, and 0.99322, respectively. The overall correlation coefficient R is 0.99317. This means that developed neural network model represents the drilling mud process for estimating the actual shear stress depending on the shear rate and temperature succesfully.

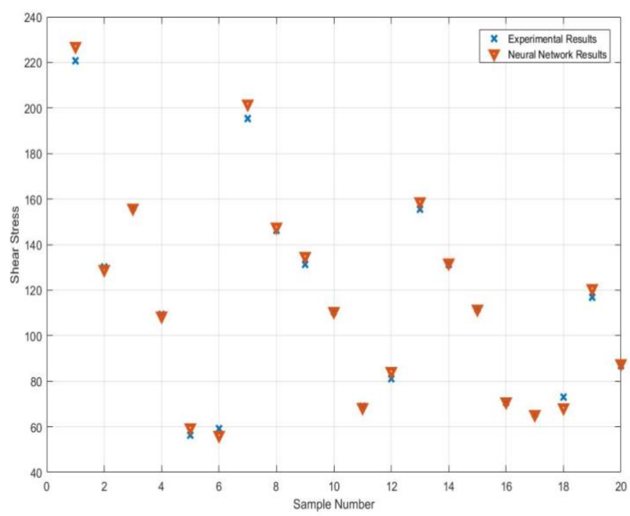

Figure 4. The predicted shear stress versus experimental values

for the testing data sets

As mentioned above, 20 different data sets were used for testing the estimation performance of the neural network architecture developed. Table 2 illustrates the results of percentage errors between values estimated by ANN and the experimental values corresponding to the inputs such as shear rate and temperature. The results show that the absolute average percentage error (AAPE) values vary between 0.0282 and 6.3330. Consequently, when the total error for estimation is calculated, the shear stress values of the drilling mud are estimated with an mean the absolute average percentage error of 2.0431 using ANN. In the previous literature, any study isnt found regarding the estimation of shear stress of drilling mud using artificial neural networks due to shear rate and temperature. However, Elkatatny [3] estimated the dial reading values with % 3.51 and % 3.27 errors at 600 and 300 (rpm), respectively. Also, Elkatatny et al [20] predicted viscometer readings with an average absolute error 3.7 and 3.48 at 600 rpm and 300 rpm, respectively. The developed neural network model illustrates that it can predict shear stress values of water-based drilling muds with high accuracy. This error performance is acceptable for the prediction of shear stress and this performance provides us with the means to reduce spending time and data collection effort since the neural network gives approximate results quickly instead of doing long-term experiments.

In order to facilitate the analysis of results, comparison between data estimated by the ANN and experimental data approach is also showed in Figure 4 clearly. The x-axis of the graph shows the number of the data sets which are given in the first column in Table 2 and y-axis denotes the shear stresses of the sample water-based mud. It can be clearly seen that the estimated and real data are very close to each other for each test data set. Nevertheless, it can be said that predicted values relatively far away from the actual values at 600 rpm comparatively to the other shear rate.

Table 2. Accuracy of ANN and correlations for shear stress—testing set

	Inputs		Output		
			Shear Stress (dynes/cm^2)		
Number of test data sets	Shear Rate (rpm)	Temperature (°F)	Experimental	Neural Network	AAPE (%)
1	600,069339	76,280001	220,711418	227,116433397176	2.902
2	199,961992	122,179997	130,139046	129,124913019282	0.7793
3	300,014671	77,9	156,09928	156,051258251427	0.0308
4	100,044328	169,340005	109,370859	108,689632943637	0.6229
5	6,089757	259,7	56,296603	59,6344213054872	5.9290
6	2,949049	304,880011	59,181073	56,3201907967738	4.8341
7	599,989346	166,820003	195,328078	201,783034843783	3.3047
8	300,054668	121,639999	146,292081	147,740418497273	0.99
9	199,95534	78,260001	131,292835	134,874179821297	2.7278
10	99,939331	78,8	110,524647	110,702923516035	0.1613
11	6,048092	78,980001	68,988273	68,5600630654917	0.6207
12	3,057378	169,520003	81,103049	84,3658863884235	4.0231
13	600,015997	256,820003	155,522386	158,881879212880	2.1601
14	299,948003	214,7	131,292835	131,990017687632	0.5310
15	199,975338	214,879997	111,678436	111,709956036522	0.0282
16	99,892672	259,879997	70,718955	71,0000093695075	0.3974
17	5,90643	215,240005	65,526908	65,4469514928737	0.1220
18	3,144874	78,980001	73,026532	68,4017784749716	6.3330
19	600,082644	302,9	116,870482	120,745531748773	3.3157
20	199,862	259,7	86,87199	87,7832372946993	1.049
				AAPE total (%)	2.0431

4. Conclusions

In this study, an alternative way to achieve reliable results for the determination of shear stress values of water-based drilling fluids was proposed because the experiments take a very long time, high effort and high cost. A neural network architecture was designed for prediction of the shear stress depending on the shear rate and temperature. A feed-forward back propagation method was used for estimation and the correlation coeffcient error performance of the network was observed depending on the training data used. The correlation coefficient of train validation and test data were approximately equal to 0.99 and as a result the overall performance of the ANN was calculated as 0.99317. After that 20 different test data were used to test the developed neural network algorithm and the average error of test data was 2.0431 %. These results show that the developed neural network model provided very good predictions of the shear stress values. Thus, this model presents excellent performance when estimating the shear stress of drilling fluids with temperature changes under different shear rate values depending on the ranges of the training input data. This inexpensive technique, which can determine shear stress values quickly, will lead to a reduction in the total cost and time loss of the drilling operations. In addition, it will help drilling engineers to better control the drilling operation.

