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Intelligent data-driven decision-making to mitigate or stop lost circulation

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INTELLIGENT DATA-DRIVEN DECISION-MAKING TO MITIGATE OR STOP LOST CIRCULATION

by

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ABSTRACT

Lost circulation is a challenging problem in the oil and gas industry. Each year, millions of dollars are spent to mitigate or stop this problem. The aim of this work is to utilize machine learning and other intelligent solutions to help to make better decision to mitigate or stop lost circulation. A detailed literature review on the applications of decision tree analysis, expected monetary value, and artificial neural networks in the oil and gas industry was provided. Data for more than 3000 wells were gathered from many sources around the world. Detailed economics and probability analyses for lost circulation treatments' strategies were conducted for three formations in southern Iraq which are the Dammam, Hartha, and Shuaiba formations.

Multiple machine learning methods such as support vector machine, decision trees, logistic regression, artificial neural networks, and ensemble trees were used to create models that can predict lost circulation and recommend the best lost circulation treatment based on the type of loss and reason of loss. The results showed that the created models can predict lost circulation and recommend the best lost circulation strategy within a reasonable margin of error. The created models can be used globally which avoids the shortcoming in the literature. Intelligence solutions and machine learning have proven their applicability to solve complicated problems and make better future decisions. With the large data available in the oil and gas industry, these methods can help the decision-makers to make better future decisions that will save time and money.

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1. INTRODUCTION

Drilling fluid losses and problems associated with lost circulation while drilling represent a major expense in drilling oil and gas wells, by industry estimates, more than 2 billion USD is spent to combat and mitigate this problem each year (Arshad et al., 2015).

There is a wide range of lost circulation treatments available applied to control or eliminate lost circulation events. These systems can be divided into conventional systems, which include granular, fibrous and flaky materials that are mixed with the drilling fluids during either the drilling phase or with the cement slurries during the drilling and primary cementing phases. The other approach to controlling lost circulation is specialized cement, dilatant slurries, soft or hard reinforcing plugs, cross-linked polymers, and silicate systems that are also used during the drilling/cementing phases.

The materials of the drilling fluid are so expensive, companies spent $7.2 billion in 2011 and it is expected to reach $12.31 billion in 2018 as the global market for drilling fluid indicates, which shows a vigorous yearly maximize by 10.13% (Transparency Market Research, 2013). The cost of the drilling mud is equivalent to averages 10% of total well costs; however, drilling-fluid can extremely impact the ultimate expenditure (Darley and Gray, 1988). Lost circulation events, defined as the loss of drilling fluids into the formation, are known to be one of the most challenging problems to be prevented or mitigated during the drilling phase. The severity of the consequences varies depending on the loss severity; it could start as just losing the drilling fluid and it could end in a blowout (Messenger, 1981). Among the top ten drilling challenges facing the oil and gas industry today is the problem of lost circulation. Major progress has been made to understand this problem and how to combat it. However, most of the products and guidelines available for combating lost circulation are often biased towards advertisement for service companies.

Expected Monetary Value (EMV) is defined as “the average outcome of a random experiment if the experiment is conducted numerous times” (Kelkar, 2013). Decision Tree Analysis (DTA) is an extension of probability analysis. The combination of EMV and DTA is one of the most common methods used in the decision-making process. If EMV is positive, the decision is considered to be feasible. However, that doesn’t mean the decision will be successful at all times. It simply means that if a similar decision is made for a larger number of cases, the decision will be successful. EMV will basically account for the uncertainty in the probability.

DTA and EMV have been widely used in the petroleum industry to help in the decision-making process. Xu (2013) used a combination of DTA and stochastic simulation for the decision-making process. Xu showed a real example of how to make the decision using DTA and stochastic simulation of an infill drilling project in a North Sea field. Xu concluded that the combination of DTA and stochastic simulation will deliver more understanding about the uncertainty which will lead to making a better decision. Sprowso et al. (1979) presented a model called IPEX that uses DTAs and EMV. IPEX can handle three types of project evaluations; Farm-In, In-House and Government Bid. DTA and EMV have been also used in the evaluation and materials selection for the completion process of a new field that is characterized by high H_2S and CO_2 content (Cheldi et al., 1997). Cheldi et al. used EMV to find the cost and implemented a Monte Carlo simulation to find the probability. Finally, DTA was carried out to select the best material. In addition, Gu et al.

(2005) utilized DTA and data mining methodology to identify the correlation between the presence of stress corrosion cracking and environmental/ loading conditions.

Gatta (1999) used DTA and risk modeling to appraise investments on major oil filed projects. Gatta showed a real example of project development in North Kuwait oilfield. Gatta used Monte Carlo simulation to assess the risk and uncertainty. The conclusion made by Gatta is that DTA and Monte Carlo simulation each has its own advantages and disadvantages. A comparison between the DTA and stochastic simulation to optimize the decision-making process has shown that the results for the DTA and the stochastic simulation were different (Erdogan et al., 2001; Schulze et al., 2012). Moreover, DTA used to decide the best artificial lift method that should be installed in the well in order to help in the decision-making process (Heinze et al., 1995).

This dissertation provides basic information on lost circulation, including an introduction to the problem, identifies a range of factors that affect lost circulation, and reviews historical work in lost circulation materials. The dissertation uses intelligent data-driven decision-making methods to mitigate or stop mud loss and recommend the best lost circulation treatments' strategies in Southern Iraq oil fields and worldwide. Lost circulation screening criteria are presented for these fields, based on the type of mud loss and reason of mud loss.

1.1. OBJECTIVES OF THE STUDY

There is a wide range of lost circulation treatments and materials available in the oil and gas industry. It is always difficult to select the best lost circulation treatments and materials to treat each type of mud loss. However, choosing the right treatment is subjective to the decision maker's experience and knowledge. The availability of large data sets, as well as the revolution of data analytics, have given incentives to researchers to use data analytics and machine learning to help in guiding the decision-making process and to make better decisions in the future for the oil and gas industry. This dissertation used large real field data collected from multiple locations in southern Iraq and other data sets around the world collected from the literature. The idea is to develop a systematic approach to optimize the treatment strategies for the lost circulation problem based on the type of loss as well as other factors.

Moreover, this work aims to provide a systematic review of the current lost circulation treatments and materials used by the petroleum industry in addition to reviewing the current machine learning and artificial intelligence methods that were applied by the oil and gas industry to assist in the decision-making process.

To overcome the identified gaps in the literature, the main research objective of this dissertation is to use probabilities, expected monetary value (EMV), decision tree analysis (DTA), and applications of machine learning to recommend the best-lost circulation strategy for each type of loss in Southern of Iraq oil fields and worldwide.

The main objective can be broken down to the following sub-objectives:

1. To gather data of lost circulation events as well as data of lost circulation treatments and materials in Southern of Iraq oil fields.
2. To find detailed cost and probabilities for each treatment used in Southern of Iraq oil fields.
3. To find alternative approaches (using advances in drilling technology) if conventional treatments don’t remedy lost circulation to live with losses.

4. To considers economics and probability in the decision-making process (the concept of EMV) and recommend the best treatment strategy for lost circulation in Southern Iraq oil fields based on the type of losses.
5. To collect more lost circulation events and treatments in various wells drilled worldwide and classify the data based on the type of losses and lithology.
6. Use machine learning to create models to predict mud losses and recommend the best treatments strategy based on the lithology of the formation worldwide.
7. To develop practical guidelines that will serve as a reference material for lost circulation control at the well-site for drilling personnel.

1.2. RESEARCH METHODOLOGY

After reading a good number of technical papers, a comprehensive literature review was provided for the applications of decision tree analysis (DTA) and artificial neural networks (ANNs) in the oil and gas industry with integrated analysis. The applications of DTA were separated into three categories; applications of DTA for the whole oil and gas prospect projects, applications of DTA for a specific operation or development, applications of DTA, Monte Carlo simulations, and other methods to assess the value of information. In addition, a detailed methodology on how to successfully apply DTA in the oil and gas industry was provided. In the same vein, the applications of ANNs in the oil and gas industry were tabulated and classified into four categories; exploration, drilling, production, and reservoir. Moreover, a comprehensive approach on how to successfully apply ANNs to any oil and gas application was conducted.

Lost circulation data were collected from many sources around the world such as the literature, daily drilling reports (DDR), daily mud reports, daily mud logging reports, primary cementing reports, end-of-well report and non-productive time analyses, and well logging data. More than 3000 wells were utilized in this study. The data first went through a processing step and all outliers were removed from the data. Then, the events of lost circulation were classified based on the type of loss to partial, severe, and complete loss.

Probability and economics (the concept of expected monetary value (EMV)) were utilized to select the best lost circulation strategy based on the type of loss for the Dammam, Hartha, and Shuaiba formations in southern Iraq. Thousands of scenarios were considered, the lowest EMV scenario was selected to stop lost circulation. Two criteria were utilized to choose the treatment strategy for each type of loss. The first criterion is that the treatment strategy has to have the lowest EMV, and the second criterion is the treatment strategy has to be practically applicable in the field. Both criteria have to be met in order to choose the treatment strategy. All treatment strategies end up with liner hanger if the lost circulation did not stop after applying all treatments.

Multiple machine learning methods such as support vector machine, decision trees, logistic regression, artificial neural networks, and ensemble trees were utilized to predict lost circulation prior to drilling and to recommend the best lost circulation strategy based on the type of loss (partial, severe, and complete) and reason of loss (natural fractures, induced fractures, or vugs and caves).

After testing the multiple machine learning algorithms, artificial neural networks algorithm was selected to predict mud loss, while support vector machine was chosen to recommend the best lost circulation strategy since they had the best performance among the other algorithms. For the artificial neural networks, two models were created to predict lost circulation prior to drilling for natural and induced fractured formations using key drilling parameters (e.g. mud weight (MW) in gm/cc, equivalent circulation density (ECD) in gm/cc, plastic viscosity (PV) in cp, yield point (Yp) in lb/100ft^2, flow rate (Q) in L/min, revolutions per minute (RPM), weight on bit (WOB) in Tons, nozzles total flow area (TFA) in inch^2). The data were divided into three sets; training (60%), verification (20%), and testing (20%). The training data used to develop the ANN model, the desired output is used to help the network adjust the weights of each input. The error will backpropagate in the network and adjust the weights until calibration is reached, this method is called feedforward backpropagation algorithm. It should be noted that the network should not be overtrained since the network will lose its ability to generalize. Verification set is used to measure the network generalization, and to stop the training when generalization stops improving. Testing set used to test the accuracy of the network after the training and the verification steps. Any neural network consists of three layers; one input layer, one or multiple hidden layers, and one output layer. The number of hidden layers, as well as the number of neurons in the hidden layer, were selected based on trial and error to minimize the mean square of error (MSE).

Quadratic support vector machine algorithm had the best performance among the other machine learning algorithms to recommend the best lost circulation strategy based on the type of loss and reason of loss. The inputs for the model were selected based on the trial and error to meet two goals, the first one is to have the highest accuracy, and the second one is to minimize the number of predictors. 5-fold cross-validation was conducted to ensure the model is not overtrained and can generalize to new data.

1.3. DATA UTILIZATION FOR LOST CIRCULATION PROBLEM ANALYSIS

1.3.1. Extensive Literature Review. Obtaining data is very time-consuming. A good number of technical papers were summarized and discussed to widen the knowledge about the state-of-the-art of lost circulation treatments and materials. In addition, a large data set for the lost circulation treatments and materials was acquired from the literature review as well as over 3000 real field data that were collected from southern Iraq oilfields.

1.3.2. Well Logging Data. Well logs were utilized to expand the understanding of the mud loss problem. Multiple well logs were obtained to help achieve the aforementioned goal.

1.3.3. Daily Drilling Reports. This is a very time-consuming process. Each well had many daily drilling reports. In order to extract information from each report, digging each report and trying to find information was the only way to do this. It was a very tedious process since the format of these reports are in pdf. In addition, some of these reports are not searchable (scanned), that also made it more difficult to deal with them.

1.3.4. Daily Mud Reports. These reports are very essential since they contain information about the drilling fluid properties such as mud density, yield point, plastic viscosity, filtration, sand content, etc. Each parameter was studied carefully since each property has a vital effect on the drilling operations.

1.3.5. Daily Mud Logging Reports. These reports were used to recognize the overpressurized formations.

1.3.6. Primary Cementing Reports. To find the appropriate plug treatment, the cementing reports can be utilized in order to achieve this goal.

1.3.7. End-of-Well Report and Non-Productive Time Analyses. These are very useful reports. Basically, they are a summary of the whole drilling operations in the specific field. They were used to extract valuable economical information that assisted in the decision-making process.

PAPER

I. REVIEW OF THE APPLICATIONS OF DECISION TREE ANALYSIS IN PETROLEUM ENGINEERING WITH A RIGOROUS ANALYSIS

ABSTRACT

As oil prices are fluctuating, decision makers are challenged to make the "best" decisions for field's developments. Decision Tree Analysis (DTA) can be used to guide the decision-making process and to reduce the risks associated with decisions since DTA accounts for the uncertainties.

After reading and summarizing a good number of papers and cases history about the applications of DTA in petroleum engineering, it was concluded that the applications can be classified into three main categories; applications for whole field's developments, applications for a specific operation, and applications to assess the value of information. Then, these applications were summarized and tabulated into various tables.

A clear methodology accomplished by flowchart that explains how to successfully apply DTA for any petroleum engineering application was provided. The method consists of three main steps: 1) how many scenarios need to be considered 2) collection of the required data 3) use the visual tool (DTA) or programming to find Expected Monetary Value (EMV). Each of the previous steps has its own challenges, thus these challenges were addressed and solutions to overcome them were provided. Finally, practical guidelines were developed that when used with the accompanying flow chart will serve as a quick reference guide to apply DTA for any petroleum engineering application.

DTA is a very important tool for the decision makers to make the "best" decision. This paper provides a clear methodology on how to successfully apply DTA, which can serve as a reference for any future DTA applications in petroleum engineering.

1. INTRODUCTION

Decision Tree Analysis (DTA) is a graphical diagram containing nodes and branches (Taylor, 2019). DTA focuses on managerial decisions, such as whether to do workover or not, whether the additional information will be valuable or not, should the field be developed or not. The DTA accounts for the uncertainty in the probability analysis (Galli et al., 1999). Expected Monetary Value (EMV) is defined as "the average outcome of a random experiment if the experiment is conducted numerous times" (Kelkar, 2013). The combination of EMV and DTA is one of the most common methods used in the decision-making process. If EMV is positive, the decision is considered to be feasible. However, that doesn't mean the decision will be successful at all times. It simply means that if a similar decision is made for a larger number of cases, the decision will be successful. EMV can be calculated using the following Equation (Kelkar, 2013):

$$\mathrm{EMV} = \sum_{i=1}^{n} p_i(\mathrm{NPV}) \qquad \text{Eq. 1}$$

Where n is the number of possible outcomes, NPV is the net present value of the outcome i, and pi is the probability of the outcome i.

A simple example of the DTA analysis is shown in Figure 1. Let's assume an operator wants to develop a new field. The operator has to decide between three scenarios: scenario 1 (install a large platform), scenario 2 (install a small platform), or scenario 3 (drill appraisal well). Each scenario has its own uncertainties, if the field turned out to be large, then scenario 1 will be the best option. On the other hand, if the field turned out to be very small, then scenario 3 will be the best option. The decision maker is challenged to pick the “best” scenario among those three. Assuming the decision maker knows enough about the net present values (NPV) and the probabilities of each scenario, DTA analysis can be used to help the decision maker to make the “best” decision. The boxes in Figure 1 are referred to decision nodes, the circles are referred to probability nodes, and the triangles are referred to the end of the branch. The EMV should be calculated for each probability node, then the highest EMV scenario should be chosen. In the example in Figure 1, the decision of drilling an appraisal well should be carried out since it has the highest EMV. Now the question is- did the decision maker make the right decision? The answer for this question can be referred back to the definition of EMV, the decision made by EMV will not always be successful but it simply means if a similar decision is made for a larger number of cases, the decision will be successful. One important point to mention is the EMV calculations should be performed from the far right end to the far left end.

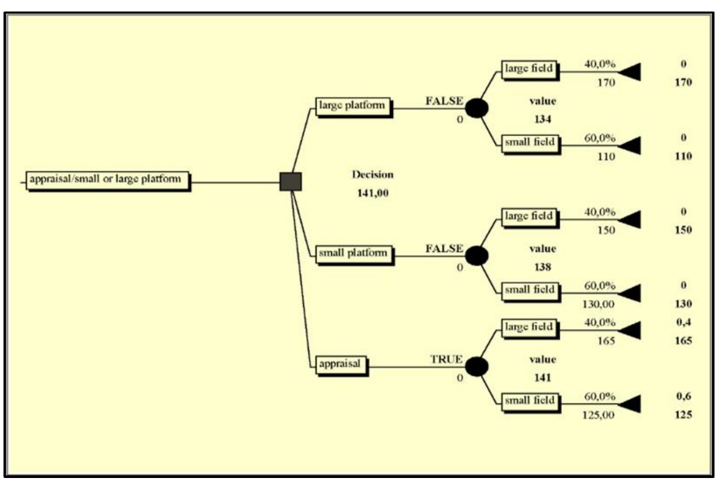

Figure 1. Example of Decision Tree with Three Scenarios (After Galli et al., 1999)

2. APPLICATION OF DTA AND EMV IN PETROLEUM ENGINEERING

DTA and EMV have been utilized in the petroleum industry to help to make decisions when having multiple alternatives. In this section, a comprehensive review of DTA and EMV applications will be presented. The applications of DTA and EMV in the literature can be divided into three categories:

2.1. APPLICATIONS OF DTA AND EMV FOR THE WHOLE OIL AND GAS PROSPECT PROJECTS

This means considering all the risks and uncertainties associated with the project exploration and developments as well as the short and long terms profits. Table 1 shows a summary of the applications used to evaluate oil and gas prospect projects.

