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# Drilling Stuck Pipe Prediction in Iranian Oil Fields: An Artificial Neural Network Approach

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## Abstract
*Stuck pipe is one of the most serious drilling problems, estimated to cost the petroleum industry hundreds of millions of dollars annually. One way to avoid stuck pipe risks is to predict the stuck pipe with the available drilling parameters which can be employed to modify drilling variables. In this work, Artificial Neural Network (ANN) was used for stuck pipe prediction according to the fact that this method is applicable when relationships of parameters are too complicated. Based on the drilling fluid condition from one of the Iranian oil fields, stuck pipe instances were divided into static and dynamic types. The results of this study show more than 90% accuracy for stuck pipe prediction in the investigated oilfield. The methodology presented in this paper enables the Iranian drilling industry to estimate the risk of stuck pipe occurrenc during the well planning procedure.*

**Keywords:** *Artificial Neural Network, Stuck pipe, Iranian Oil field, Differential Sticking, Risk of Sticking, Static and Dynamic*

## 1- Introduction
Stuck pipe costs are a major drilling trouble cost for the drilling industry. Various estimates indicate stuck pipe costs exceed $250 million per year [1]. Problems associated with this phenomenon can range in severity from minor inconvenience, which can increase costs slightly, to major complications, which can have significantly negative results, such as loss of the drill string or complete loss of the well [2]. The risk of mechanical or differentially stuck pipe will be increased because of pore pressure reduction in drilling of the majority of mature oilfields in Iran. This is because of the fact that decreasing pore pressure increases the chance of differential pressure stuck pipe. On the other hand, using lower mud weights to have reasonable differential pressure may increase the risk of wellbore instability and related problems such as mechanical sticking in the open hole section. Prediction of stuck pipe can be considered as the mentioned procedure through which the

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risk of getting stuck can be minimized by modifying drilling variables for the condition of high risk of sticking. In this work ANN was utilized for stuck pipe prediction either mechanically or differentially. The first use of this method for prediction of differential stuck pipe was developed by Siruvuri, et al. in the Gulf of Mexico [3].

In this paper, after some introductory material regarding the mechanisms of stuck pipe, ANN, along with the training of this network will be presented. Data acquisition, selection of the parameter, data pre-processing, and the allocated network architecture design will be described in the material and methods section. The result of this work presents the outcome analysis of drilling stuck pipe by ANN, which is summarized by dynamic and static analysis. After a detailed discussion about the results of this work, the successful remarks will be shown in the conclusions section. The methodology presented in this paper enables the Iranian drilling industry to estimate the risk of stuck pipe occurrence during the well planning procedure.

**1.1- Stuck pipe description**

Often during drilling operations the drill string becomes stuck. Sticking can occur while drilling, making a connection, logging, testing, or during any kind of operation which may involves leaving the equipment in the hole [1]. Generally, stuck pipe problems are divided into two categories: mechanical sticking and differential sticking. Mechanical sticking usually occurs when the drill string is moving and is caused by a physical obstruction or restriction [4]. Mechanical sticking can be classified into two major subgroups: a) Hole pack-off and bridges; stuck pipes which are related to wellbore instability or settled cuttings are in this category and b) Wellbore geometry interferences; this refers to stuck pipes which are related to the condition of wellbore geometry such as key seats or an under-gage hole.

Major causes of mechanical stuck pipe are wellbore instability and improper hole cleaning. Most wellbore instability problems are related to shale layers due to swelling and hole enlargements resulting from compressive failure owing to excessively low wellbore pressure [5]. Adequate hole cleaning, on the other hand, is an essential part of the drilling operation. If the cuttings are not removed from the well properly, they settle around the drill string causing the drill collars to become stuck. This problem is encountered often in over gauge sections where annular velocities are low. Also, risk of hole cleaning increases in directional wells. The directional well having an inclination angle between 30-60$^o$ is the worst condition for hole cleaning [2].