Nomenclature

AAPE : Absolute Average Percent Error

ANN : Artificial Neural Network

MAE : Mean Absolute Error

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Appendix

The used experimental data for training are as follows [21]

	Inputs		Output		Inputs		Output
No	Shear Rate (rpm)	Temperature (°F)	Shear Stress (dynes/cm^2)	No	Shear Rate (rpm)	Temperature (°F)	Shear Stress (dynes/cm^2)
1	599,576032	74,6600010	247,825441	101	100,012662	122,360001	109,947753
2	599,909352	74,8399990	235,710665	102	99,9693390	122,360001	109,947753
3	599,962654	75,7399990	224,172783	103	99,9076650	169,159995	108,217071
4	599,936003	75,9199990	223,018995	104	100,022661	169,159995	107,063283
5	599,962654	76,8199990	218,403842	105	100,089329	169,340005	108,793965
6	599,989346	77,1800010	218,403842	106	100,179322	169,340005	109,947753
7	599,602683	164,479997	224,749677	107	99,9660020	169,340005	109,947753

8	599,989346	165,200000	208,596643	108	100,064326	169,340005	109,370859
9	599,909352	166,279997	198,789443	109	99,7110080	214,879997	86,2950960
10	599,989346	167	193,597396	110	100,022661	215,059995	89,7564600
11	599,962654	167,720003	191,866714	111	99,9026710	215,059995	89,7564600
12	599,936003	168,259995	190,136032	112	99,7976740	215,059995	88,6026720
13	599,456001	209,659995	222,442101	113	99,8826720	215,240005	89,7564600
14	600,135987	210,920003	197,058761	114	99,9393310	215,240005	90,3333540
15	600,135987	211,820003	190,712926	115	100,029334	305,600000	59,1810730
16	599,962654	212,540005	186,674667	116	99,9776700	305,600000	59,1810730
17	599,962654	213,079997	184,367091	117	100,061000	305,600000	59,1810730
18	599,962654	213,800000	182,059514	118	99,6926780	305,600000	55,7197090
19	599,629334	254,479997	184,943985	119	100,130994	305,780011	57,4503910
20	599,762670	255,920003	161,868221	120	99,8826720	305,780011	58,6041790
21	600,362663	256,459995	158,406857	121	6,01892600	78,8	60,9117560
22	600,042648	257,540005	152,061022	122	5,78143500	78,8	51,6814500
23	600,015997	258,079997	149,753445	123	6,06142400	78,9800010	73,6034260
24	599,936003	258,800000	147,445869	124	6,03559200	78,9800010	73,6034260
25	599,709328	299,480011	151,484128	125	5,98642700	78,9800010	73,0265320
26	600,109336	301,100000	122,639423	126	5,96642800	78,9800010	66,6806970
27	599,962654	302,359995	118,024271	127	6,08475600	122,360001	71,2958490
28	600,069339	303,440005	115,716694	128	5,96892800	122,360001	74,7572140
29	599,909352	304,159995	113,986012	129	6,03559200	122,539999	77,0647900
30	599,962654	304,700000	112,832224	130	6,01475900	122,539999	77,6416840
31	300,194657	77,3600010	153,214810	131	5,90143100	122,539999	78,2185780
32	300,014671	77,5399990	154,368598	132	5,87726500	122,539999	79,3723670
33	299,961329	77,7199990	156,099280	133	5,84726600	169,340005	60,3348620
34	299,948003	77,7199990	154,945492	134	6,00809300	169,520003	80,5261550
35	299,974675	77,9	156,099280	135	5,98892700	169,520003	82,2568370
36	299,961329	78,0800010	156,099280	136	5,96892800	169,520003	81,1030490
37	300,774630	121,639999	145,138293	137	5,94476200	169,520003	78,2185780
38	300,081339	121,639999	147,445869	138	5,92143000	169,520003	75,9110020
39	300,081339	121,820003	148,022763	139	6,14475400	259,700000	59,7579680
40	299,961329	121,820003	148,022763	140	6,11058900	259,700000	58,6041790
41	300,041322	122	148,022763	141	6,07475700	259,700000	55,1428150
42	300,027997	122	148,599657	142	5,90143100	259,700000	56,8734970
43	300,547975	168,440005	141,100034	143	5,87643100	259,700000	56,8734970
44	300,041322	168,440005	142,830716	144	5,76893600	259,700000	38,9897800
45	299,988000	168,440005	143,407610	145	6,03725800	305,240005	52,2583440
46	299,848011	168,620003	143,407610	146	5,96226200	305,240005	53,4121330
47	300,014671	168,800000	143,984505	147	5,76060300	305,240005	55,7197090
48	299,888008	168,979997	143,984505	148	6,00226000	305,419989	50,5276620
49	300,014671	214,159995	129,562152	149	5,67810600	305,419989	35,5284160
50	299,948003	214,159995	130,139046	150	5,94726200	305,600000	44,1818270
51	300,014671	214,340005	131,292835	151	3,17154000	78,9800010	74,1803200
52	299,928005	214,340005	131,292835	152	3,13987400	78,9800010	74,7572140
53	299,914679	214,520003	131,292835	153	3,02071300	78,9800010	73,0265320
54	299,948003	214,700000	131,869729	154	2,97654800	78,9800010	74,1803200
55	300,307995	259,159995	102,448130	155	2,94238200	78,9800010	66,1038030
56	300,101338	259,159995	103,025024	156	2,91571700	78,9800010	68,4113790
57	300,014671	259,340005	103,601918	157	3,06154400	122,360001	78,7954720
58	299,874662	259,340005	103,601918	158	2,94488200	122,360001	78,2185780
59	300,041322	259,520003	103,025024	159	3,03904500	122,539999	77,0647900
60	299,961329	259,520003	103,601918	160	3,02071300	122,539999	77,6416840
61	200,135325	122,179997	130,139046	161	2,98571400	122,539999	77,0647900
62	200,025324	122,179997	126,677682	162	2,91321700	122,539999	76,4878960
63	200,005325	122,179997	129,562152	163	3,03154500	214,879997	68,9882730
64	199,995336	122,179997	129,562152	164	2,89405100	214,879997	66,6806970
65	199,975338	122,179997	130,139046	165	3,00988000	215,059995	65,5269080
66	199,961992	122,179997	128,985258	166	2,99154700	215,059995	66,6806970
67	200,065321	168,979997	127,831470	167	2,86571900	215,240005	61,4886500
68	200,058668	168,979997	126,100788	168	2,84905300	215,240005	60,3348620
69	200,045322	168,979997	127,831470	169	3,07987700	259,159995	64,9500140