Table 1. Applications of DTA and EMV for the First Category

Author(s)	Application	Notes
Sprowso et al. (1979)	Project evaluation	Presented a model called IPEX to help to evaluate projects
Gatta (1999)	Appraise investments in major oil filed projects	A real example of project development in North Kuwait
Galli et al. (1999)	Comparisons between three methods for evaluation of oil projects	Compared between option pricing, EMV, and Monte Carlo simulations and showed the similarities and differences between these methods
Begg et al. (2002)	Investments	Managing the uncertainty in the oil and gas investments
Floris & Peersmann (2002)	Hydrocarbons assets	Used EMV to help to make better decisions about assets of hydrocarbons
Coopersmith et al. (2003)	Appraisal and development strategies	Presented a method to frame appraisal and developments strategies
Hayashi et al. (2007)	Offshore petroleum fields developments	Used EMV to evaluate the value of information coming from developments of offshore fields
Hayashi et al. (2010)	Risk mitigation in petroleum field development	Presented a methodology to quantify the risk of a modular implantation
Burkholder et al. (2012)	Uncertainties in the unconventional plays	Used EMV to frame, evaluate, and compare appraisal strategies in unconventional plays
Coopersmith et al. (2012)	Uncertainty assessments	Used EMV concept to assess the long-term uncertainty
Deore (2012)	Decision making in the upstream oil and gas industry	Presented several methodologies (including EMV) to help to make decisions in the upstream oil industry

2.2. APPLICATIONS OF DTA AND EMV FOR A SPECIFIC OPERATION OR DEVELOPMENT

Some examples include deciding whether to add additional infill wells, choose between artificial lift methods, completions methods, and etc. Table 2 shows examples of the application of EMV and DTA for specific operations or developments.

Table 2. Applications of DTA and EMV for the Second Category

Author(s)	Application	Notes
Jensen (1979)	Production forecast uncertainty	Estimated the production forecast uncertainty for the PL018 production license in the Norwegian Sector
Newendorp (1984)	Risk analysis for analyzing drilling prospects	Used EMV and other methodologies to assess the risk with drilling prospects
Zammerilli (1991)	Ranking horizontal well sites	Described a method to examine the location of the new horizontal well in a naturally fractured shale gas basin
Cunha (1994)	Fishing operations	How to optimize the fishing operation to save money and time
Heinze et al. (1995)	Artificial lift	Find the best artificial lift methods
Cheldi et al. (1997)	Materials selection	Evaluation and materials selection for the completion process of a new field that is characterized by high H_2S and CO_2 content
Palsson et al. (2003)	Water injection	Showed a case history of a water injection project in the North Sea
Gu et al. (2005)	Corrosion	Identify the correlation between the presence of stress corrosion cracking and environmental/ loading conditions
Rodrigues et al. (2006)	Water injection uncertainty	Considered the uncertainty in the geomechanical data related to water injection to decide the best way to inject water into the reservoir
Kartoatmodjo et al. (2007)	Acid stimulation	Proposed a methodology to acid stimulation candidate selection with an application in the Bokor field in Malaysia
Zhu & Arcos (2008)	Well completions	Asses various alternatives in the completion of a well (e.g. vertical, horizontal or multilateral)
Nogueria & Schiozer (2009)	Production optimization	Proposed a new methodology for production optimization
Ordu et al. (2011)	Well completions	Evaluated the risk of recompleting a well in a water-flooded reservoir
Schulze et al. (2012)	Uncertainty in the subsurface data	Presented a methodology of combining the DTA and Monte Carlo simulation to eliminate uncertainty in the decision making
Coopersmith et al. (2013)	Pilot spacing for unconventional resources	Used EMV to help make a decision about the optimal pilot spacing for unconventional resources
Ghosh & King (2013)	Smart well completions	Determining the optimal placement of interval control valves and their flow settings
Xu (2013)	Infill drilling project, North Sea	Find the “best” locations of new wells
Shrivastava et al. (2016)	Decision analysis of complex appraisal and sequencing selection	Proposed a methodology to help to make a better decision regarding complex appraisal and sequencing selection with case history
Asmandiyarov et al. (2017)	Optimization	Optimization of appraisal wells addition
Santos & Schiozer (2017)	Influence of well control parameters in the development of petroleum fields	Performed reactive and proactive optimization under uncertainty in Namorado field

2.3. APPLICATIONS OF DTA, EMV, MONTE CARLO SIMULATIONS, AND OTHER METHODS TO ASSESS THE VALUE OF INFORMATION

This is applied to assess the value coming from a specific operation such as reservoir surveillance, seismic data, and etc. Table 3 shows a summary of applications of EMV and DTA to assess the value of information.

Table 3. Applications of DTA and EMV for the Third Category

Author(s)	Application	Notes
Lohrenz (1988)	Determine the net value of information	Showed that the value of information can have many uncertainties and some information can have a higher value when the oil prices are lower
Koninx (2000)	Assessment of the value of new information	Presented a methodology to assess the value of information as well as cost cutting
Mudford (2000)	Comparison between EMV and simulation methodologies	Showed an example of a typical Gulf of Mexico project from exploration to developments
Coopersmith & Cunningham (2002)	Value of information in the upstream industry	Used EMV to help make decisions regarding the value of information for the upstream oil and gas industry
Berteussen (2006)	Seismic explorations	Asses the value of 4D seismic data and decide whether to do it or not
Coopersmith et al. (2006)	Spend money to gather information	Used EMV to evaluate whether seismic data and core samples are valuable and should the money be spent on that or not
Coopersmith & Burkholder (2013)	Valuing seismic data at the drilling program level	Introduced a method to assess whether it is valuable to shot seismic at the drilling program level for sweet spot identifications
Martinelli & Surovtsev (2014)	Value of 3D seismic	Analyzed the contribution of adding 3D seismic information in exploration prospect assessment project and showed a case history of a conventional onshore oil prospect
Coopersmith et al. (2014)	Assessments for the early production systems offshore	Introduced a method to assess the value of early production systems offshore
Ferreira (2015)	Quantify the value of information of 4D seismic projects	Asses the value of information coming from 4D seismic to help in reservoir management
David et al. (2016)	Value of information in a gas reservoir	Presented a methodology to assess the value of information coming from an appraisal leg of well to test for fluid contact
Santos & Schiozer (2017)	Assessment of the value of information	Used an example of the benchmark reservoir model

3. HOW TO SUCCESSFULLY APPLY THE EMV AND DTA IN PETROLEUM ENGINEERING

The DTA and EMV are very useful and powerful methods used to evaluate economic projects, asses the value of information, and for selection processes. There are many steps that need to be followed in order to successfully apply the DTA and EMV.

In this section the process of how to successfully apply the DTA and EMV will be presented with an arbitrary example about lost circulation. Let's assume a decision maker wants to decide which lost circulation treatment strategy should be used for partial mud losses (Alkinani et al., 2019). The decision maker is challenged to decide the "best' treatment strategy for partial mud losses, this can be done using DTA and EMV. The following steps have to be followed in order to successfully apply the DTA and EMV (Figure 2 shows a summarized workflow to successfully applying the DTA and EMV):

3.1. HOW MANY SCENARIOS NEED TO BE CONSIDERED AND WHAT ARE THEY?

This is a very important step in having a rigorous analysis. First, the decision maker has to decide how many scenarios should be considered. It is up to the decision maker of how complicated the scenarios can be. The decision maker can choose an easy path or a very complicated path (can be a few scenarios up to thousands of scenarios). Going back to the lost circulation example, let's assume there are three partial losses treatments to create the "best" treatment strategy for partial losses. If the decision maker decided to make it simple, the repetition of the treatments will not be considered, thus the number of scenarios will be six. On the other hand, if the decision maker decided to go for a very complex path, then the repetition of the treatments will be considered, the number of scenarios, in this case, is twenty-seven. Hence, the decision of whether to have complex or simple scenarios is up to the decision maker.

3.2. COLLECTION OF THE REQUIRED DATA

After deciding how many scenarios that should be considered, the second step is to collect the required data for each scenario. This is the hardest part of applying the DTA and EMV method since data collection is very time consuming and it is very challenging since many data that are required to do this analysis are not easy to be found. Going back to the lost circulation example, there are many drilling data have to be available in order to have a rigorous analysis such as daily drilling reports, daily mud reports, daily mud logging reports, primary cementing reports, end of well report and non-productive time analysis. These data sources are used to calculate the cost of each treatment as well as the probability of success and fail for each treatment. For the cost calculations part, the cost of the materials to prepare the treatments, as well as the non-productive time associated with the treatment (due to the waiting period and due to trip in and trip out), should be considered. For the probability part, the probability of success and failure for each treatment has to be evaluated and depending on how complicated the scenarios, the conditional probability may also be required.

3.3. USE THE VISUAL TOOL (DTA) OR PROGRAMMING TO FIND EMV

DTA is a visual tool that helps to decide the best scenario based on the EMV. However, sometimes if there are thousands of scenarios it is impossible to draw decision trees for all scenarios. That is when computer programming has to be used to find the EMV for each scenario. Thus, if there are a few scenarios, a tree can be plotted for each scenario to find EMV. But if there are thousands of scenarios, a generalized equation can be obtained and computer programming can be used to find EMV for each scenario.

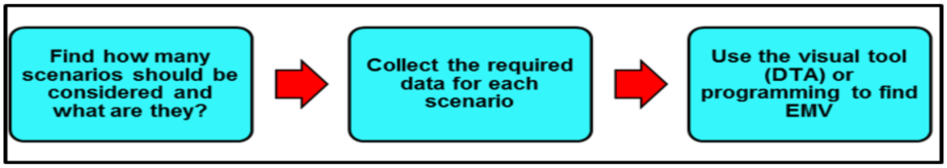

Figure 2. Summarized Workflow to Successfully Applying the DTA and EMV

4. CONCLUSION

As the petroleum engineering applications becoming more complicated nowadays, accomplished by the oil prices fluctuations, the decision-making processes becoming more difficult. The DTA is a very important tool for the decision makers to make the “best” decision. After reading and summarizing more than 200 papers and cases history about the applications of DTA and EMV in petroleum engineering accomplished by rigorous analysis, the following conclusions were made:

- As the decision-making process becoming more difficult nowadays, the decision makers are challenged to make the “best” decisions. However, having many uncertainties, it is not easy to make good decisions.
- That is why some decision-making tools such as the DTA is a very powerful tool to help to make decisions since it accounts for the uncertainties in the probability analysis.
- The applications of DTA in the literature were divided into three categories; applications for whole field’s developments, applications for a specific operation, and applications to assess the value of information.
- Practical guidelines have been developed that when used with the accompanying flow chart will serve as a quick reference guide to apply the DTA for any petroleum

engineering application. This paper provides a clear methodology on how to successfully apply the DTA which can serve as a reference for any future DTA applications in petroleum engineering.

- The decisions made by EMV doesn't mean the decision will be always successful, it simply means that if a similar decision is made for a larger number of cases, the decision will be successful.

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II. ROBUST METHODOLOGY TO SELECT THE BEST LOST CIRCULATION TREATMENT USING DECISION TREE ANALYSIS

ABSTRACT

Lost circulation is a unique challenge unlike other factors contributing to non-productive time (NPT). Due to the variability in the nature and type of lost circulation prone formations, there is no universal solution to this challenge. This publication presents a new approach to guide the decision-making process of which and when to apply a certain treatment as compared to another. If implemented correctly, a significant reduction in NPT related to lost circulation can be expected. In addition, examination of the cost of each treatment and the NPT were conducted. Lost circulation events for three carbonate formations which are the Dammam (dolomite), Hartha (limestone), and Shuaiba (limestone) were gathered from over 1000 wells. The treatments were categorized based on the type of loss, cost, and type of formations.

This work uses decision tree analysis (DTA) and expected monetary value (EMV) in the decision-making process. Thousands of treatments scenarios were considered to treat partial, severe, and complete losses. Two criteria were utilized to choose the treatments strategy for each type of losses. The first criterion is that the treatment strategy has to have the lowest EMV, and the second criterion is the treatment strategy has to be practically applicable in the field. Both criteria have to be met in order to choose the treatment strategy. All treatment strategies end up with liner hanger if the lost circulation did not stop after applying all treatments.

Moreover, this study provides comprehensive treatment strategies to handle lost circulation in three carbonate formations to assist the drilling personnel to deal with lost circulation in an efficient and cost-effective way.

This study provides a new method to select the best lost circulation treatments strategy for each type of losses and three carbonate formation. Due to the inconsistency of methods to respond to the lost circulation problem, this study can serve a reference to handle lost circulation in any formation worldwide.

1. INTRODUCTION

Lost circulation phenomenon causes oil and gas industry unwanted problems and an increase in spending for operation purposes. Not only it increases the budget, but it also delays the duration of the planning calendar (Aadnoy et al. 2007). Lost circulation can occur due to highly permeable formation, depleted reservoirs, and fractured or cavernous formations (Moore 1986). Figure 1 shows the candidate formations for lost circulation. There are two conditions that can cause lost circulation downhole (Osisanya 2002):

i. The pressure in the wellbore exceeding the pore pressure, and

ii. There must be a flow pathway for the losses to occur

Depending on the rate of losses, the severity of lost circulation can be categorized as follows (Basra Oil Company 2007):

- Partial loss: up to 10 m^3/hr
- Severe loss: up to 15 m^3/hr
- Complete loss: no return

The Dammam formation is the first formation that is prone to mud losses in Basra oil fields, Iraq. The top of this formation is found between 435 to 490 meters. The interval is composed of interbedded limestone and dolomite. The top of Dammam was eroded after burial and is karstified. The karst features are the reason behind lost circulation while drilling the Dammam formation (Arshad et al. 2015). The Hartha formation is the second formation that is susceptible to mud losses problems. The Hartha formation occurs approximately from 1530 to 1640 meters in Basra oil fields, Iraq. It is located below transitional formations that have abnormal pressure and H2S flow which are the Tayarat and Ummer-Radhuma formations. The Shuaiba formation occurs at approximately 2900 meters and is limestone with little to no visible porosity. However, the formation is highly fractured and prone to more complicated lost circulation problem than the Dammam and Hartha formations. In some cases, lost circulation in the Shuaiba formation can lead to the abandonment of the entire well (Alkinani et al. 2019). Table 1 shows the lithology in Southern Iraq.

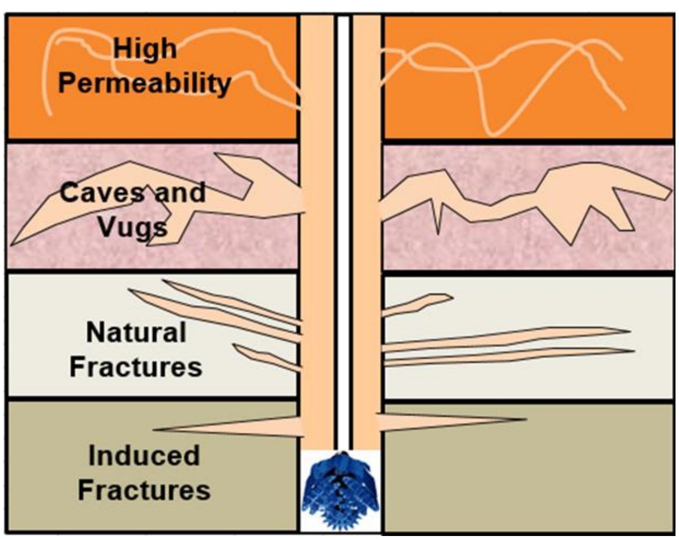

Figure 1. Candidate Formations for Lost Circulation

DTA and EMV have been widely used in the petroleum industry to help in the decision-making process for a long time. Heinze et al. (1995) utilized DTA and EMV in the selection of artificial lift methods to help to decide which method is the best based on some inputs. DTA and EMV have been used for the project evaluation to help to make better future decisions (Sprowso et al. 1997). DTA has been used to evaluate an investment in a major oil field located in Kuwait (Gatta 1999). Cheldi et al. (1997) utilized EMV and DTA to select the best completion method for fields with high H2S and CO2 contents. A comparison between DTA and stochastic simulations has been carried out and the results showed that both methodologies were different from each other (Schulze et al. 2012; Erdogan et al. 2001). DTA and data mining have been used to evaluate the relationship between the stress corrosion cracking and loading/environmental conditions (Gu et al. 2005). Xu (2013) used stochastic simulations and DTA to evaluate the value of infill drilling project in the North Sea. Moreover, DTA and EMV have been utilized to evaluate the value of information coming from exploration and developments of petroleum assets (Ibarra et al. 2017)

Alkinani et al. (2018a) presented an updated classification of lost circulation treatments and materials based on data from the literature and wells drilled in Basra oil fields, Iraq. Mud losses treatments strategies have been presented in the literature for the Dammam, Hartha, and Shuaiba formations. However, no economics was considered in the previous studies (Al-Hameedi et al. 2017a; Al-Hameedi et al. 2017c; Al-Hameedi et al. 2017d; Alkinani et al. 2018b; Alkinani et al. 2019). Al-Hameedi et al. (2017b; 2018a; 2017e) presented all mud losses treatments descriptions, mixing methods, required additions used in this study.

This paper presents a methodology to choose the best lost circulation treatment for partial, severe, and complete losses. Data of more than 1000 wells drilled through the Dammam, Hartha, and Shuaiba formations in Basra oil fields, Iraq were gathered and the probability of success and failure were calculated. DTA and EMV were utilized to help to choose the best treatment that will stop the lost circulation problem with minimum cost. Thus, economic and probability concepts will be both used to make decisions.