As the next category of stuck pipe, differential sticking is due to differential pressure forces from an overbalanced mud column acting on the drill string against a filter cake deposited on a permeable formation. The area of the pipe that is embedded into the mud-cake has a pressure equal to the formation pressure acting on it, while the pressure which acts on the other section of pipe is hydrostatic pressure in the drilling mud. When the hydrostatic pressure ($P_h$) in the well bore is higher than the formation pressure ($P_f$), there will be a net force pushing the collar towards the borehole wall. The resultant force of the overbalance acting on an area of drill string is the force that sticks the string. This type of sticking does not occur in shales and other very low permeability formations where mud filter cakes normally do not form. Commonly, differential sticking occurs when the drill string or tool is stationary (or sometimes when it is moving very slowly) [5]. If the pipe becomes stuck, every effort should be made to free it quickly. The probability of freeing stuck pipe successfully diminishes rapidly with time. Early identification of the most likely cause of a sticking problem is crucial, since each cause must be remedied with different measures. An improper reaction to a sticking problem could easily make it worse. An evaluation of the events leading up to the stuck pipe occurrence frequently indicates the most probable cause and can lead to the proper corrective measures [2].

**1.2- ANN description**

ANNs are information processing systems that are a rough approximation and simplified simulation of a biological learning process and have performance characteristics similar to those of biological neural networks [6,7]. These are adaptive, parallel information processing systems, which are able to develop associations, transformations or mappings between objects or data and have proven to have potential in solving problems that require pattern recognition [8]. The basic elements of an ANN are the neurons (the processing elements) and their connection strengths (weights). The input to each neuron is multiplied by its associated weighting factor and then summed with the product of each of the other input nodes and their respective weighting factors. An activation threshold is then added to this sum and the result is processed by a transform function within the neuron. The most common transform function, and the one used in this study, is s-shaped sigmoid function. The logistic function provides non-linearity to the model and constrains the neuron's output signal to fall within a fixed range (0, 1 or -1, 1). It is also smooth and has easily differentiable characteristics that facilitate network training algorithms [9]. A multilayer network usually consists of an input layer, one or more hidden layers, and an output layer. The layer of input neurons receives the data from the input files. The number of neurons in the input layer corresponds to the number of parameters that are being presented to the network as input. The same is true for the output layer. The neurons in the hidden layer or layers are responsible primarily for feature extraction. They provide increased dimensionality and accommodate such tasks as classification and pattern recognition [7].

There are several types of ANNs; the most common types are the feed-forward and back-propagation architectures which are used in this study. A feed-forward network has a layered structure and feed-forward topology. Each layer consists of units which receive their input from units of a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer. The term back propagation refers to the mechanism of adjusting network weights and biases for reduction of error, which is propagated back through the system causing changes to the weights and biases of the network [6, 9].

### 1.3- ANN training

In a typical neural data processing procedure, the database is divided into three separate portions: training, validation, and testing. The training set is used to calibrate the model. The validation set is used to ensure the generalization of the developed network during the training phase. The testing set is used to examine the final performance of the network. In the training process, the desired output in the training set is used to help the network adjust the weights between its neurons or processing elements [7-10].

Given a topology of the network structure expressing how the neurons are connected, a learning algorithm takes an initial model with some prior connection weights (usually random numbers) and produces a final model by numerical iterations. Hence learning implies the derivation of the posterior connection weights when a performance criterion is established. Learning can be performed by supervised or unsupervised algorithm. The former requires a set of known input-output data patterns (or training patterns), while the latter requires only the input patterns [8].