70	200,025324	168,979997	127,254576	170	3,05571100	259,159995	64,9500140
71	199,872010	168,979997	124,947000	171	3,04654500	259,340005	62,0655440
72	200,045322	169,159995	127,831470	172	2,83572000	259,340005	61,4886500
73	199,955340	214,700000	111,678436	173	3,02987900	259,520003	59,1810730
74	200,025324	214,879997	111,678436	174	2,81655400	259,520003	55,7197090
75	200,011998	214,879997	111,678436	175	3,01987900	304,519989	61,4886500
76	199,995336	214,879997	111,678436	176	2,97321400	304,519989	60,9117560
77	199,961992	214,879997	111,678436	177	2,96738100	304,700000	59,7579680
78	199,795332	214,879997	109,947753	178	2,98738000	305,059995	54,5659210
79	200,038670	259,520003	87,4488840	179	2,93321600	305,059995	55,7197090
80	200,548639	259,700000	86,2950960	180	2,71489200	305,059995	51,6814500
81	200,075330	259,700000	86,8719900	181	599,602683	119,479997	238,018241
82	200,068657	259,700000	87,4488840	182	599,909352	120,379997	209,173537
83	199,998673	259,700000	87,4488840	183	599,962654	121,100000	201,673913
84	199,862000	259,700000	87,4488840	184	300,447983	305,240005	79,3723670
85	200,075330	305,600000	70,1420610	185	300,114663	305,600000	81,1030490
86	200,068657	305,600000	70,1420610	186	299,948003	305,600000	81,1030490
87	200,045322	305,600000	69,5651670	187	200,128652	78,2600010	133,600411
88	200,005325	305,600000	69,5651670	188	200,145335	78,4399990	134,177305
89	199,842002	305,600000	68,4113790	189	199,955340	78,4399990	134,754199
90	199,828676	305,600000	70,1420610	190	99,8960080	259,700000	70,7189550
91	99,9976680	78,6199990	105,909495	191	99,9876690	259,700000	71,2958490
92	100,102665	78,8	111,101541	192	100,054327	259,879997	70,1420610
93	99,9560030	78,8	109,947753	193	6,18475300	215,240005	66,1038030
94	100,029334	78,8	110,524647	194	5,90393000	215,240005	64,9500140
95	99,8643420	78,8	110,524647	195	6,09725600	215,420003	63,7962260
96	100,007667	78,8	110,524647	196	3,12487500	169,340005	83,4106250
97	100,029334	122,179997	107,640177	197	3,01238000	169,340005	83,9875190
98	100,061000	122,360001	109,370859	198	3,04904500	169,520003	82,2568370
99	99,9243370	122,360001	109,370859				
100	99,8410070	122,360001	108,793965				