Table 1. Lithology (Basra Oil Company 2011)

System	Series	Stage	Formation	Lithology	Interval (m)	Problems	Hole Size	Casing Size
TERTIARY	Pliocene Late Miocene	Serravallian Aquitian	Dibdiba	Sand & Pebble	200 or less	High gel strength, sand content, and filtration	16"	13 3/8"
	Middle Miocene		Lower Fars	Argillaceous Limestone	200 – 315	High viscosity and balling		
			Ghar	Sand & Pebble	315 – 440	Wash pipe and corrosion		
	Middle Eocene	Priabonian Lutetian	Dammam	Dolomite	440 – 700	Lost Circulation due to vugs	12 1/4"	9 5/8"
	Paleocene - Early Eocene	Ypresian	Rus	Anhydrite	690 – 860	High contamination of Ca^{++}		
		Thanetian Danian	Umm Er-Radhuma	Dolomite	860 – 1310	H_2S flow		
CRETACEOUS	Upper	Maastrichtian	Tayarat	Shale	1300 – 1550	H_2S flow		
			Shiranish	Argillaceous Limestone	1550 – 1660	Stuck pipe and low penetration rate		
		Campanian	Hartha	Limestone	1660 – 1850	Lost Circulation		
		Santonian Coniacian	Sadi	Limestone	1850 – 2150	Kick due to high pressure	8 1/2"	7"
			Tanuma	Shale	2150 – 2200	Shale sloughing and collapse		
		Turonian	Khasib	Limestone	2200 – 2250	Formation hardness is high		
		Cenomanian	Mishrif	Limestone	2240 – 2390	Blowout due to abnormal pressure		
			Rumaila	Limestone	2400 – 2490	Low penetration rate		
			Ahmadi	Shale	2490 – 2635	Shale sloughing and collapse		
	Lower	Albian	Mauddud	Limestone	2630 – 2723	Partial mud losses		
			Nahr Umr	Shale	2720 – 2990	Shale collapse and stuck pipe		
		Aptian	Shuaiba	Limestone	2990 – 3090	Lost circulation due to fractures		
			U. Shale Zubair	Shale	3090 – 3205	Shale collapse and stuck pipe		
			U. Sandstone Zubair	Sandstone	3205 – 3390	Low penetration rate		
		Barremian	M. Shale Zubair	Shale	3390 – 3445	Shale collapse and stuck pipe		
			L. Sandstone Zubair	Sandstone	3445 – 3515	Low penetration rate		

2. DATA AND METHODS

Lost circulation treatments data were collected from many sources for each type of losses (e.g. partial, severe, and complete losses). EMV can be calculated using the following Equation (Kelkar 2013):

$$EMV = \sum_{i=1}^{n} p_i (NPV) \qquad \text{Eq.1}$$

Where n is the number of possible outcomes, NPV is the net present value of the outcome i, and pi is the probability of the outcome i.

Calculations of the total cost for partial, severe, and complete losses will be conducted separately since the trip in and out and the pumping method will be different which leads to a different NPT. Also, the calculations will be conducted for each formation since the depths of each formation is different, the expected losses section for each formation is different, and mud used to drill each formation is different. The usual drilling practice after pumping any lost circulation treatment is to raise the BHA to the casing shoe to avoid any problems that might occur due to the thickening time of the treatments (e.g. stuck pipe, collapse issues) (Alkinani et al. 2018c).

All treatments scenarios are considered in the analysis to find the best scenario for each type of mud losses (partial, severe, and complete) with the following assumptions (Alkinani et al. 2018c):

1. The treatments order is important.
2. The repetition of the treatments is not permitted.

3. If partial losses occurred, it is assumed to use three partial losses treatments, if that did not work, then it is assumed to use three severe losses treatments. If that also did not work, three complete losses should be used.
4. In the case of severe losses, four treatments of severe losses should be used. If they did not work, five complete losses treatments should be used.
5. For complete losses, calculations for using three to eight treatments are considered.
6. All scenarios end up with liner hanger if all treatments did not work.

Permutation for all scenarios can be calculated from the following Equation (Uspensky 1937):

$$P_k = \frac{k!}{(k-r)!} \qquad \text{Eq. 2}$$

Where Pk is the number of scenarios, k is the total number of treatment to choose from (e.g. six for partial losses, ten for severe losses, and eight for complete losses), and r is the number of treatment chosen to be used for a specific scenario (Alkinani et al. 2018c). MATLAB codes were utilized to conduct the treatment scenarios for each type of loss and for each formation (a sample of the code used to conduct the partial loss treatment scenarios for the Dammam formation is shown the Appendix).

Tables 2-4 show some of the input data used to calculate the cost for the Dammam, Hartha, and Shuaiba formations, respectively. The average volume loss is calculated using the following Equation 3:

$$Avol(m^3) = \frac{OH^2}{1974} * L \qquad \text{Eq. 3}$$

Table 2. Some Inputs for the Total Cost (Dammam)

Parameter	Input
Rig Rental	40,000 $/24 hrs (1667 $/hr)
Hole Size (OH)	12.25 in
Length of Losses Section (L)	170 m
Average Volume Loss (Avol)	13 m^3
Cost of Liner Hanger	297,255 ($)
Cost of OEDP	26,672 ($)

Table 3. Some Inputs for the Total Cost (Hartha)

Parameter	Input
Rig Rental	40,000 $/24 hrs (1667 $/hr)
Hole Size (OH)	12.25 in
Length of Losses Section (L)	150 m
Average Volume Loss (Avol)	11 m^3
Cost of Liner Hanger	445,276 ($)
Cost of OEDP	43,342 ($)

Table 4. Some Inputs for the Total Cost (Shuaiba)

Parameter	Input
Rig Rental	40,000 $/24 hrs (1667 $/hr)
Hole Size (OH)	8.5 in
Length of Losses Section (L)	75 m
Average Volume Loss (Avol)	3 m^3
Cost of Liner Hanger	562,886 ($)
Cost of OEDP	56,678 ($)

However, since the Dammam formation is the first formation in the second hole, the NPT associated with raising the BHA after the pumping the treatment will not be considered in this analysis since it takes only a few minutes to raise the BHA to the casing shoe. Nevertheless, for the Hartha formation, after pumping any treatment, the BHA will be lifted to the casing shoe located above the Dammam formation (as shown in Table 1). For the Shuaiba formation, after pumping any treatment, the BHA will be lifted to the casing shoe located above the Sadi formation (as shown in Table 1).

The total cost of the successful treatments will be different from the total cost of the failure treatments since sometimes the treatments have to be applied multiple times to stop mud losses. Thus, this repetition will be considered in the total cost only since this analysis is done per well not per treatment. Table 5 shows an example of how the final cost is calculated.

Table 5. Example of How to Calculate Final Cost

Type of Loss	Well	Treatment	Repetition	Results	Cost	Final Cost
Partial	1	X	2	Success	Total cost *2	$\frac{\text{Cost}}{\text{Number of Wells (3)}}$
Partial	2	X	3	Success	Total cost *3	
Partial	3	X	4	Success	Total cost *4	

When it comes to the probability calculations, if the treatment is used multiple times in the same well and it was successful, it will be considered as one successful treatment when calculating the probability of success since the probability is calculated per well not per treatment. Table 6 shows an example of how the probability of success is calculated.

Table 6. Example of How the Calculations of the Probability

Well	Treatment	Result	Number of Successful Wells Used to Calculate Probability
Well A	X	Success	1
Well A	X	Success	
Well B	Y	Success	1
Well B	Y	Success	
Well C	Z	Success	1

2.1. DAMMAM FORMATION

In this sub-section, the methodology of cost and probability calculations for the Dammam formation will be explained for partial, severe, and complete losses, respectively.

2.1.1. Partial Losses (1-10 m^3/hr). Table 7 shows the partial losses treatments and their required materials addition. All partial losses treatments are pumped through the BHA (no need to trip out and pump through open end drill pipe (OEDP)). Thus, there is no trip in and trip out NPT. The final cost of success and failure for partial losses can be calculated using the following Equations:

$$Total\ Cost\ (\$) = Average\ Treatment\ Cost\ (\$) + Total\ NPT (\$) \quad \text{Eq. 4}$$

$$Average\ Treatment\ Cost\ (\$) = Treatment\ Cost\ \left(\frac{\$}{m^3}\right) * Avol\ (m^3) \quad \text{Eq. 5}$$

$$Total\ NPT\ (\$) = Thickening\ Time\ (hr) * Rig\ Cost\ \left(\frac{\$}{hr}\right) \quad \text{Eq. 6}$$

$$Final\ Cost\ of\ Success\ (\$) = \frac{Total\ Cost\ (\$) * Number\ of\ Successful\ Treatment\ Usage}{Successful\ Wells} \quad \text{Eq. 7}$$

$$Final\ Cost\ of\ Failure\ (\$) = \frac{Total\ Cost\ (\$) * Number\ of Failure\ Treatments\ Usage}{Failed\ Wells} \quad \text{Eq. 8}$$

Table 7. Partial Losses Treatments (Dammam Formation)

Treatment Number	**Treatment Name**	**Required Addition (kg/m^3)**
1	Waiting Method	None
2	High Viscosity (H.V) Mud Patch	Bentonite (100), Caustic Soda (2), Soda Ash (2), and CMC-LV (7)
3	Pill of LCM (Low Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), CMC-LV (7), Mica Fine (15), Mica Medium (15), Nut Plug (15), $CaCO_3$ Medium (15), and $CaCO_3$ Coarse (15)
4	Plugging Materials, Fine and Medium Mica (Low Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), Mica Fine (25), and Mica Medium (25)
5	Plugging Materials, Medium and Coarse $CaCO_3$ (Low Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), Medium $CaCO_3$ (25), and Coarse $CaCO_3$ (25)
6	Plugging Materials Nut Plug (Low Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), CMC-LV (7), and Nut Plug (25)

Note that the cost of failure treatments will be different from the cost of successful treatments. That is because sometimes the treatment has to be applied multiple times to be successful (Equations 7 and 8 show the method of calculating the final cost of success and failure). For partial losses particularly, the final cost of applying a specific treatment is the same as the cost of repeating the treatment because all treatments are pumped through the BHA and there is no NPT related to trip in and out since the Dammam is the first formation in the second hole (Alkinani et al. 2018c). Table 8 summarizes the total cost calculations for partial losses. The probability of success and failure for partial, severe, and complete losses can be calculated using the following Equations:

$$P_s = \frac{Successful\ Wells\ for\ Specific\ Treatment}{Total\ Wells\ for\ Specific\ Treatment} \qquad \text{Eq. 9}$$

$$P_f = 1 - P_s \qquad \text{Eq. 10}$$

Where P_s and P_f are the probabilities of success and fail respectively. Note that the repetition of the treatments in the same well is not considered in the probability calculations, it is considered only in the final cost calculations.

Table 8. Total Cost Calculation for Partial Losses Treatments (Dammam)

Treatment Number	Treatment Name	Treatment Cost ($/m^3)	Cost of the Average Volume Loss ($)	Waiting Period, (hrs)	NPT Cost ($/1hr)	Total Cost ($)
1	Waiting Method	0.00	0.00	3	1667	5000
2	High Viscosity (H.V) Mud Patch	58	758	2.5	1667	4925
3	Pill of LCM (Low Concentration)	93	1205	3	1667	6205
4	Plugging Materials, Fine and Medium Mica (Low Concentration)	80	1045	3	1667	6045
5	Plugging Materials, Medium and Coarse $CaCO_3$ (Low Concentration)	67	870	3	1667	5870

2.1.2. Severe Losses (1-10 m^3/hr) and Complete Losses (No Return). Table 9 shows the severe losses treatments and their required materials addition. There are two cases of the severe losses treatments; the first case is pumping treatment through the BHA (similar to the partial losses treatments). The second case is pumping through the OEDP (to avoid nozzles plugging) which requires tripping out of the hole and take off the BHA and tripping in again. In the second case, there will be NPT related to tripping in and out of the hole. The final cost calculation method for the severe losses treatments that pumped through BHA is the same as the method for calculating the final cost for partial losses (Equations 4-8). However, the calculation method is different for the treatments pumped through OEDP since three will be an additional NPT due to trip in and out of the hole (Alkinani et al. 2018c).

Treatments pumped through OEDP will be different if the treatment is applied first versus if the treatment is applied after using any OEDP treatment. That is because the trip in and out will be only required when applying the first treatment, once the OEDP is in place, no trip in and out will be needed for the second treatment. Thus, there will be two costs for treatments pumped through OEDP, the first one if the treatment is applied at the beginning (trip in and out NPT for placing the OEDP will be included). The second one will not consider the NPT for placing the OEDP since it was already placed during the first treatment (Alkinani et al. 2018c). Table 10 shows the total cost calculations for the severe losses treatments.

The following Equations are utilized to calculate the final cost for severe losses treatments pumped through OEDP (assuming the treatment is applied at the beginning, the NPT due to trip in and out is considered):

Table 9. Severe Losses Treatments (Dammam Formation)

Treatment Number	Treatment Name	Required Addition (kg/m^3)	Pumping Method
1	Pill of LCM (High Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), CMC-LV (7), Mica Fine (30), Mica Medium (30), Nut Plug (30), $CaCO_3$ Medium (30), and $CaCO_3$ Coarse (30)	BHA
2	Super Stop Material	125	OEDP
3	H.V Mud + Blend of LCM (High Concentration)	Bentonite (100), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), and Blend LCM (45)	BHA
4	Cement Plug	1029	OEDP
5	High Filtration Spot Pills, High Filtration Mixtures (200-400 cc API)	Attapulgite (45), Bentonite (37.5), Lime (1.5), Diatomite (150), Mica (12.5), Granular LCM (20), and Fibrous LCM (6.5)	OEDP
6	High Filtration Spot Pills, Very High Filtration Mixtures (> 600cc API)	Attapulgite (20), Lime (150), Diatomite (300), Lamellar LCM (10), Granular LCM (17.5), and Fibrous LCM (10)	OEDP
7	Plugging Materials, Blend of Mica (High Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), and Blend of Mica (50)	BHA
8	Plugging Materials, Blend of Nut Plug (High Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), and Blend of Nut Plug (50)	BHA
9	Plugging Materials, Blend Magma Fiber (High Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), and Blend of Magma Fiber (50)	BHA
10	Plugging Materials, Blend of $CaCO_3$ (High Concentration)	Bentonite (75), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), and Blend of $CaCO_3$ (50)	BHA

$$Total\ Cost\ (\$) = Average\ Treatment\ Cost\ (\$) + Total\ NPT(\$) \qquad \text{Eq. 11}$$

$$Average\ Treatment\ Cost\ (\$) = Treatment\ Cost\ \left(\frac{\$}{m^3}\right) * Avol\ (m^3) \qquad \text{Eq. 12}$$

$$Total\ NPT\ (\$) = [Thickening\ Time\ (hr) + Trip\ in\ and\ out\ (hr)] * Rig\ Cost\ \left(\frac{\$}{hr}\right) \qquad \text{Eq. 13}$$

$$Cost\ of\ Successful\ Repeated\ Treatment\ (\$) = \left[Average\ Treatment\ Cost\ (\$) + Thickenning\ Time(hr) * Rig\ Cost\ \left(\frac{\$}{hr}\right)\right] * Number\ of\ Successful\ Usage \qquad \text{Eq. 14}$$

$$Cost\ of\ Failed\ Repeated\ Treatment\ (\$) = \left[Average\ Treatment\ Cost\ (\$) + Thickening\ Time(hr) * Rig\ Cost\ \left(\frac{\$}{hr}\right)\right] * Number\ of\ failure\ Usage \qquad \text{Eq. 15}$$

$$Final\ Cost\ of\ Success\ (\$) = \frac{Total\ Cost * Successful\ Wells + Cost\ of\ Repeated\ Treatment}{Successful\ Wells}$$

Eq. 16

$$Final\ Cost\ of\ Failure (\$) = \frac{Total\ Cost * Failed\ Wells + Cost\ of\ Failed\ Repeated\ Treatment}{Failed\ Wells}$$

Eq.17

Table 10. Total Cost Calculation for Severe Losses Treatments (Dammam)

Treatment Number	Treatment Name	Treatment Cost ($/m^3)	Cost of Average Volume Loss ($)	Waiting Period (hr)	Trip in and out (hr)	Total NPT (hr)	NPT Cost ($/hr)	Total Cost ($)
1	Pill of LCM	135	1756	3	0	3	1667	6756
2	Super Stop Material	150	1950	4.5	16	20.5	1667	36117
3	H.V Mud + Blend of LCM	99	1284	4	0	4	1667	7951
4	Cement Plug	327	4254	10	16	26	1667	47587
5	High Filtration Spot Pills, High Filtration Mixtures (200-400 cc API)	177	2298	5	16	21	1667	37298
6	High Filtration Spot Pills, Very High Filtration Mixtures (> 600cc API)	324	4213	5	16	21	1667	39213
7	Plugging Materials, Blend of Mica	110	1435	3	0	3	1667	6435
8	Plugging Materials, Blend of Nut Plug	115	1500	3	0	3	1667	6500

Table 11 shows the complete losses treatments and their required materials addition. All complete losses treatments are pumped through the OEDP to avoid the nozzles plugging. The final cost calculations for complete losses are the same as the OEDP calculations for the severe losses (Equations 11-17). Equations 9 and 10 are utilized to calculate the probability of success and failure, respectively. Table 12 shows the total cost calculations for the complete losses treatments.

Table 11. Complete Losses Treatments (Dammam Formation)

Treatment Number	Treatment Name	Required Addition (kg/m^3)
1	Cement Plug	1029
2	Cement Plug + HV Mud	Bentonite (100), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), and Cement (1029)
3	Diesel Oil Bentonite (DOB) Plug	The formula for 1 m^3 Oil base 0.70 m^3 Bentonite 800 kg
4	Diesel Oil Bentonite Cement (DOBC) Plug	The formula for 1 m^3 Oil base 0.72 m^3 Bentonite 450 kg Cement 450 kg
5	Gilsonite Cement	Gilsonite (200) and Cement (1029)
6	InstandSeal	InstandSeal
7	Blend of Fibers in Cement	Blend of Fiber (90) and Cement (1029)
8	High Filtration Spot Pills, Very High Filtration Mixtures (> 600cc API)	Attapulgite (20), Lime (150), Diatomite (300), Lamellar LCM (10), Granular LCM (17.5), Fibrous LCM (10)

Table 12. Total Cost Calculation for Complete Losses Treatments (Dammam Formation)

Treatment Number	Treatment Name	Treatment Cost ($/m^3)	Cost of the Average Volume Loss ($)	Waiting Period (hr)	Trip in and out (hr)	Total NPT (hr)	NPT Cost ($/hr)	Total Cost ($)
1	Cement Plug	327	4254	10	16	26	1667	47587
2	Cement Plug + HV Mud	386	5012	12	16	28	1667	51678
3	DOB Plug	604	7847	9	16	25	1667	49513
4	DOBC Plug	646	8395	11	16	27	1667	53395
5	Gilsonite cement	627	8154	8	16	24	1667	48154
6	InstandSeal	475	6175	18	16	34	1667	62842
7	Blend of Fibers in Cement	399	5190	12	16	28	1667	51857
8	High Filtration Spot Pills, Very High Filtration Mixtures (> 600cc API)	324	4213	5	16	21	1667	39213

2.2. HARTHA AND SHUAIBA FORMATIONS

In this sub-section, the methodology of cost and probability calculations for the Hartha formation will be explained for partial, severe, and complete losses, respectively. The calculations method of costs and probabilities for partial, severe, and complete losses for the Shuaiba formation is the same as the method used in the Hartha formation, the only difference is the input data. Thus, only the Hartha formation calculations methodology will be explained in this section.