Through the course of training, the network is continuously trying to correct itself and achieve the lowest possible error (global minimum). Usually, there are locations on the error surface that will cause temporary convergence, even before sufficient learning has taken place by the network. This occurs when the network system finds an error that is lower than the surrounding possibilities but does not ultimately reach the smallest possible error. This problem is called the local minima problem [6, 11]. In order to overcome this problem, some practical recommendations are suggested such as randomizing the initial weights with small numbers in an interval [- 1/n, 1/n], where n is the number of the neuronal inputs or using another formula for calculating the output error. Probabilistic methods can help to avoid this problem, but they tend to be slow [12, 13]. During the training process, the question of when to stop the training arises. How many times should the network go through the data in the training set to learn the system behavior? When should the training stop? These are legitimate questions because a network can be over trained. In the neural-network-related literature, overtraining is also referred to as memorization. Once the network memorizes a data set, it is incapable of generalization, even if it fits the training data set very accurately [7, 14].

## 2- Material and methods

It is clear that the performance of ANNs hinges heavily on the data. If one does not have data that cover a significant portion of the operating conditions or if they are noisy, then **ANN** technology is probably not the right solution. On the other hand, if there is plenty of data and the problem is poorly understood to derive an approximate model, such as drilling stuck problems, then ANN technology is a good choice. At present, ANNs are emerging as the technology of choice for many applications, such as pattern recognition, prediction, system identification, and control.

According to the fact that this method is applicable when relationships of parameters are too complicated, ANN technology was applied for drilling stuck pipe prediction in this work. The sigmoid function which is the most common transform function, was used in this study. Based on a typical neural data processing procedure, a partitioning ratio of 8:1:1 was considered for splitting data into three subsets (i.e., training subset constitutes 80% of the total data and each of the validation and testing subsets include 10% of the database). In the first part of this section, data acquisition will be presented. Selection of the appropriate parameters will be explained as the main factors that had to be chosen as input data for ANN. Data pre-processing and network architecture design will be described at the end of this section.

**2.1- Data acquisition**

A total number of 275 cases were collected from the daily drilling reports (DDRs) in one of the Iranian oil fields. The data contained 115 stuck and 160 non-stuck cases. Non-stuck data were collected from days that the wells were completely safe and had not become stuck in the same general areas of operation. According to the drilling fluid condition in the different hole sections, stuck pipes can be divided into dynamic and static types. In dynamic condition the drilling fluid is in circulation, while it is not circulating during static condition. Run in Hole (RIH), Pull out of Hole (POOH), pipe connection and surveying could be categorized in static condition. From the 115 stuck cases in this study, 40 stuck pipe cases occurred during dynamic condition and 75 cases occurred during static conditions. The parameters that were collected as the input data are as follows: mud properties, depths, hole geometry information, hydraulics, bottom hole assembly size, inclination angle, drill pipe size, Weight on Bit (WOB), formation pressure, and mud loss volume at formation. Mud properties are Mud Weight (MW), Plastic Viscosity (PV), Yield Point (YP), 10-Second Gel Strength ($GL_1$) & 10-Minute Gel Strength ($GL_2$), Marsh funnel viscosity, pH or Alkalinity of any solution (ALK) for Oil Base Mud (OBM), Fluid loss (conventional API or High Temperature High Pressure (HPHT) API), Chloride Content (CL), Calcium Content (CA) or Stability of Mud (ES) for OBM), Solid percent, and Oil/Water ratio.

**2.2- Selection of the parameters**

Understanding the influence of the input parameters is considered the primary concern when developing ANN models. Introducing more input parameters than required will result in a large network size and consequently decrease learning speed and efficiency [14]. Since the drilling process has many effective parameters, it is essential to find the best set of variables that are related to stuck pipe. The following criteria can be applied [15]:

1) There must be a spread of values of the parameter in the databases. This allows the neural network to more easily approximate the function.
2) The variable must not be dependent on other input variables only. A parameter may be dependent on other input variables, but must also be dependent on

a parameter that is not an input variable. In this way the variable will provide information about the well that is not already provided by the other variables.