2.2.1. Partial Losses (1-10 m^3/hr). The final cost of success and failure for partial losses can be calculated using the following Equations:

$$Total\ Cost\ (\$) = Average\ Treatment\ Cost\ (\$) + Total\ NPT(\$) \qquad \text{Eq. 18}$$

$$Average\ Treatment\ Cost\ (\$) = Treatment\ Cost\ \left(\frac{\$}{m^3}\right) * Avol\ (m^3) \qquad \text{Eq. 19}$$

$$Total\ NPT\ (\$) = [Thickening\ Time\ (hr) + Round\ Trip\ to\ Casing\ Shoe\ (hr)] * Rig\ Cost\ \left(\frac{\$}{hr}\right) \qquad \text{Eq. 20}$$

$$Final\ Cost\ of\ Success\ (\$) = \frac{Total\ Cost\ (\$) * Number\ of\ Successful\ Treatment\ Usage}{Successful\ Wells} \qquad \text{Eq. 21}$$

$$Final\ Cost\ of\ Failure\ (\$) = \frac{Total\ Cost\ (\$) * Number\ of Failure\ Treatments\ Usage}{Failed\ Wells} \qquad \text{Eq. 22}$$

For partial losses particularly, the final cost of applying a specific treatment is the same as the cost of repeating the treatment because all treatments are pumped through the OEDP and there is no NPT related to trip in and out to replace the OEDP. The probability of success and failure for partial, severe, and complete losses can be calculated using Equations 9 and 10, respectively. Table 13 shows the total cost calculations for the partial losses treatments.

2.2.2. Severe Losses (1-10 m^3/hr) and Complete Losses (No Return). Table 14 shows the total cost of the severe losses treatments. The following Equations are utilized to calculate the final cost for severe losses treatments pumped through OEDP (assuming the treatment is applied at the beginning, the NPT due to trip in and out is considered):

Table 13. Total Cost Calculation for Partial Losses Treatments (Hartha)

Treatment Number	**Treatment Name**	**Required Addition (kg/m^3)**	**Treatment Cost (\$/m^3)**	**Cost of Average Volume Loss (\$)**	**Waiting Period, (hr)**	**NPT Cost (\$/hr)**	**Total Cost (\$)**
1	Waiting Method	0	0	0	8	1667	13333
2	H.V Mud Patch	Bentonite (100), Caustic Soda (2), Soda Ash (2), and CMC-LV (7)	58.3	641	7.5	1667	13141
3	Pill of LCM	Bentonite (75), Caustic Soda (2), Soda Ash (2), CMC-LV (7), Mica Fine (15), Mica Medium (15), Nut Plug (15), $CaCO_3$ Medium (15), $CaCO_3$ Coarse (15), Lignosulfonate (7), and Barite (100)	138.92	1528	8	1667	14861
4	Plugging Materials, Fine and Medium Mica	Bentonite (75), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), Mica Fine (25), Mica Medium (25), Lignosulfonate (7), and Barite (100)	126.575	1392	8	1667	14726
5	Plugging Materials, Medium and Coarse $CaCO_3$	Bentonite (75), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), Medium $CaCO_3$ (25), Coarse $CaCO_3$ (25), Lignosulfonate (7), and Barite (100)	113.15	1245	8	1667	14578
6	Plugging Materials Nut Plug	Bentonite (75), Caustic Soda (2), Soda Ash (2), CMC-LV (7), Nut Plug (25), Lignosulfonate (7), and Barite (100)	144.575	1590	8	1667	14924

$$Total\ Cost\ (\$) = Average\ Treatment\ Cost\ (\$) + Total\ NPT (\$) \quad \text{Eq. 23}$$

$$Average\ Treatment\ Cost\ (\$) = Treatment\ Cost\ \left(\frac{\$}{m^3}\right) * Avol\ (m^3) \quad \text{Eq. 24}$$

$$Total\ NPT\ (\$) = [Thickening\ Time\ (hr) + Round\ Trip\ to\ Casing\ Shoe\ (hr) + Trip\ out\ and\ in\ to\ Place\ the\ OEDP\ (hr)] * Rig\ Cost\ \left(\frac{\$}{hr}\right) \quad \text{Eq. 25}$$

$$Cost\ of\ Successful\ Repeated\ Treatment\ (\$) = \Big[Average\ Treatment\ Cost\ (\$) + (Thickenning\ Time (hr) + Round\ Trip\ to\ Casing\ Shoe\ (hr)) * Rig\ Cost \left(\frac{\$}{hr}\right)\Big] * Number\ of\ Successful\ Usage \quad \text{Eq. 26}$$

$$Cost\ of\ Failed\ Repeated\ Treatment\ (\$) = \Big[Average\ Treatment\ Cost\ (\$) + (Thickenning\ Time (hr) + Round\ Trip\ to\ Casing\ Shoe\ (hr)) * Rig\ Cost \left(\frac{\$}{hr}\right)\Big] * Number\ of\ failure\ Usage \quad \text{Eq. 27}$$

$$Final\ Cost\ of\ Sucess\ (\$) = \frac{Total\ Cost * Successful\ Wells + Cost\ of\ Repeated\ Treatment}{Successful\ Wells} \quad \text{Eq. 28}$$

$$Final\ Cost\ of\ Failure(\$) = \frac{Total\ Cost * Failure\ Wells + Cost\ of\ Failed\ Repeated\ Treatment}{Failed\ Wells} \quad \text{Eq. 29}$$

Table 14. Total Cost Calculation for Severe Losses Treatments (Hartha)

Treatment Number	**Treatment Name**	**Treatment Cost ($/m^3)**	**Cost of Average Volume Loss ($)**	**Waiting Period (hr)**	**Trip in and out (hr)**	**Total NPT (hr)**	**NPT Cost ($/hr)**	**Total Cost ($)**	**Treatment Number**
1	Pill of LCM	Bentonite (75), Caustic Soda (2), Soda Ash (2), CMC-LV (7), Mica Fine (30), Mica Medium (30), Nut Plug (30), $CaCO_3$ Medium (30), $CaCO_3$ Coarse (30), Lignosulfonate (7), and Barite (100)	181	1994	8	0	8	1667	15327
2	Super Stop Material	125	150	1650	9	0	9	1667	16650
3	H.V Mud + Blend of LCM	Bentonite (100), Caustic Soda (2), Soda Ash (2), CMC-LV (7), and Blend LCM (45)	99	1087	9	0	9	1667	16087
4	Cement Plug	1029	327	3599	12	0	12	1667	23599
5	High Filtration Spot Pills, High Filtration Mixtures (200-400 cc API)	Attapulgite (45), Bentonite (37.5), Lime (1.5), Diatomite (150), Mica (12.5), Granular LCM (20), and Fibrous LCM (6.5)	177	1945	10	0	10	1667	18611
6	High Filtration Spot Pills, Very High Filtration Mixtures (> 600cc API)	Attapulgite (20), Lime (150), Diatomite (300), Lamellar LCM (10), Granular LCM (17.5), and Fibrous LCM (10)	324	3565	10	0	10	1667	20231

The final cost calculations for complete losses are the same as the OEDP calculations for the severe losses (Equations 23-29). Table 15 shows the total cost of the complete losses treatments. All complete losses treatments are pumped through the OEDP to avoid the nozzles plugging. The probabilities of success and failure are calculated using Equations 9 and 10, respectively.

Table 15. Total Cost Calculation for Complete Losses Treatments (Hartha)

Treatment Number	Treatment Name	Treatment Cost ($/m^3)	Cost of Average Volume Loss ($)	Waiting Period (hr)	Trip in and out (hr)	Total NPT (hr)	NPT Cost ($/hr)	Total Cost ($)	Treatment Number
1	Cement Plug	1029	327	3599	12	0	12	1667	23599
2	Cement Plug + HV Mud	Bentonite (100), Caustic Soda (2), Soda Ash (2), and CMC-LV (7), and Cement (1029)	386	4241	15	0	15	1667	29241
3	DOB Plug	Formula for 1 m^3 Oil base 0.70 m^3 Bentonite 800 kg	604	6640	12	0	12	1667	26640
4	DOBC Plug	Formula for 1 m^3 Oil base 0.72 m^3 Bentonite 450 kg Cement 450 kg	646	7103	15	0	15	1667	32103
5	Gilsonite cement	Gilsonite (200) and Cement (1029)	627	6899	12	0	12	1667	26899
6	InstandSeal	InstandSeal	475	5225	20	0	20	1667	38558
7	Blend of Fibers in Cement	Blend of Fiber (90) and Cement (1029)	399	4391	15	0	15	1667	29391
8	High Filtration Spot Pills, Very High Filtration Mixtures (> 600cc API)	Attapulgite (20), Lime (150), Diatomite (300), Lamellar LCM (10), Granular LCM (17.5), Fibrous LCM (10)	324	3565	10	0	10	1667	20231

3. RESULTS

In this section, the results for the Dammam, Hartha, and Shuaiba formations will be presented separately.

3.1. DAMMAM FORMATION

Table 16, Table 17, and Table 18 show the final cost calculations and the probability of success and failure for each treatment for partial, severe, and complete losses, respectively.

Table 16. Final Cost and Probability Results for Partial Losses Treatments (Dammam Formation)

Treatment Number	Treatment Name	Final Total Cost ($), for Success	Ps	Final Total Cost ($), for Failure	Pf
1	Waiting Method	5000	0.20	5000	0.80
2	High Viscosity (H.V) Mud Patch	5055	0.70	5410	0.30
3	Pill of LCM (Low Concentration)	6994	0.86	7569	0.14
4	Plugging Materials, Fine and Medium Mica (Low Concentration)	6849	0.55	6463	0.45
5	Plugging Materials, Medium and Coarse $CaCO_3$ (Low Concentration)	6688	0.64	6508	0.36
6	Plugging Materials Nut Plug (Low Concentration)	6863	0.61	7325	0.39

Table 17. Final Cost and Probability Results for Severe Losses Treatments (Dammam Formation)

Treatment Number	Treatment Name	Final Total Cost ($), for Success	Ps	Final Total Cost ($), for Failure	Pf
1	Pill of LCM	8061	0.52	7866	0.48
2	Super Stop Material	12150	0.44	11047	0.56
3	H.V Mud + Blend of LCM	8536	0.67	8621	0.33
4	Cement Plug	23720	0.80	23792	0.20
5	High Filtration Spot Pills, High Filtration Mixtures (200-400 cc API)	13599	0.44	12994	0.56

Table 18. Final Cost and Probability Results for Complete Losses Treatments (Dammam Formation)

Treatment Number	Treatment Name	Final Total Cost ($), for Success	Ps	Final Total Cost ($), for Failure	Pf
1	Cement Plug	24509	0.56	22096	0.44
2	Cement Plug + HV Mud	30473	0.70	27653	0.30
3	DOB Plug	30671	0.72	31822	0.28
4	DOBC Plug	36224	0.78	39456	0.22
5	Gilsonite cement	32231	0.80	31254	0.20
6	InstandSeal	56390	0.83	56846	0.17
7	Blend of Fibers in Cement	33278	0.62	30746	0.38
8	High Filtration Spot Pills, Very High Filtration Mixtures (> 600cc API)	27780	0.42	17168	0.58

Due to a large number of treatments scenarios, examples of only the highest twenty scenarios of partial, severe, and complete losses treatments are shown in Figures 2, 3, and 4. The consideration of 3-8 complete losses treatments scenarios is shown in Figure 4.

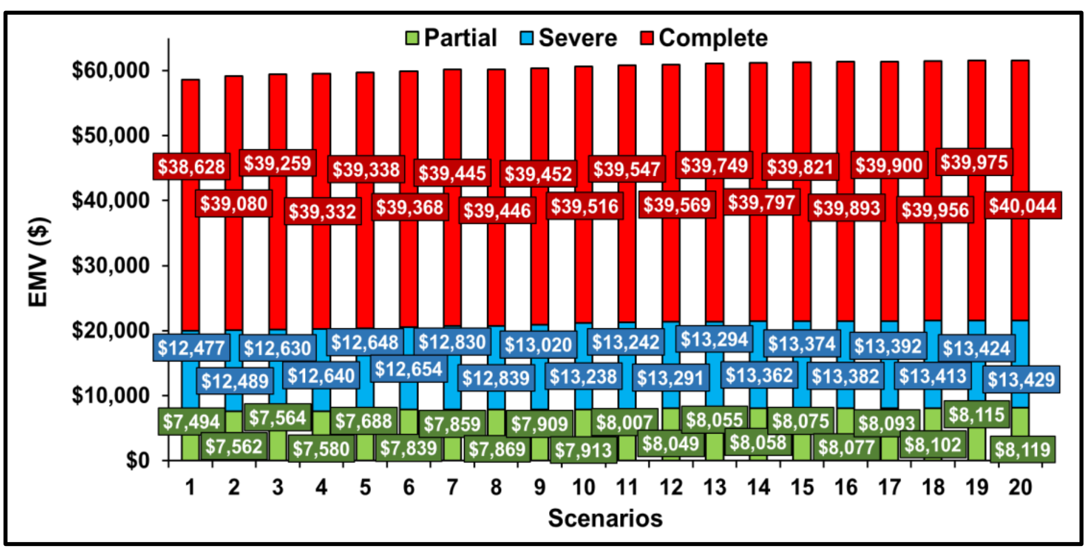

Figure 2. Treatments Scenarios for Partial Losses (Dammam Formation)

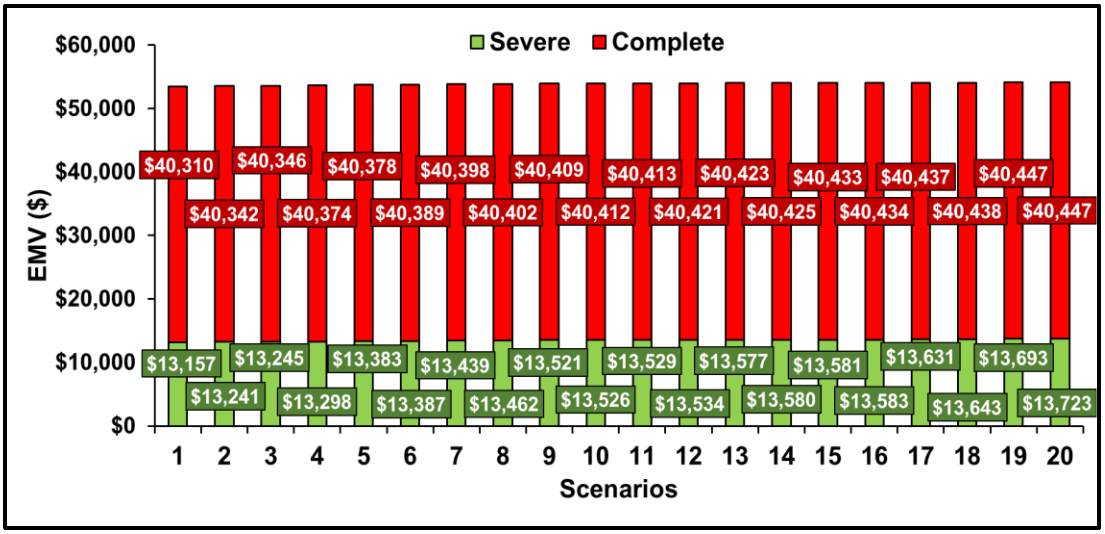

Figure 3. Treatments Scenarios for Severe Losses (Dammam Formation)

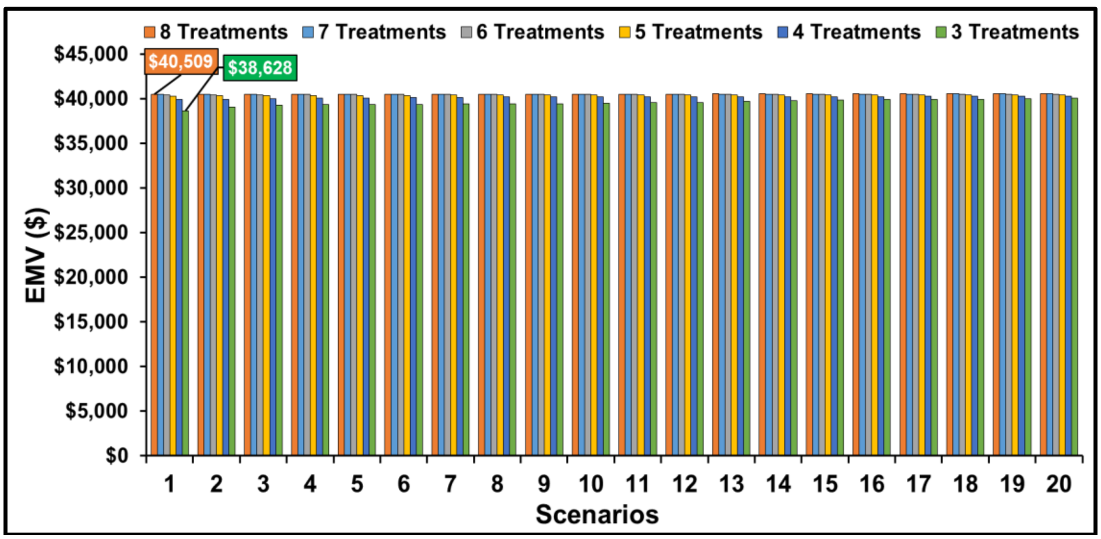

Figure 4. Treatments Scenarios for Complete Losses (Dammam Formation)

3.2. HARTHA AND SHUAIBA FORMATIONS

Figures 5-7 show the lowest twenty EMV scenarios for the Hartha formation for partial, severe, and complete losses. Figure 7 shows the EMV's of using of 3-8 treatments to stop complete loss. In the same vein, Figures 8-10 show the lowest twenty EMV scenarios for the Shuaiba formation for partial, severe, and complete loss, respectively.