In this work, the above criteria were considered, and finally, some parameters were removed from the analysis. These parameters are WOB, CA, MW, True Vertical Depth (TVD), Solid percent, Flow rate, API Fluid loss, loss at formation and $P_f$. Among these variables, WOB was removed considering the first criterion. There are three types of values for API fluid loss: a) conventional API fluid loss, b) HTHP fluid loss, and 3) finally, No-control in some cases. Obviously these types differ considerably and cannot be considered as a single parameter. Also, converting these types into a single new parameter is difficult and may be impossible. Therefore, it cannot be included in the analysis. Other parameters were removed by considering the last criterion.

For the purpose of reducing the remaining parameters, a new dimensionless parameter was defined as Geometric Factor (GF) in this study. This parameter is a function of the following parameters: a) open hole length, b) bottom hole assembly length, c) outside diameter of drill collar, d) hole size and inclination angle. As shown by most researchers, these parameters are some causes of stuck pipe occurrences [16-23]. According to the relationship of parameters of GF with the likelihood of sticking, this function was defined in this work as equation 1:

$$GF = \frac{m.l.OH}{D_{eff}} \tag{1}$$

where:

*m* and *l* are constants which are related to the inclination angle ($\theta$) and Bottom Hole Assembly length ($L_{BHA}$), and can be obtained from Table 1 and Table 2. OH is the open hole length in meters. $D_{eff}$ is the effective diameter in inches according to equation 2:

$$D_{eff} = \frac{D_{hole}^2}{OD_{collar}} \tag{2}$$

**Table 1.** *m* parameter in GF for various ranges of inclination angle

| Inclination Angle | $\theta < 10^o$ | $10^o < \theta < 30^o$ | $\theta > 30^o$ |
|---|---|---|---|
| *m* | 1 | 2 | 3 |

**Table 2.** *l* parameter in GF according to BHA length

| BHA Length | $L_{BHA} < 40m$ | $40m < L_{BHA} < 100m$ | $L_{BHA} > 100m$ |
|---|---|---|---|
| *l* | 1 | 2 | 3 |

The new defined function was used in the analysis instead of its parameters. Hence, the final selected parameters are pH, PV, YP, $GL_2$, CL, $P_{diff}$, GF, Annular Velocity ($V_{ann}$), Revolutions per Minute (RPM) and Rate of Penetration (ROP), in which the last three items refer to dynamic conditions only.

**2.3- Data pre-processing**

Before supplying the available data to the neural network, it is crucial to pre-process the data. Data pre-processing helps to speed up the learning process and ensures that every parameter receives equal attention by the network and improving the overall network performance. Before training, it is often useful to scale the inputs and targets so that they always fall within a specified range [14]. In this work, the available data have been normalized into the range of 0 to 1 by using equation 3:

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (3)$$

where:

$X_n$: normalized value, $X_{min}$: minimum of original values, $X_{max}$: maximum of original values, and X: original value.

Applying the above procedure in this work resulted in significant improvement in the performance of the ANN. Table 3 and Table 4 show the statistical properties of the selected parameters before normalizing. In order to improve the final performance of the ANN and also minimize the distribution of differential pressure parameter, values greater than 1500 psi were considered as 1500 psi. Similarly, this concept is true for GF and was applied in this work.

**Table 3.** Statistical properties of selected parameters **for dynamic analysis**

| Parameter | Minimum | Maximum | Average | STDEV |
|---|---|---|---|---|
| $P_{diff}$ (psi) | 10 | 1500 | 496.4 | 330.9 |
| PV (cp) | 1 | 64 | 26.6 | 14.5 |
| YP ($lbs/100ft^2$) | 1 | 43 | 11.5 | 7.5 |
| GL 2 ($lbs/100ft^2$) | 1 | 21 | 4.99 | 3.39 |
| pH or ALK | 2 | 11 | 5.64 | 2.84 |
| CL (ppm) | 4000 | 440000 | 285.5 | 75.1 |
| $V_{ann}$(ft/min) | 125.2 | 351.3 | 224.9 | 43.4 |
| GF | 0.25 | 400 | 203.8 | 123.4 |
| RPM | 20 | 180 | 113.7 | 49.34 |
| ROP (m/h) | 0.3 | 12 | 2.71 | 1.88 |