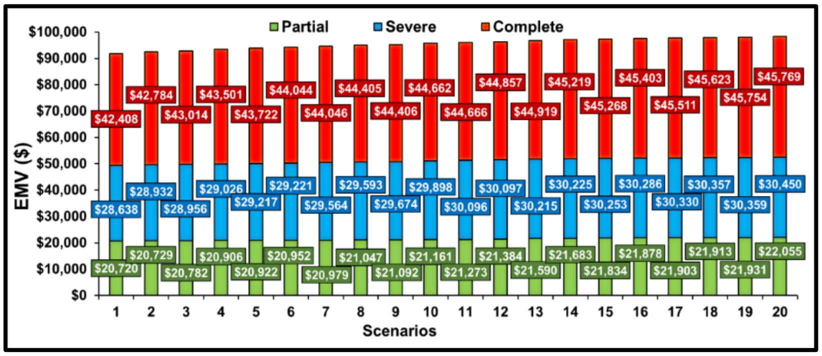

Figure 5. Treatments Scenarios for Partial Losses (Hartha Formation)

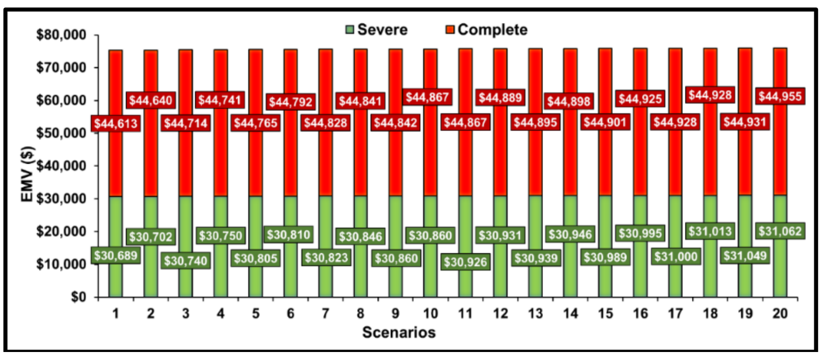

Figure 6. Treatments Scenarios for Severe Losses (Hartha Formation)

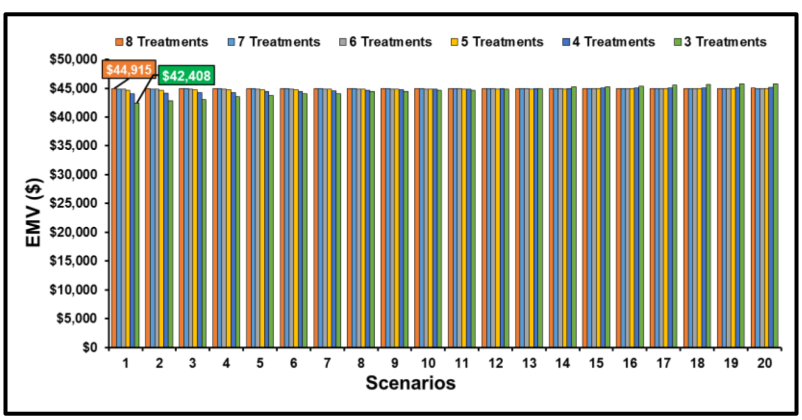

Figure 7. Treatments Scenarios for Complete Losses (Hartha Formation)

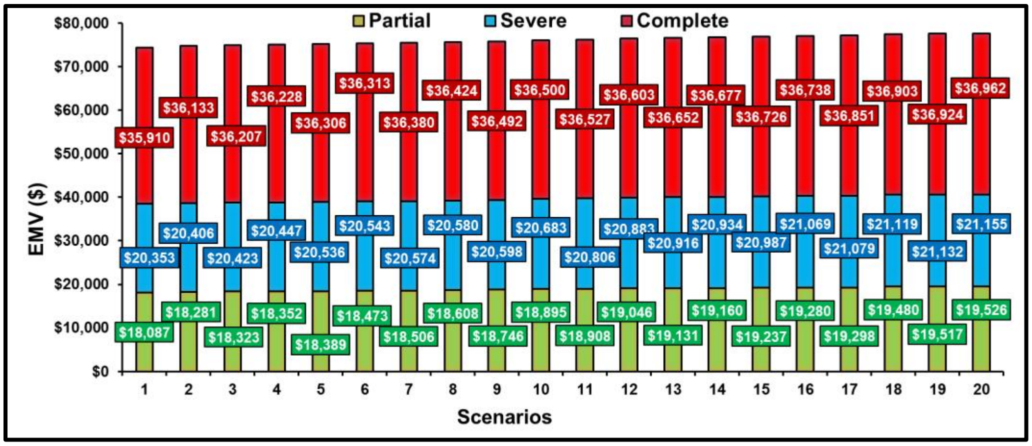

Figure 8. Treatments Scenarios for Partial Losses (Shuaiba Formation)

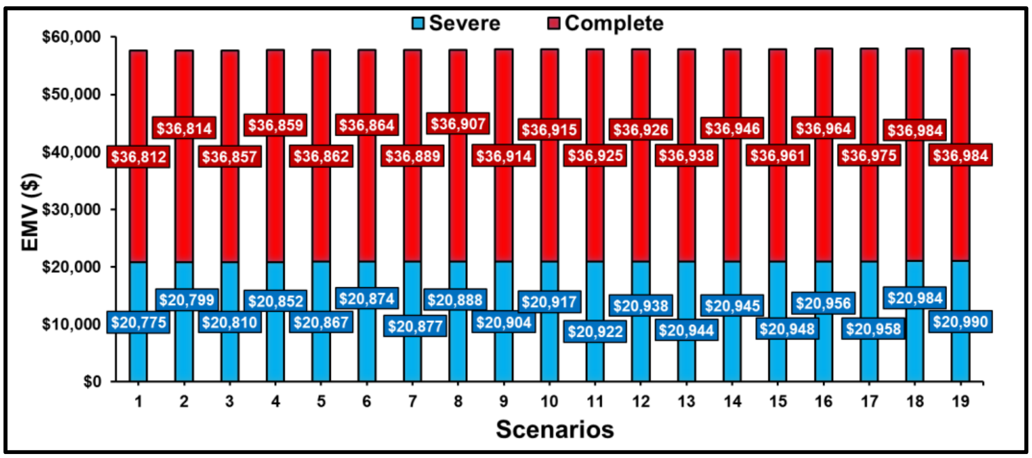

Figure 9. Treatments Scenarios for Severe Losses (Shuaiba Formation)

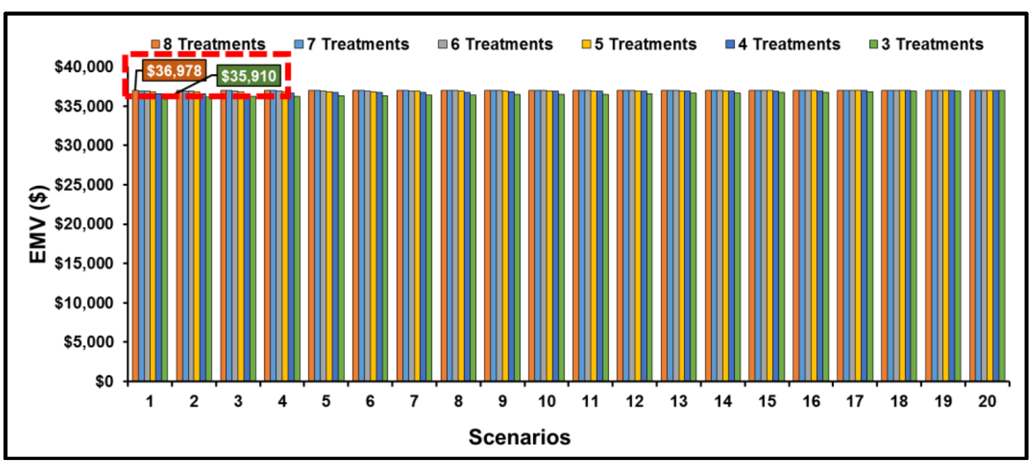

Figure 10. Treatments Scenarios for Complete Losses (Shuaiba Formation)

4. DISCUSSION

The treatments of complete loss are the most expensive treatments among the other treatments. Since the costs of the treatments are incorporated in the EMV calculation, the decision made here is based on the cost and efficiency of the treatments. Good knowledge of the application of each treatment in the field is required to help to select the best lost circulation strategies. As an example, the waiting method treatment only used if it was the first treatment in the treatments strategy. In different words, it is not practical to uses other treatments then use waiting method. As an example, scenario 1 for partial loss treatments for the Dammam formation (green color) in Figure 2 suggests using the treatments shown in Figure 11. However, waiting methods cannot be utilized unless it is used in the beginning. Thus, this scenario will not be considered since it is not practically applicable in the field.

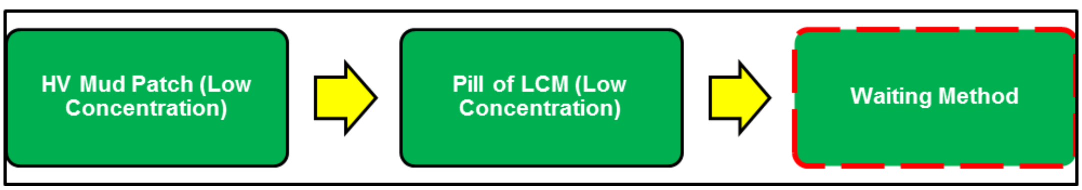

Figure 11. Scenario # 1 for Partial Loss Treatments

Thus, the decision-making process cannot be solely made based on the lowest EMV scenario since some scenarios are not practically applicable in the Field. Consequently, two criteria were utilized to select the treatment strategies: i) the treatment strategies has to have the lowest EMV and ii) the treatment strategies have to be practically applied in the field. Both criteria have to be met in order to select the best decision.

In Figure 11, taking scenario 1 as an example, the EMV for using 3 treatments is \$38628, while the EMV for using 8 treatments is \$40509. Only \$2000 difference is not considered significant in the EMV between utilizing 3 and 8 treatments. The reason behind having close EMV between 3 and 8 treatment scenarios is because EMV does not solely use cost in the calculations, it uses probability as well. In addition, the EMV calculations are conducted with decision trees that have many branches. Thus, the \$2000 difference is not a cost difference, it is the difference in EMV. If only the cost of using 3 versus 8 treatments is considered, this number would be much higher. The same is true for Figure 7 and Figure 10 since there is not a significant difference in EMV, a decision was made to use 8 complete loss to stop this type of loss.

Figures 12-14 show treatment strategies for partial, severe, and complete losses for the Dammam formation chosen based on the two criteria mentioned earlier. All treatment strategies end up of liner hanger.

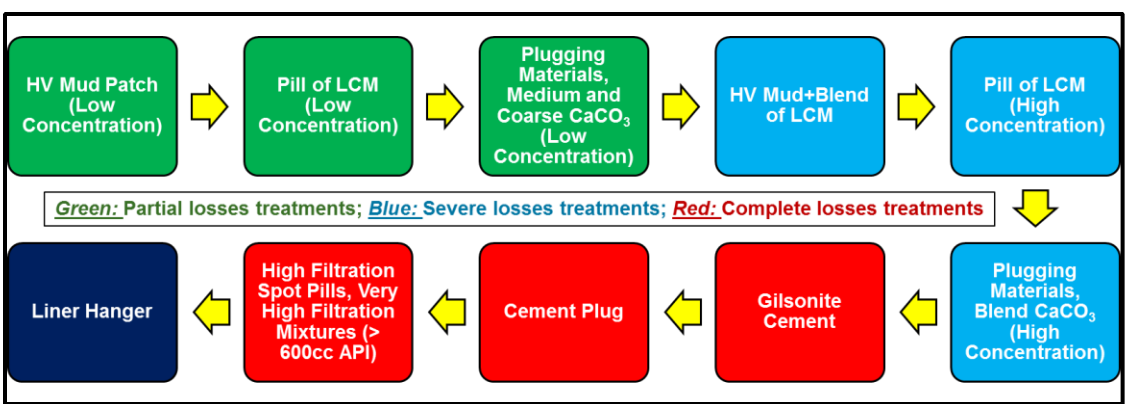

Figure 12. Partial Losses Treatments Strategy (Dammam Formation)

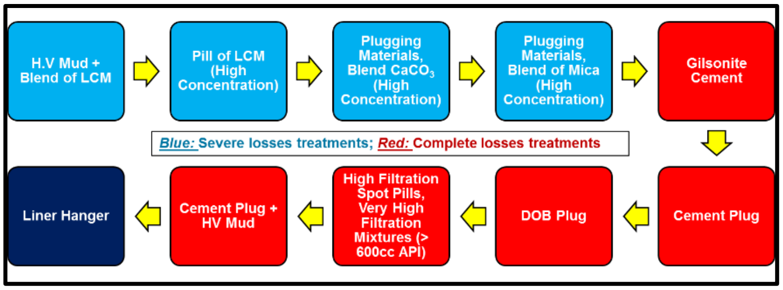

Figure 13. Severe Losses Treatments Strategy (Dammam Formation)

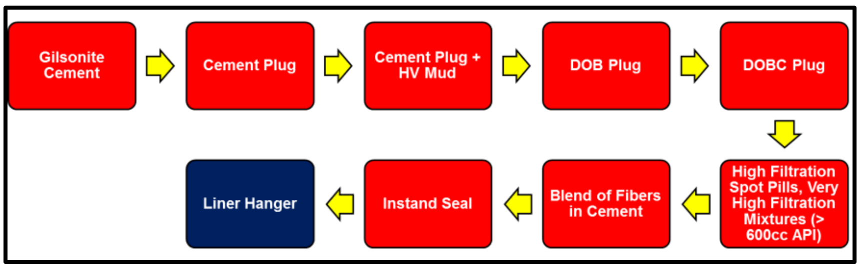

Figure 14. Complete Losses Treatments Strategy (Dammam Formation)

Figures 15-17 show the treatment strategies for partial severe, and complete losses in the Hartha formation. Figures 18-20 show the selected treatment strategies that are practically applicable in the field and has the lowest EMV for the Shuaiba formation for partial, severe, and complete loss, respectively.

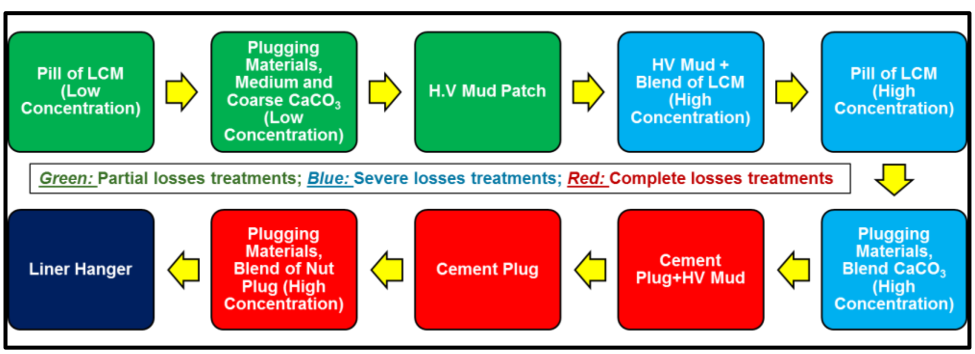

Figure 15. Partial Losses Treatments Strategy (Hartha Formation)

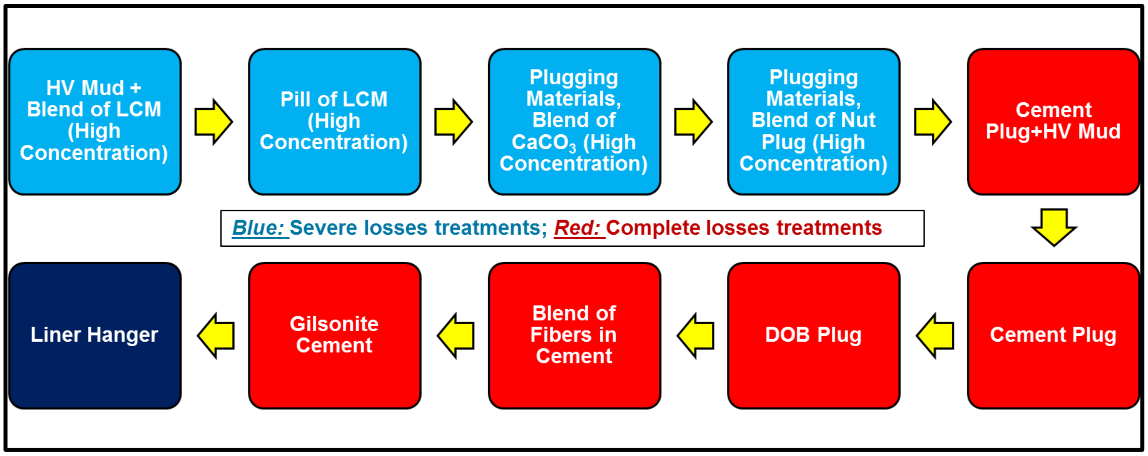

Figure 16. Severe Losses Treatments Strategy (Hartha Formation)

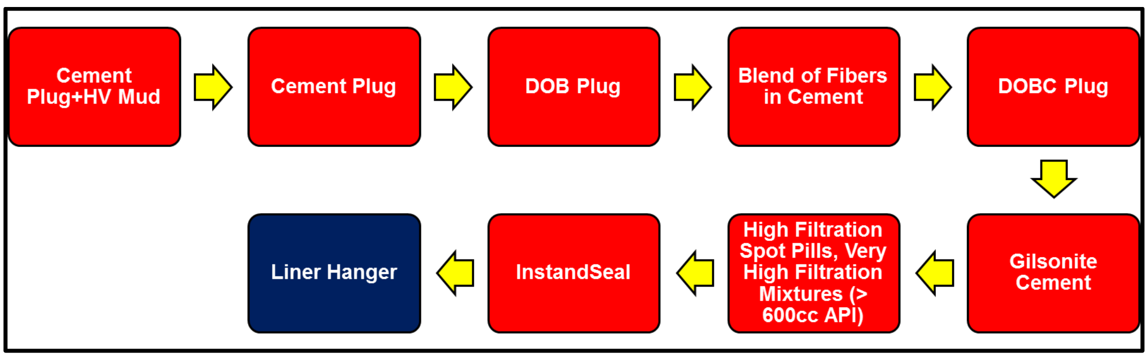

Figure 17. Complete Losses Treatments Strategy (Hartha Formation)

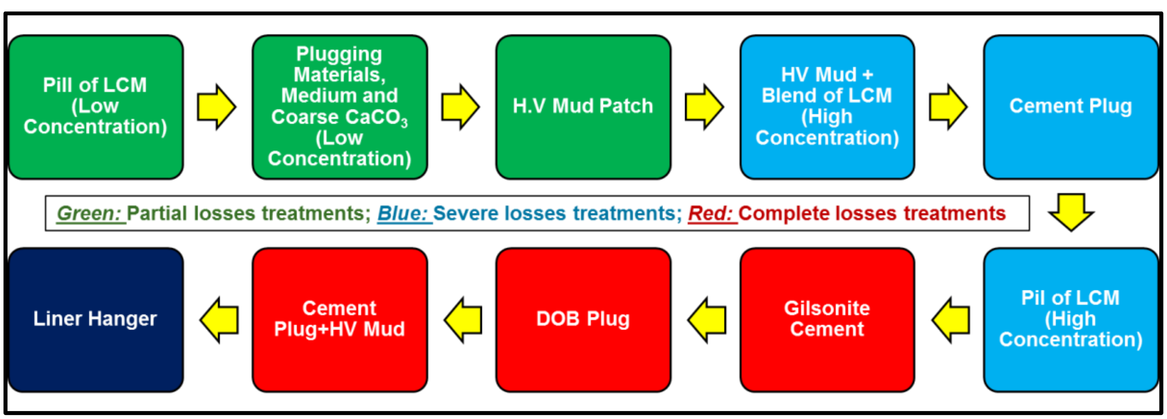

Figure 18. Partial Losses Treatments Strategy (Shuaiba Formation)

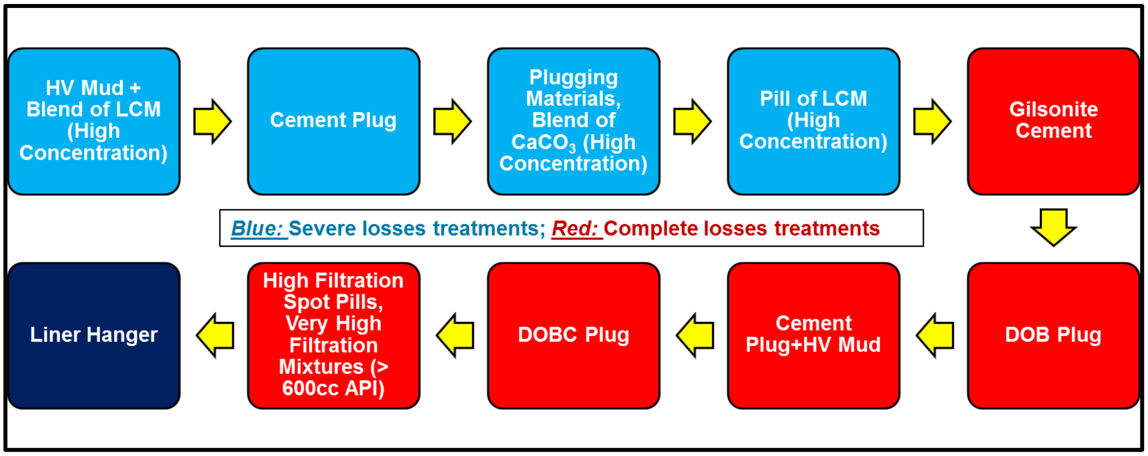

Figure 19. Severe Losses Treatments Strategy (Shuaiba Formation)

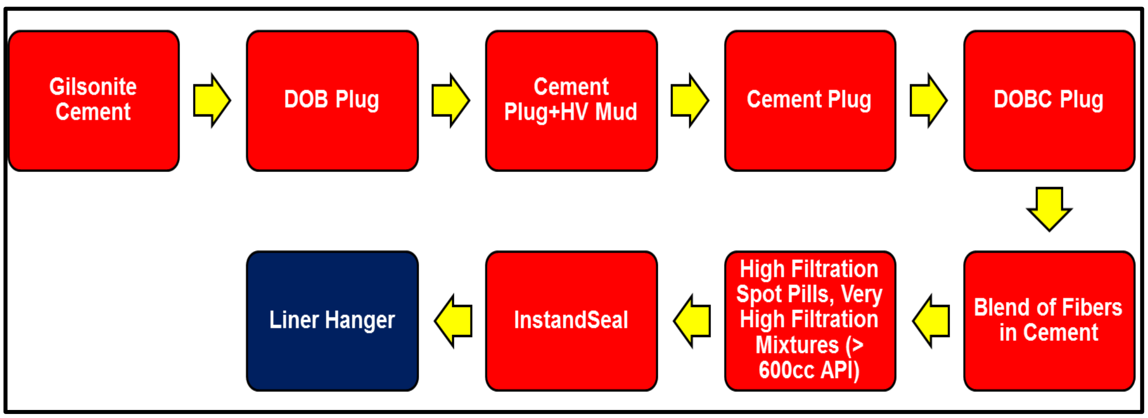

Figure 20. Complete Losses Treatments Strategy (Shuaiba Formation)

5. CONCLUSION

Lost circulation is a complicated problem in Basra oil fields, Iraq. It is not easy to choose which treatment to be used to stop lost circulation. Economics is a very important factor that has to be considered in the decision-making process. Data from over 1000 wells drilled in Basra oil fields, Iraq were gathered and analyzed to create the best-lost circulation treatment strategy for each type of mud losses with the consideration of economics. The goal is to minimize non-productive time and cost. Based on this study, the following conclusions were made:

- Both probability and detailed economics were considered in this study to create the best-lost circulation strategies for all type of mud losses. All previous studies did not consider economics in the decision-making process
- Treatments scenarios with the lowest EMV and practically applicable in the field were chosen to stop partial, severe, and complete mud losses in the Dammam, Hartha, and Shuaiba formation. A formalized methodology accomplished with flowchart was provided for each type of mud losses for all three formations.
- The methodology used in this study can be utilized to stop mud losses in any formation worldwide if the required data were available.

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III. APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS IN THE PETROLEUM INDUSTRY: A REVIEW

ABSTRACT

Oil/gas exploration, drilling, production, and reservoir management are challenging these days since most oil and gas conventional sources are already discovered and have been producing for many years. That is why petroleum engineers are trying to use advanced tools such as artificial neural networks (ANNs) to help to make the decision to reduce non-productive time and cost.

A good number of papers about the applications of ANNs in the petroleum literature were reviewed and summarized in tables. The applications were classified into four groups; applications of ANNs in explorations, drilling, production, and reservoir engineering. A good number of applications in the literature of petroleum engineering were tabulated. Also, a formalized methodology to apply the ANNs for any petroleum application was presented and accomplished by a flowchart that can serve as a practical reference to apply the ANNs for any petroleum application. The method was broken down into steps that can be followed easily. The availability of huge data sets in the petroleum industry gives the opportunity to use these data to make better decisions and predict future outcomes. This paper will provide a review of applications of ANNs in petroleum engineering as well as a clear methodology on how to apply the ANNs for any petroleum application.

1. BACKGROUND

The first neural networks research was by McCulloch and Pitts (1943). Rosenblatt (1957) invented the perceptron and proved that a perceptron would develop a weight vector that separates the classes. Rosenblatt (1957) believed that structures of more layers can overcome the limitations of the simple perceptron. However, there weren’t any learning algorithms that can determine the weights for a given calculation (Mohaghegh, 2000). Few years after, Widrow (1962) developed a network called Adeline. Minsky and Papert (1969) showed that the single layer perceptron can’t elementary calculations problems. After that, the neural network's research stopped for 20 years (Hertz et al., 1991). Then, Hopfield (1982) proposed new algorithms, such as backpropagation, that brought life for the neural network's research. Since then, the neural networks applications has gone viral (Mohaghegh, 2000).

2. NEURAL NETWORK STRUCTURE

An artificial neural network is “an information-processing system that has certain performance characteristics in common with biological neural network” (Mohaghegh, 2000). All organisms are made up from cells. Neurons are the basic building blocks of the nervous system. A typical biological neuron consists of a cell body, an axon, and dendrites as shown in Figure 1. Information in the cell body enters through the dendrites. The cell body then provides an output which travels through the axon then to another receiving neuron, the output from the first neuron becomes an input for the second neuron and so on (Mohaghegh, 2000).

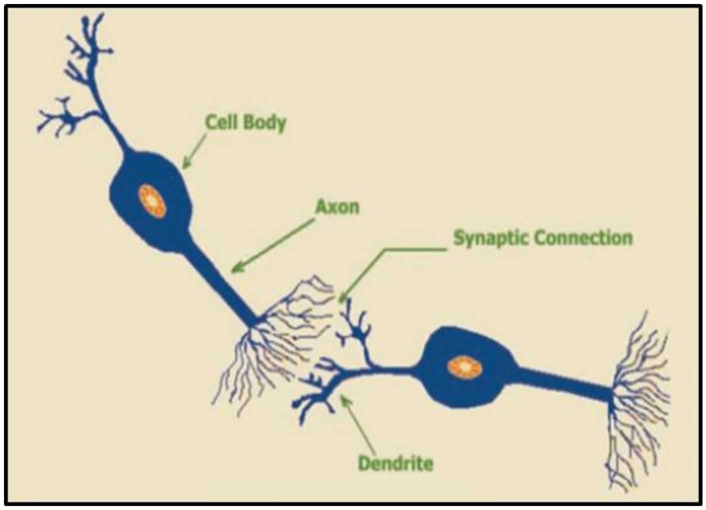

Figure 1. Two Bipolar Neurons (After Mohaghegh, 2000)

The human brain contains 10-500 billion neurons (Rumelhart and McClelland, 1986). These neurons are divided into sections, each section contains about 500 neural networks (Stubbs, 1988). Each neural network contains about 100,000 neurons where these neurons are connected to thousands of other neurons (Mohaghegh, 2000). This structure is behind human's complex behavior. A simple task such as moving hands, walking, or catching a cup of coffee, requires very complex calculations that sophisticated computer can't perform but the human brain is able to do them. Although computers are faster than human brains (human brain cycle is 10 to 100 milliseconds while computer chips cycle is in nanoseconds), the human brain can still much more perform complex activities than computer due to the sophisticated structures of the neurons.

Artificial neural networks (ANNs) are a simulation for the biological process explained above. ANNs are developed based on mathematical models with the following assumptions (Mohaghegh, 2000):

1. The information is processed through elements called neurons.

2. There are connections links between the neurons that let the information to pass through.
3. Each connection links have their own weights.
4. Once the inputs received by the neurons, the neurons will apply an action function to determine the outputs.

Figure 2 is a schematic of an artificial neuron, the outputs from other neurons are multiplied by the connection links weights and enter the neuron. The inputs then are summed and the activation function of the neuron is applied which leads to an output. Thus, a neuron has multiple inputs and only one output. An artificial neural network consists of one input layer, one or more hidden layers, and one output layer. The input and output layers are obviously for inputs and outputs. The hidden layer is responsible for extraction the features from the data (Mohaghegh, 2000). ANNs can be simple three layers as shown in Figure 3, or ANNs can be more complicated as shown in Figure 4.

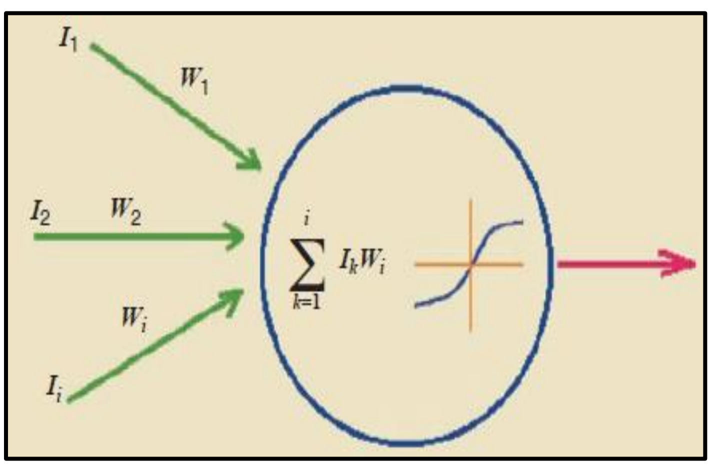

Figure 2. Schematic of Artificial Neuron (After Mohaghegh, 2000)

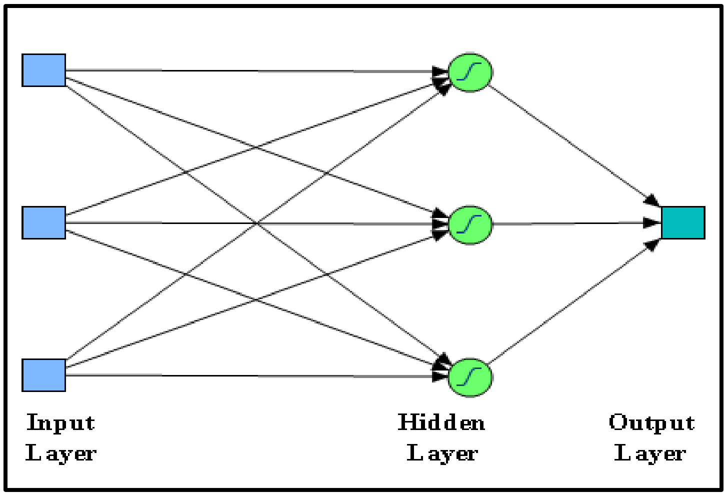

Figure 3. Example of a Simple Neural Network

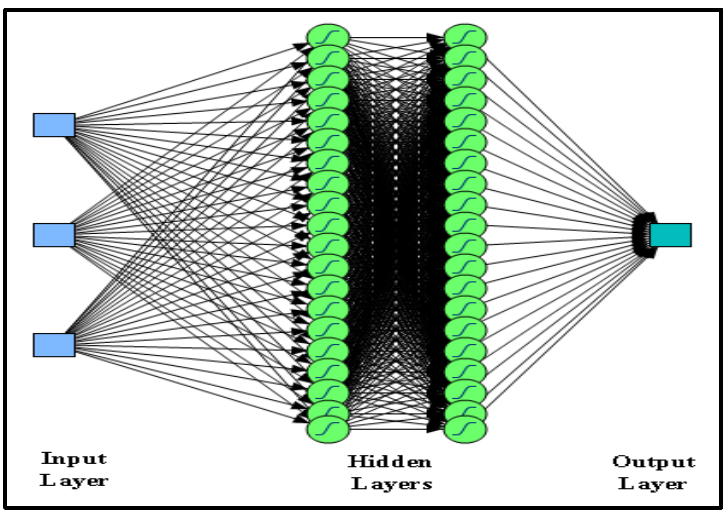

Figure 4. Example of a Complex Neural Network

3. HOW TO SUCCESSFULLY APPLY ANNS TO ANY PETROLEUM APPLICATIONS

In this section, a methodology of how to successfully apply ANNs to any petroleum applications will be presented. The focus will be on supervised ANNs since most petroleum applications are based on supervised training algorithms (Mohaghegh, 2000). Figure 5 shows a summary flowchart for how to successfully apply ANNs in the petroleum industry.

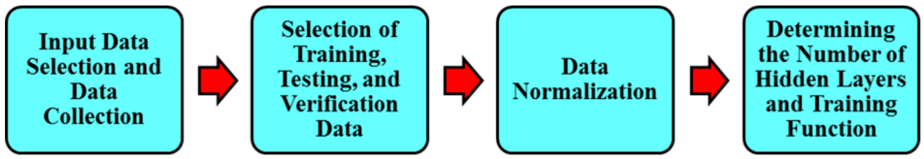

Figure 5. Flowchart for How to Successfully Apply ANNs in the Petroleum Industry

3.1. INPUT DATA SELECTION AND DATA COLLECTION

Depending on the application, the input data for ANNs will be different. Inputs can be chosen based on experimental tests, modeling, simulation, sensitivity analysis, expert opinion, statistical analysis and etc. Once the input data are chosen, data collection is the next step. Since most applications of oil and gas industry are supervised, this means data for inputs and outputs should be obtained.

3.2. SELECTION OF TRAINING, TESTING, AND VERIFICATION DATA

Typically, data are divided into three sections; training, testing, and verification sets. The training data used to develop the ANN model, the desired output is used to help the network adjust the weights of each input. The error will backpropagate in the network and adjust the weights until calibration is reached, this method is called feedforward backpropagation algorithm. It should be noted that the network should not be overtrained since the network won't be efficient. Testing sets are used to measure the network generalization and to stop the training when generalization stops improving (Demuth et al., 2007). Finally, the verification set (data not used to create the network) will be used to evaluate the performance of the network.

3.3. DATA NORMALIZATION

Sometimes, if the input or the output data are too small or too large; therefore, scaling of the data should be performed (Saeedi et al., 2007; Zabihi et al., 2011). One method of normalizing data to have values between -1 and 1 is shown in Equation 1 (Demuth et al., 2007).

$$X_i' = 2\left[\frac{X_i - X_{min}}{X_{max} - X_{min}}\right] - 1 \qquad \text{Eq.1}$$

Where Xi is the original value of the parameter, X_i^' is the normalized value of Xi, Xmax and Xmin are the maximum and the minimum values of Xi, respectively.

3.4. DETERMINING THE NUMBER OF HIDDEN LAYERS AND TRAINING FUNCTION

It is important to evaluate the optimum number of hidden layers and the number of neurons in each hidden layers. To find the optimum number of hidden layers, iteration should be performed until obtaining the optimum number of hidden layers. Typically, to obtain the number of neurons in each hidden layer, the total average absolute deviation (TAAD) or mean square of error (MSE) (or any form of error calculations) should be calculated such that starting with one neuron until reaching a number of neurons that have the lowest error.