**Table 4.** Statistical properties of selected parameters **for static analysis**

| Parameter | Minimum | Maximum | Average | STDEV |
|---|---|---|---|---|
| $P_{diff}$ (psi) | 20 | 1500 | 571.3 | 379.8 |
| PV (cp) | 1 | 60 | 26.1 | 13.98 |
| YP ($lbs/100ft^2$) | 1 | 38 | 10.35 | 6.04 |
| GL 2 ($lbs/100ft^2$) | 1 | 18 | 4.45 | 3.03 |
| pH or ALK | 2 | 11 | 6.22 | 3.09 |
| CL (ppm) | 4000 | 440000 | 281.7 | 72.8 |
| GF | 0.38 | 400 | 195.02 | 122.02 |

### 2.4- Network architecture design

As mentioned earlier the number of neurons in the input and output layers quite simply determine the number of input and output parameters. In this work, there is one output parameter and hence one neuron in the output layer, which is a percentage representing the probability of stuck pipe. For hidden layers it has been stated that a network with a single hidden layer and sigmoidal transfer function is able to model any continuous relationship. The use of two hidden layers was also examined, but two hidden layer networks generally have more connections and need more data [15]. Consequently, a network with one hidden layer was selected for this work. The number of hidden neurons was selected according to some guidelines in references [11, 15]. Considering those guidelines, six elements and later a fewer number of processing elements was selected for finding the best network.

## 3- Results

### 3.1- Dynamic condition

Based on a partitioning ratio of 8:1:1, the numbers of training, validation, and testing data sets for dynamic condition were 155, 20 and 20 respectively. Initially a network with six processing elements in its hidden layer was selected. Then, the number of neurons was reduced and finally a network with 3 neurons in its hidden layer was selected. Through eliminating unnecessary parameters, the appropriate parameters were selected to improve network performance. For this purpose different parameters were removed individually and the network performance was examined. This procedure led to reducing the number of inputs to 6 parameters. Final parameters were differential pressure, pH, GF, RPM, ROP and PV. It was observed that the performance in the new condition and the prediction of stuck pipe was performed with high accuracy. There are two reasons wherein this behaviour is confirmed; first, it was seen that other parameters do not play an important role in stuck pipe occurrences in the essence of this study. Second, the decreased input parameters had caused numerous connections in the network, and consequently a higher number of training data sets are required.

The final selected network has a three layer feed-forward and back-propagation with a sigmoid type activation function in the hidden and output layers. The numbers of neurons in the input, hidden, and output layers are 6, 3 and 1 respectively. This network is shown in Fig. 1.

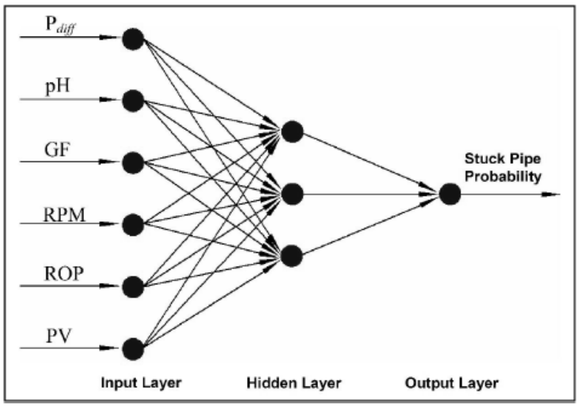


**Figure 1.** Selected network for dynamic analysis.

Weights and biases which are related to the final network for stuck pipe prediction are shown in Table 5. Results of the selected network for three data sets and their respective errors are shown in Table 6.