After evaluating the optimum number of hidden layers and the number of neurons in each hidden layer, the training function should be chosen so that the error is minimized.

Examples of training function that can be tested are Variable Learning Rate Backpropagation (GDX), Resilient Backpropagation (RP), Fletcher-Powell Conjugate Gradient (CGF), Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM), Levenberg-Marquardt with Bayesian Regularization (BR), Quasi-Newton (BFG), and One Step Secant (OS) (Demuth et al., 2007).

4. APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS IN THE PETROLEUM INDUSTRY

ANNs have been used to solve complicated problems in the petroleum industry. ANNs should not be used to solve mathematical problems or problems that can be modeled analytically since the purpose of neural networks is to solve complicated problems that can't be solved in conventional modeling tools due to the complexity of the problem. After reading a good number of papers and case histories in the petroleum literature, the decision was made to classify the applications into four categories: applications for exploration, drilling, production, and reservoir.

4.1. EXPLORATION

This section gives examples of the applications of ANNs in exploration. This mainly consists of applications of ANNs of seismic data as shown in Table 1.

4.2. DRILLING

ANNs have been utilized in drilling engineering for a long time. Table 2 shows some applications of ANNs in drilling engineering.

Table 1. Application of ANNs in Exploration

Author(s)	Application	Notes
Guo et al. (1992)	Feature recognition	Used ANNs to extract structural lineaments and lithologic information from seismic data
Hansen (1993)	Primary reflection identifications	Used ANNs to successfully identify the primary reflection from seismic data
Karrenbach et al. (2000)	Seismic data processing	Used ANNs for seismic data processing
Fogg (2000)	Petro-seismic characterization	Used ANNs for petro-seismic characterization of a 96,000 trace 3D seismic migrated volume
Xiangjun et al. (2000)	Hydrocarbon prediction	Used ANNs to predict hydrocarbon and presented a case history from DaQing field
Sun et al. (2000); Russell et al. (2002)	Amplitude variation with offset (AVO)	Used ANNs to solve the interpretation problem associated with AVO since it is hard to distinguish between wet sand and gas sand
Aminzadeh & deGroot (2005)	Object detection	Used ANNs to detect several seismic objects using seismic data
Huang et al. (2006)	Parameters determinations and seismic pattern detection	Used ANNs to detect line pattern of the direct wave and hyperbola pattern of reflection wave in a seismogram
Kononov et al. (2007)	Travel time computation	Used ANNs to compute travel times for a complete 3D volume model.
Huang & Yang (2008)	Seismic velocity picking	Used ANNs to for velocity picking in the time-velocity semblance image of seismic data
Clifford & Aminzadeh (2011)	Gas detection	Used ANNs to detect gas from absorption attributes and amplitude in Grand Bay field
Aminzadeh et al. (2011)	Micro-seismic	Used ANNs to autopick micro-seismic earthquake data
Verma et al. (2012)	Mapping	Used ANNs to map high frackability and high total organic content zones in the Barnett Shale
Hami-Eddine et al. (2015)	Amplitude variation with angle of incidence (AVA) prediction	Used ANNs to predict AVA to help to evaluate the comparative risk between prospects for ranking purposes.
Refunjol et al. (2016)	Identifying unconventional potential	Used ANNs to identify the unconventional potential using seismic inversion in the Eagle Ford
Ross (2017)	Improve resolution and clarity of seismic data	Used ANNs to improve resolution and clarity of seismic data in the tight sand that has lower porosity, higher bulk density, and velocity. Also, used a practical example form the Permian Basin
Ogiesoba & Ambrose (2017)	Depositional environment investigation	Used ANNs to instigate depositional environments and hydrocarbon sweet-spot distribution in Serbin field in Texas
Canning et al. (2017)	Seismic data enhancement	Used ANNs for enhancing the frequency spectrum of seismic data

Table 2. Applications of ANNs in Drilling

Author(s)	Application	Notes
Arehart (1990)	Drill bit diagnosis	Used ANNs to determine the grade (state of wear) of the drill bit while drilling
Dashevskiy et al. (1999)	Real-time drilling dynamic	Used ANNs to model the dynamic behavior of the non-linear, multi0inputs/outputs drilling system
Bilgesu et al. (2001)	Drill bit selection	Used ANNs to select the “best” bit based on some inputs
Ozbaoglu et al. (2002)	Bed height for horizontal wells	Used ANNs to predict bed heights in horizontal or highly-inclined wellbores
Vassallo et al. (2004)	Bit bounce detection	Used ANNs to detect bit bounce that can be used as a proactive approach to prevent anomalous drilling conditions such as bit whirl and stick-slip
Fruhwirth et al. (2006); Wang and Salehi (2015)	Drilling hydraulics optimization and prediction	Used ANNs to optimize and predict drilling hydraulics with a practical example
Moran et al. (2010); Al-AbdulJabbar et al. (2018a)	Rate of penetration (ROP) prediction	Used ANNs to predict ROP so that the drill time can be estimated better
Gidh et al. (2012)	Bit wear prediction	Used ANNs to predict/ manage bit wear to improve ROP
Lind & Kabirova (2014)	Drilling troubles prediction	Used ANNs to predict troubles during the drilling process using a database on drilling parameters
Okpo et al. (2016)	Wellbore instability	Used ANNs to predict wellbore instability with case history from the Niger Delta oil field in Nigeria
Ahmadi et al. (2016)	Prediction of mud weight at wellbore conditions	Collected data from the literature
; Elkatatny et al. (2016); Abdelgawad et al. (2018); Al-Azani et al. (2018)	Drilling fluid rheological properties	Used ANNs to predict drilling fluid rheological properties
Cristofaro et al. (2017)	Mud losses	Used multiple artificial intelligence methods to find the best treatment for mud losses
Hoffmann et al. (2018)	Drilling reports sentence classifications	Used ANNs to develop a methodology for automatic of sentences written in drilling reports into three tables: Events, Symptom, and Action. used data of 303 wells
Li et al. (2018)	Lost circulation	Used ANNs to predict the risk level of lost circulation while drilling
Al-AbdulJabbar et al. (2018b)	Formation top prediction while drilling	Used ANNs to predict formation tops while drilling
Elzenary et al. (2018)	Equivalent circulation density (ECD) prediction	Used ANNs to predict ECD while drilling

4.3. PRODUCTION

ANNs have been applied in many applications of petroleum production engineering. Table 3 shows some applications of ANNs in petroleum production engineering.

Table 3. Applications of ANN in Production

Author(s)	Application	Notes
Thomas & Pointe (1995)	Conductive fracture identification	Used ANNs to identify conductive fractures
Denney (2000)	Fracturing restimulation candidates	Used ANNs to identify fracture restimulation candidates with case history from Red Oak field
Faga, & Oyeneyin (2000)	Gravel-pack design	Used ANNs to obtain real-time, well specific, grain size distribution for gravel-pack completion.
Al-Fattah & Startzman (2001)	Natural gas production prediction	Developed ANN model to forecast the United States gas production to the Year 2020
Salehi et al. (2009)	Casing collapse due to production	Used ANNs to predict casing collapse issues due to reservoir compaction, poroelastic effects, and corrosion. Also, used an example from a large carbonate oil field in Iran
Adeyemi, & Sulaimon (2012)	Wax formation prediction	Used ANNs to predict the wax formation
Moradi et al. (2013)	Wax disappearance temperature	Used experimental and real data of wax precipitation
Costa et al. (2014)	History matching	Built a reservoir simulation model and used ANN for history matching
Yanfang and Salehi (2014)	Re-fracture candidate selection	Used real field data from Zhongyuan oilfield
Al-Naser et al. (2016)	Application of multiphase flow patterns	Used “Unified Model” to generate the data and used experimental data for testing
Ghahfarokhi et al. (2018)	Prediction of gas production	Used ANNs to predict gas production in the Marcellus Shale
Khan et al. (2018)	Oil rate prediction	Used ANNs to predict the optimum production rate
Luo et al. (2018)	Production optimization	Used ANNs to optimize the production in the Bakken Shale
Nande (2018)	Hydraulic fracturing	Used ANNs to minimize the error in predicting closure pressure for hydraulic fracturing analysis
Nieto et al. (2018)	Completion optimization	Used ANNs to optimize the completion and to protect parent well in the Montney formation in British Columbia
Pankaj (2018)	Well spacing and well stacking	Used ANNs to optimize well spacing and well tacking in the Permian Basin
Sidaoui et al. (2018)	Carbonate acidizing	Used ANNs to predict the optimum injection rate of carbonate acidizing
Tariq (2018)	Flowing bottom hole pressure prediction	Used ANNs to predict flowing bottom hole pressure
Al-Dogail et al (2018); Basfar et al. (2018)	Inflow performance (IPR) prediction	Used ANNs to predict inflow performance of gas field and for vertical oil well

4.4. RESERVOIR

There are many applications of ANNs in reservoir engineering. Table 4 shows a summary of the main applications of ANNs in reservoir engineering.

Table 4. Applications of ANNs in Reservoir

Author(s)	Application	Notes
An & Moon (1993); Long et al. (2016)	Reservoir characterization	Used ANNs for reservoir characterization
Yang & Kim (1996)	Rock properties	Used accelerated ANNs to find rock properties
Denney (2001)	Reservoir monitoring	Used ANNs to find the optimum relationship between pressure, saturation, and seismic data. The model was applied to the Statfjord field
Alcocer & Rodrigues (2001)	Fluid properties	Used ANNs to estimate fluid properties using nuclear magnetic resonance
Denney (2003)	Well testing	Used ANNs to analyzed pressure transient data from an anisotropic faulted reservoir
Denney (2006)	Uncertainties in reservoir performance	Used ANNs in Monte Carlo simulations to eliminate to generate the probability distribution of possible outcomes.
Elshafei & Hamada (2007)	porosity and water saturation	Used ANNs to predict formation porosity and water saturation from well logs
Ayoub et al. (2007)	Viscosity correlations	Used ANNs to evaluate the below bubble point viscosity correlations
Al-Bulushi et al (2007); Khan et al. (2018)	Water saturation prediction	Used ANNs to predict water saturation for sandstone reservoirs using conventional well logs
Hegeman et al. (2009)	Downhole fluid analysis	Used ANNs to estimate gas/oil ratio (GOR) from real-time downhole fluid samples
Zabihi et al. (2011)	Permeability damage prediction	Used experimental data of Berea sandstone cores
Kohli & Arora (2014)	Permeability prediction	Used ANNs to predict permeability from well logs
Ma and Gomez (2015)	Predictions of hydrocarbon resource	Used real field data with some statistical methods and ANN
Bello et al. (2016)	Drilling system design and operation	Used multiple artificial intelligence techniques-including ANNs- to design drilling and operation systems
Li et al. (2018)	Geomechanical characterization	Used ANNs to successfully synthesize compressional and shear travel time logs
Dang et al. (2018)	EOR	Used ANNs to perform N-dimensional interpolation of relative permeability
Rashidi et al (2018)	Elastic modulus	Used ANNs to correlate between static and dynamic modulus of limestone formations. Also, used an example from two formations Asmari and Sarvak in Iran
Hadi & Nygaard (2018)	Shear wave estimation	Used ANNs to predict shear wave in carbonate reservoirs
Rashidi & Asadi,(2018)	Pore pressure estimation	Used ANNs to predict formation pore pressure from drilling data
Hamam & Ertekin (2018)	CO_2 injection	Used ANNs to develop a screening tool for CO_2 injection in naturally fractured reservoirs.
Hasan et al. (2018)	Temperature distribution	Used ANNs to predict thermal distribution in thermal EOR methods

5. CONCLUSIONS

ANNs are very useful tool which can be used to solve problems that are hard to be modeled analytically. ANNs have been applied to many petroleum applications and have shown a reasonable accuracy. After reviewing a good number of papers about the applications of ANNs in the petroleum industry, the following conclusions were made:

- Due to the availability of huge historical data in the petroleum industry, this data can be used for predictions of future outcomes to help to make better decisions. Future predictions are always challenging, due to the large uncertainties in the future. ANNs can be used for future prediction or real-time predictions with a good accuracy so that the decision makers can prepare to solve the problems ahead of time.
- Some petroleum engineering problems are hard to be solved analytically. Thus, ANNs can be used to solve such problems with a good accuracy.
- Many application of ANNs from the literature were summarized in this paper. Also, the applications were divided and tabulated into four categories; applications for exploration, drilling, production, and reservoir.
- Practical guidelines have been developed that when used with the accompanying flow chart will serve as a quick reference guide to apply the ANNs for any petroleum application. This paper provides a clear methodology on how to successfully apply the ANNs which can serve as a reference for any future ANNs applications in the petroleum industry.

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IV. ARTIFICIAL NEURAL NETWORK MODELS TO PREDICT LOST CIRCULATION FOR NATURAL AND INDUCED FRACTURES FORMATIONS

ABSTRACT

Lost circulation is a complicated problem to be predicted with conventional statistical tools. As the drilling environment is getting more complicated nowadays, more advanced techniques such as artificial neural networks (ANNs) are required to help predicting mud loss before drilling. The aim of this work is to estimate mud losses for natural and induced fractures formations before drilling to assist the drilling personnel in preparing remedies for this problem before entering the zone of losses. Once the severity of losses is known, the drilling parameters can be adjusted to mitigate mud loss as a proactive approach. Lost circulation data were gathered from over 1500 wells drilled worldwide. The data were separated into three sets; training, validation, and testing datasets. 60% of the data were utilized for training, 20% for validation, and the rest for testing. Any ANN consists of the following layers, the input layer, hidden layer(s), and the output layer. A determination of the optimum number of hidden layers and the number of neurons in each hidden layer is required to have the best estimation, this is done using the mean square of error (MSE). Two supervised ANNs were created for natural and induced fractures formations. For both networks, a decision was made to have one hidden layer in the network with ten neurons in the hidden layer. Since there are many training algorithms to choose from, it was necessary to choose the best algorithm for this specific dataset. Eight different training algorithms were tested, the Levenberg-Marquardt (LM) algorithm was chosen since it gave the lowest MSE and it had the highest R^2. The final results showed

that the supervised ANN has the ability to predict lost circulation with an overall R^2 of 0.956 for natural fractures formations, and 0.925 for the induced fractures formations. This is a very good estimation that will help the drilling personnel prepare remedies before entering the losses zone as well as adjusting the drilling parameters to mitigate mud loss as a proactive approach. This ANN can be used globally for any natural and induced fractures formations that are suffering from the lost circulation problem to estimate mud losses. As the demand for energy increases, the drilling process is becoming more challenging. Thus, more advanced tools such as ANNs are required to better tackle these problems. The ANN built in this paper can be adapted to commercial software that predicts lost circulation for any natural or induced fractures formations globally.

1. INTRODUCTION

The first neural networks research was by McCulloch and Pitts (1943). Rosenblatt (1957) developed the perceptron and proved that a perceptron would create a vector that divides the classes. Rosenblatt (1957) believed that structures of more layers can conquer the limitations of simple perceptron. Nevertheless, there were not any learning algorithms that can determine the weights for a given calculation (Mohaghegh, 2000). Few years after, a network called Adeline was created by Widrow (1962). Minsky and Papert (1969) proved that the single layer perceptron cannot elementary calculations problems. After that, the neural network's research stopped for 20 years (Hertz et al., 1991). Then, Hopfield (1982) proposed new algorithms, such as backpropagation, that brought life for the neural network's research. Since then, the neural networks applications has gone viral (Mohaghegh, 2000).

An artificial neural network is a mimic for the biological neuron that has the ability to process information. Neurons are the basic building blocks of the nervous system. A typical biological neuron consists of a cell body, an axon, and dendrites as shown in Figure 1. Information in the cell body enters through the dendrites. The cell body then gives an output which travels via the axon then to another receiving neuron, the output from the first neuron becomes an input for the second neuron and so on (Mohaghegh, 2000).

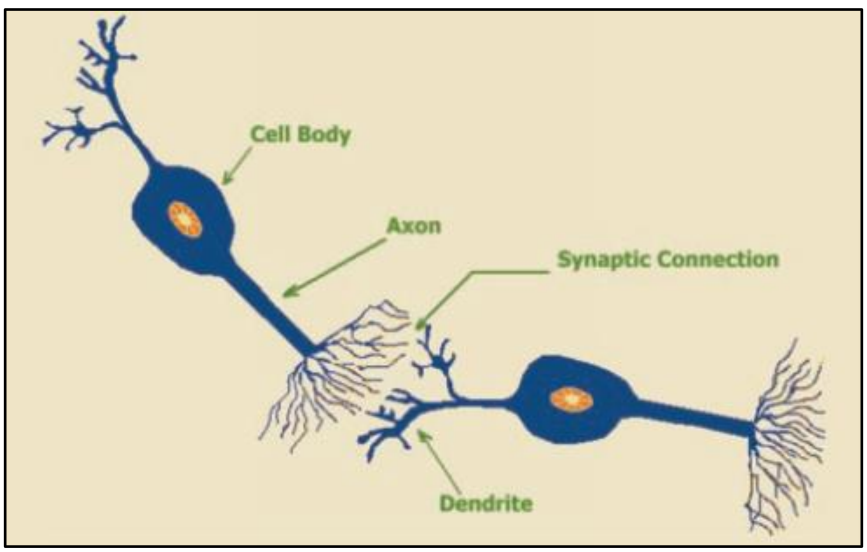

Figure 1. Two Bipolar Neurons (Mohaghegh, 2000)

The human brain contains 10-500 billion neurons (Rumelhart & McClelland, 1986). These neurons are separated into sections, each section contains about 500 neural networks (Stubbs, 1988). Every neural network contains approximately 100,000 neurons where these neurons are connected to thousands of other neurons (Mohaghegh, 2000).