**Table 5.** Weights and biases of selected network in the dynamic condition

| From/to | | Input layer neurons | | | | | | Biases |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | |
| Hidden layer | 1 | -3.6296 | -0.065145 | -5.0362 | 0.6431 | 4.0016 | -0.50607 | 0.82606 |
| | 2 | -6.8894 | -1.6201 | -7.3272 | -2.3979 | -0.57441 | 2.1175 | 10.5576 |
| | 3 | -3.6973 | -1.1914 | -5.301 | 1.6227 | 1.9595 | -3.896 | 3.4529 |
| _ | | Hidden layer neurons | | | | | | _ |
| _ | | 1 | | 2 | | 3 | | |
| Output layer | | -6.9462 | | -10.7272 | | 8.0237 | | 1.4217 |

**Table 6.** Results of selected network for three data sets and their respective error in the dynamic condition

| Data sets | | Total | Correct | Incorrect | Error Percent |
|---|---|---|---|---|---|
| Training | Stuck | 32 | 26 | 6 | 3.9% |
| | Non-Stuck | 123 | 123 | 0 | |
| Validation | Stuck | 4 | 3 | 1 | 5% |
| | Non-Stuck | 16 | 16 | 0 | |
| Testing | Stuck | 4 | 3 | 1 | 5% |
| | Non-Stuck | 16 | 16 | 0 | |

### 3.2- Static condition

The same partitioning ratio of 8:1:1 was selected in the static condition, in which the numbers of data sets were 184, 23 and 24 for training, validation, and testing respectively. Similar to the dynamic condition, reducing the number of hidden neurons and eliminating unnecessary input parameters was considered. At the end, four processing elements and six input parameters were selected for the network. Final parameters are differential pressure, GF, pH, YP, PV and GL. The final network is a three layer feed-forward back-propagation network with six, four and one neuron in its input, hidden and output layer correspondingly. Activation functions are “tansig” and “logsig” in the hidden and output layer respectively. Fig. 2 shows this network graphically. Weights and biases of the final network are shown in Table 7. Table 8 summarizes the results of the selected network for three data sets and their respective errors.

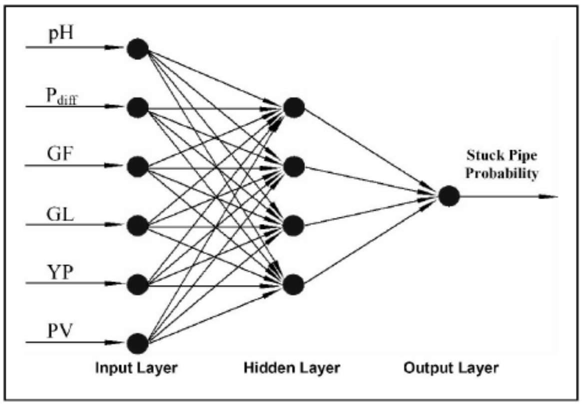


**Figure 2.** Selected network for static analysis.

**Table 7.** Weights and biases of selected network in static condition

| From/to | | Input layer neurons | | | | | | Biases |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | |
| Hidden layer | 1 | 1.2872 | 5.4524 | 1.6615 | -1.3616 | -3.7108 | -4.1069 | -1.5491 |
| | 2 | -10.737 | 10.7375 | 5.0644 | 4.1072 | -17.128 | 0.72931 | -2.1242 |
| | 3 | 6.4941 | -4.6956 | 8.3363 | 8.4551 | -20.8118 | 3.7133 | -4.856 |
| | 4 | -0.21699 | -0.86425 | -4.1659 | -4.2272 | 17.8594 | 0.20981 | -0.45055 |
| – | | Hidden layer neurons | | | | | | – |
| – | | 1 | 2 | | 3 | 4 | | |
| Output layer | | 34.391 | 29.0688 | | 28.6556 | 42.9459 | | 12.9845 |

**Table 8.** Results of selected network for three data sets and their respective error in static condition

| Data sets | | Total | Correct | Incorrect | Error Percent |
|---|---|---|---|---|---|
| Training | Stuck | 60 | 51 | 9 | 6% |
| | Non-Stuck | 124 | 122 | 2 | |
| Validation | Stuck | 7 | 6 | 1 | 8.7% |
| | Non-Stuck | 16 | 15 | 1 | |
| Testing | Stuck | 8 | 6 | 2 | 8.3% |
| | Non-Stuck | 16 | 16 | 0 | |

## 4- Discussion

As shown in Table 6, analysis in the dynamic condition shows 95% accuracy for the last two data sets; validation and testing. According to Table 6, there is no error for the 123 non-stuck cases in the training data set. On the other hand, among 32 stuck cases in the same data set, the network has found 26 correct answers. Likewise, from the total number of four stuck cases, validation and testing data sets had three correct responses. Nevertheless, in those two data sets, no errors were observed in the non-stuck cases. For training data set in dynamic condition, among 155 cases, 149 correct responses were observed that show more than 96% exactness. Also, the network responses for validation and testing data sets individually include 19 correct answers out of 20 cases that show 95% accuracy.

For the static condition, total stuck data in the training data set was 60 cases, as shown in Table 8. This table shows 85% accuracy in stuck cases for static condition. Correct responses for non-stuck data were 122 out of 124 cases in the training data set (98.4% accuracy). From the total number of seven cases of stuck pipe in the validation data set, the network responded to six stuck pipe incidences (85.7% accuracy). The non-stuck cases in this set include 15 correct answers out of 16 cases (95.6% accuracy). Finally, in the case of stuck data, from eight cases, the network response for the testing data set included six correct responses (75% accuracy), while non-stuck data responded without any error (100% accuracy). Overall, in the static condition the training, validation, and testing data sets had a greater than 93% accuracy.

As the input parameters, the network topology, the performance function, and the learning rule were chosen by the network designer, the criteria to stop the training phase will be chosen by him/her too. The criteria of the desired outputs were considered 70% and 50% for stuck and non-stuck cases respectively. In this way, for stuck cases a response which is greater or equal to 70 percent is a correct response and any percent less than 70 percent is referred to as an incorrect answer. However, for the case of non-stuck, any percent less than was 50 considered as a good estimation of reality, which means such a condition has some potential for stuck pipe occurrence. As a matter of fact, 70% and 50% criteria were used to stop the training phase. So, in order to gain the lowest possible error (global minimum) and on the other hand, to avoid over-fitting or memorizing during training, the mentioned assumptions were considered in this work. Note that over-fitting includes a quick decrease in error for the training set, while error of validation and testing sets increases rapidly.

Referring to the networks responses, it can be seen that some stuck data were predicted incorrectly. The types of stuck pipe cases were compared with non-stuck pipe cases. It was observed that most of the stuck pipes occurred in a normal condition for the available drilling parameters. The existing data have some non-stuck objects which are very similar to the stuck cases, either in the selected parameters for analysis or in other parameters. Considering this similarity, it can be said that causes of sticking in these cases were not related to the available parameters. Therefore, error of prediction in these cases is not related to the networks performance, but is related to data or these kinds of sticking are related to unpredictable sources and cannot be predicted with any procedure.

## 5- Conclusions

1- Selected network can be utilized for calculating the risk of stuck pipe either mechanical or differential before any drilling operations.
2- Successful stuck pipe shows that there are analytical or statistical differences between days that the stuck pipe happened and the non-stuck days which are completely safe.
3- High accuracy for stuck pipe prediction using selected parameters illustrates that most causes of stuck pipe are due to inappropriate values of the selected parameters. Chosen parameters were pH, PV, YP, Gel, RPM, ROP, $P_{diff}$, and GF.
4- Use of GF and the success of this parameter in this work demonstrated that some parameters can be replaced with a new defined parameter. In this way, dimensionless parameters can be more beneficial.

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