This structure is behind the human's complex behavior. A simple task such as moving hands, walking, or catching a cup of coffee, requires very complex calculations that sophisticated computer can't perform but the human brain is able to do them. Although computers are faster than human brains (human brain cycle is 10 to 100 milliseconds while computer chips cycle is in nanoseconds), the human brain can still much more perform complex activities than computer due to the sophisticated structures of the neurons. Artificial neural networks (ANNs) are a simulation for the biological process explained above. ANNs are developed based on mathematical models with the following assumptions (Mohaghegh, 2000):

1. The information is processed through elements called neurons.
2. There are connections links between the neurons that let the information to pass through.
3. Each connection links have their own weights.
4. Once the inputs received by the neurons, the neurons will apply an action function to determine the outputs.

Figure 2 is a schematic of an artificial neuron, the outputs from other neurons are multiplied by the connection links weights and enter the neuron. Then, the input data are summed and the activation function of the neuron is applied which leads to an output. Thus, a neuron has multiple inputs and only one output. An artificial neural network consists of one input layer, one or more hidden layers, and one output layer. The input and output layers are obviously for inputs and outputs. The hidden layer is responsible for extraction the features from the data (Mohaghegh, 2000). ANNs can be simple three layers as shown in Figure 3, or ANNs can be more complicated as shown in Figure 4.

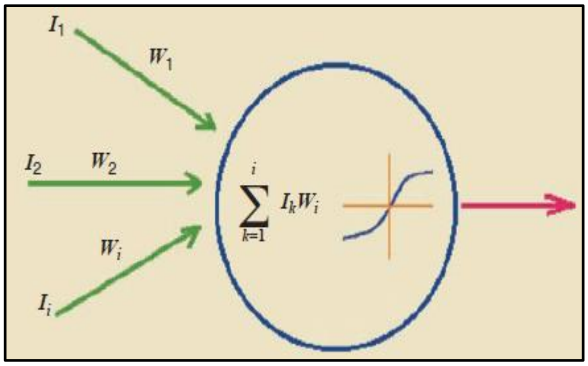

Figure 2. Schematic of Artificial Neuron (after Mohaghegh, 2000)

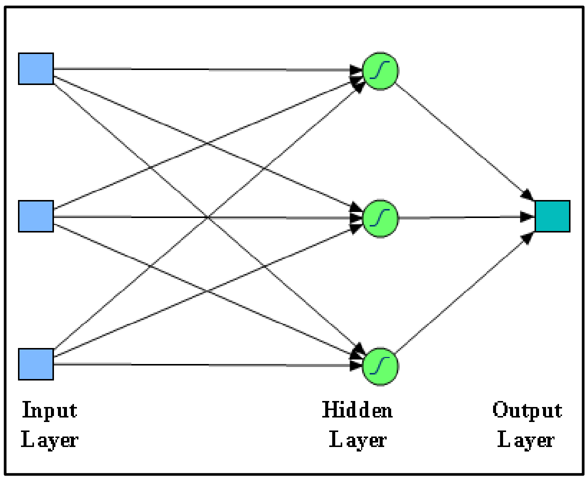

Figure 3. Example of a Simple Neural Network

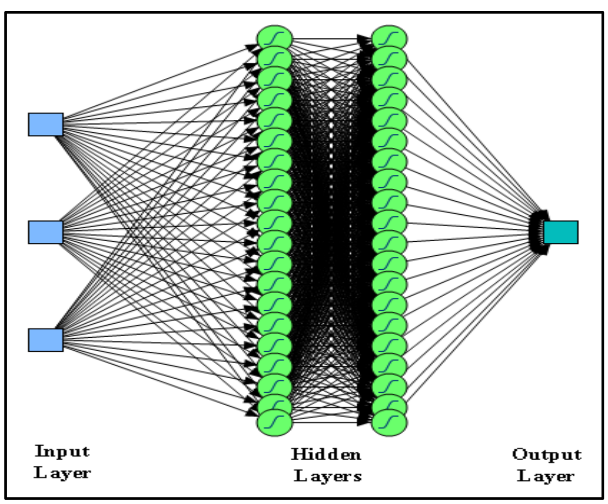

Figure 4. Example of a Complex Neural Network

ANNs have been utilized in drilling engineering for a long time. Table 1 shows some applications of ANNs in drilling engineering.

Table 1. Applications of ANNs in Drilling

Author(s)	Application	Notes
Arehart (1990)	Drill bit diagnosis	Used ANNs to determine the grade (state of wear) of the drill bit while drilling
Dashevskiy et al. (1999)	Real-time drilling dynamic	Used ANNs to model the dynamic behavior of the non-linear, multi0inputs/outputs drilling system
Bilgesu et al. (2001)	Drill bit selection	Used ANNs to select the "best" bit based on some inputs
Ozbaoglu et al. (2002)	Bed height for horizontal wells	Used ANNs to predict bed heights in horizontal or highly-inclined wellbores
Vassallo et al. (2004)	Bit bounce detection	Used ANNs to detect bit bounce that can be used as a proactive approach to prevent anomalous drilling conditions such as bit whirl and stick-slip
Fruhwirth et al. (2006); Wang and Salehi (2015)	Drilling hydraulics optimization and prediction	Used ANNs to optimize and predict drilling hydraulics with a practical example
Moran et al. (2010); Al-AbdulJabbar et al. (2018)	Rate of penetration (ROP) prediction	Used ANNs to predict ROP so that the drill time can be estimated better
Gidh et al. (2012)	Bit wear prediction	Used ANNs to predict/ manage bit wear to improve ROP
Lind & Kabirova (2014)	Drilling troubles prediction	Used ANNs to predict troubles during the drilling process using a database on drilling parameters
Okpo et al. (2016)	Wellbore instability	Used ANNs to predict wellbore instability with case history from the Niger Delta oil field in Nigeria
Ahmadi et al. (2016)	Prediction of mud weight at wellbore conditions	Collected data from the literature
Elkatatny et al. (2016); Abdelgawad et al. (2018a); Al-Azani et al. (2018)	The rheological properties of the drilling fluid	Used ANNs to estimate the rheological properties of the drilling fluid
Cristofaro et al. (2017)	Mud losses	Used multiple artificial intelligence methods to find the best treatment for mud losses
Hoffmann et al. (2018)	Drilling reports sentence classifications	Used ANNs to develop a methodology for automatic of sentences written in drilling reports into three tables: Events, Symptom, and Action. used data of 303 wells
Li et al. (2018)	Lost circulation	Used ANNs to predict the risk level of lost circulation while drilling
Al-AbdulJabbar et al. (2018b)	Formation top prediction while drilling	Used ANNs to predict formation tops while drilling
Elzenary et al. (2018)	Equivalent circulation density (ECD) prediction	Used ANNs to predict ECD while drilling

Lost circulation while drilling is a major problem in the drilling operation. Millions of dollars are spent to stop or mitigate lost circulation worldwide (Alkinani et al., 2019; Alkinani et al., 2018a; Arshad et al., 2015). Lost circulation estimation is a limited topic in the literature, only a few papers were published about this topic. Some shortcomings were identified in the previous work as follows (Al-Hameedi et al., 2017a; Al-Hameedi et al., 2017b; Al-Hameedi et al., 2018a; Al-Hameedi et al., 2018b; Cristofaro et al., 2017; Li et al., 2018):

1. Not enough data were used
2. The model is applicable only in a specific area
3. The methodologies in some papers were not explained very well

The purpose of this paper is to build two ANNs to predict mud loss before drilling for natural and induced fractures formations using data of more than 1500 wells drilled worldwide. Also, this paper will eliminate the shortcoming mentioned earlier by using huge data sets, the model will be applicable globally since the data were collected globally, and the methodology will be explained in details.

2. DATA AND METHODS

In this section, various steps for creating the feedforward backpropagation networks for the natural and induced fractures formations will be shown.

2.1. DATA COLLECTION, DATA PREPROCESSING, AND INPUT DATA SELECTION

Data collection is the most time-consuming step of this work. Key drilling parameters at the time of mud losses were collected from various sources including daily drilling reports (DDR), technical reports, mud logging reports, final drilling reports, case histories, and from the petroleum literature. Red dots in Figure 5 shows the location where data where gathered.

Figure 5. Locations where Data were Collected

Then, the data of each key drilling parameter were tested for outliers using box plot, such data any data point fall outside the minimum and the maximum of the interquartile range (IQR) will be eliminated (Alkinani et al., 2018b).

After finishing the data preprocessing step (identifying the outliers), the drilling parameters that will be used as inputs for the model should be chosen. Inputs can be chosen based on experimental tests, modeling, simulation, sensitivity analysis, expert opinion, statistical analysis and etc. The following inputs were chosen based on two criteria which are statistical and sensitivity analyses done by Al-Hameedi et al. (2017a and 2018a), and experts' opinions:

1. Effective circulation density (ECD) in gm/cc
2. Flow rate (Q) in L/min
3. Mud weight (MW) in gm/cc
4. Nozzles total flow area (TFA) in inch^2

5. Plastic viscosity (PV) in cp
6. Revolutions per minute (RPM)
7. Weight on bit (WOB) in Tons
8. Yield point (Yp) in $Ib/100ft^2$

2.2. DATA NORMALIZATION

Sometimes, if the input or the output data are too small, too large or non-normally distributed; therefore, scaling of the data should be performed (Saeedi et al., 2007; Zabihi et al., 2011). One method of normalizing data to have values between -1 and 1 is shown in Equation 1 (Demuth et al., 2007):

$$X_i' = 2\left[\frac{X_i - X_{min}}{X_{max} - X_{min}}\right] - 1 \qquad \text{Eq. 1}$$

Where X_i' is the normalized value of original value (X_i), X_{max} and X_{min} are the maximum and the minimum values of X_i, respectively.

2.3. CHOOSING THE TRANSFER FUNCTION

Figure 6 shows an elementary neuron with R inputs. Each input will be assigned to a weight (w), and each layer will be assigned to biases (b). The sum of the biases and inputs weights will be an input for transfer function (f), which is the hidden layer. The outputs from the hidden layer will be assigned weights and biases as well then they will be an input for the output transfer function, which is the output layer (Demuth et al., 2007).

The tan-sigmoid transfer function was chosen for the hidden layer, and a linear transfer function was used for the outputs layer. Using this combination will allow the network to capture the nonlinear relationship between the inputs and the outputs. The linear transfer function was chosen for the output layer since it is suitable for fitting problems (regression) (Demuth et al., 2007).

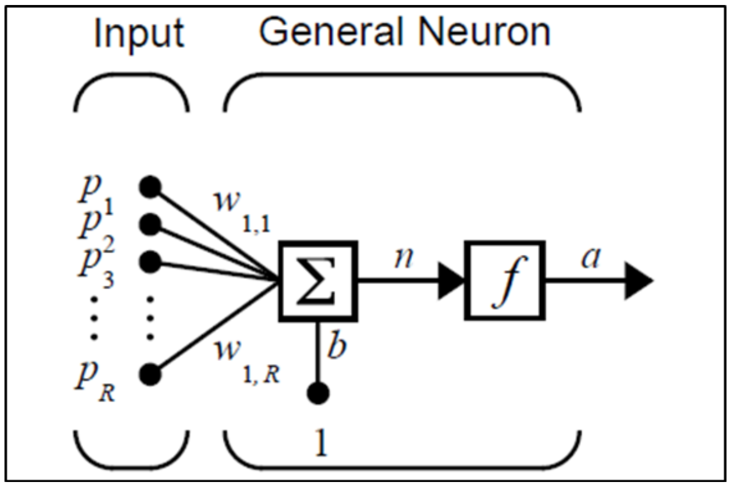

Figure 6. Elementary Neuron with R Inputs (after Demuth et al., 2007)

2.4. DIVIDING THE DATA AND FEEDFORWARD BACKPROPAGATION ALGORITHM

Typically, data are divided into three sections; training, verification, testing sets. The training data used to develop the ANN model, the desired output is used to help the network adjust the weights of each input. The error will backpropagate in the network and adjust the weights until calibration is reached, this method is called feedforward backpropagation algorithm. It should be noted that the network should not be overstrained since the network will lose its ability to generalize. Verification set (data not used to create the network) is used to measure the network generalization, and to stop the training when generalization stops improving. Testing set (also data not used to create the network) used to test the accuracy of the network after the training and the verification steps.

Since huge data are available, 60% of the data were utilized for training, 20% used for verification, and the rest for testing. Thus, only 60% of the data used to train the model, the rest used for generalization and testing.

2.5. CHOOSING THE OPTIMUM NUMBER OF HIDDEN LAYERS AND NUMBER OF NEURONS

The optimum number of hidden layers, as well as the number of neurons in the hidden layer, were chosen based on an iterative process. A various number of hidden layers and number of neurons were tested, the goal was to build a network that has the lowest mean squared error (MSE) which is the average squared error between the network estimate outputs (a) and the real output (t). MSE can be calculated using Equation 2 (Demuth et al., 2007):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \quad \text{Eq. 2}$$

Where N is the number of data points. Figure 7 summarizes the process of selecting the optimum number of hidden layers. The same process was implemented to choose the optimum number of neurons in the hidden layers such that starting with one neuron and then increase the number of neurons until reaching the lowest MSE.

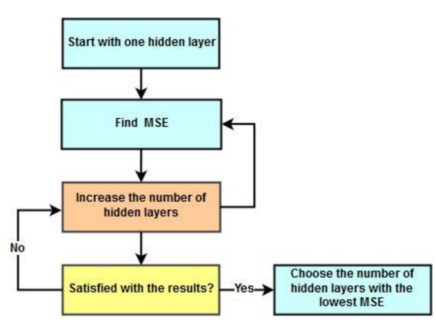

Figure 7. The Process of Selecting the Optimum Number of Hidden Layers

2.6. EX EXAMINATION OF THE TRAINING FUNCTION

This is a very pivotal step in creating the network. There are many algorithms available to choose from. Table 1 summarizes the algorithms examined in this study (more information about each algorithm can be found in Demuth et al., (2007)). After testing all algorithms, the lowest MSE with the highest R^2 algorithm was chosen to train the network. R^2 can be calculated using the following Equations:

$$R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad \text{Eq. 3}$$

Where SSR is the regression sum of squares, SST is the total sum of squares, $\hat{y}_i$ is the predicted data point, $\bar{y}$ is the average mean of the real data, and y_i is the real data point. Figure 8 summarizes the methodology used in this study.

Table 2. The Algorithms Examined in this Study

Algorithm	Abbreviations
Scaled Conjugate Gradient	SCG
Resilient Backpropagation	RP
One Step Secant	OSS
Levenberg-Marquardt	LM
Variable Learning Rate Backpropagation	GDX
Polak-Ribiére Conjugate Gradient	CGP
Fletcher-Powell Conjugate Gradient	CGF
Conjugate Gradient with Powell/Beale Restarts	CGB
Bayesian Regularization	BR
Quasi-Newton	BFG

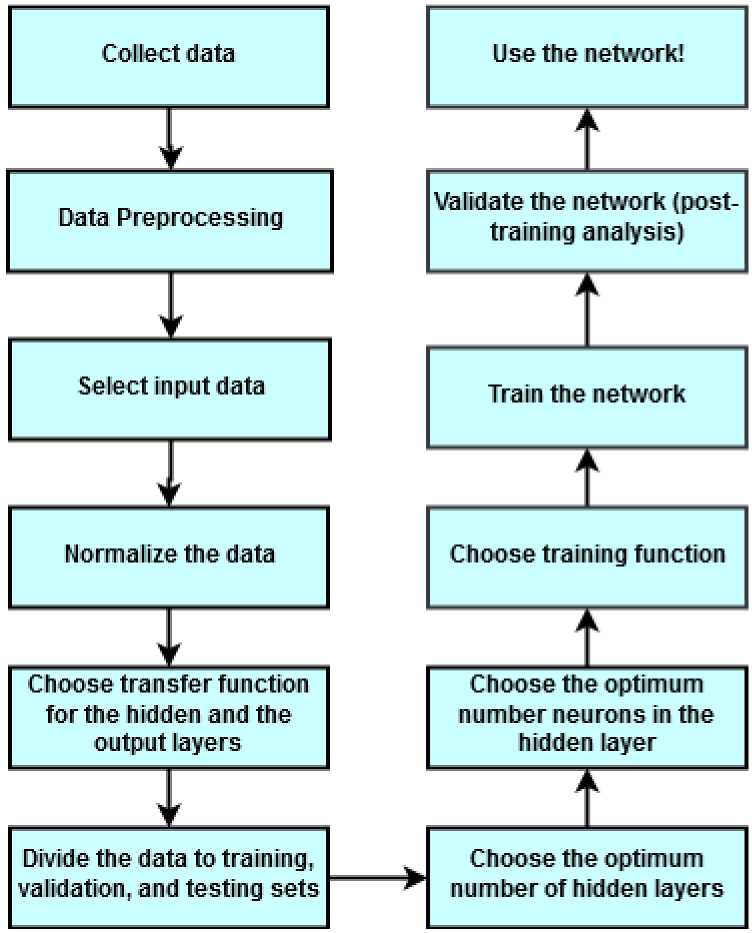

Figure 8. Summary for the Methodology Used in this Study

3. RESULTS AND DISCUSSION

Since two datasets were collected for the natural and induced fractures formations, two networks were created for the natural and induced fractures. The results are divided into natural fractures network results and induced fractures network results.

3.1. NATURAL FRACTURE FORMATIONS NETWORK

ANN with one input layer, one hidden layer with ten neurons, and one output layer was created for the natural fractures dataset. Figure 9 and 10 show the MSE and R2 for all training functions examined in this study, respectively. It is clear that LM and BR algorithms have the lowest MSE and R2 among the other algorithms with the LM algorithms being slightly better than the BR algorithm (LM has lower MSE and higher R2). BR algorithm is usually used for small or noisy datasets. Typical BR algorithm doesn't use validation to stop the network when a generalization is reached so that the training can continue until an optimal combination of error and weights is found. On the other hand, LM usually have the fastest convergence which gives accurate training. Also, the LM usually perform very well in approximation (regression) problems. Training will stop in the LM algorithm when generalization stops improving. Thus, the LM algorithm was chosen to train the network (Demuth et al., 2007).

Figure 11 shows the MSE with iterations for training, validation, and testing sets. To avoid overfitting, The MSE in the validation set is monitored and the training will stop once the lowest MSE is reached. Also, the testing and the validations MSE should have similar characteristics in order to avoid overfitting and have a rigorous network. Figure 11 shows the training stops after 33 iterations which when the MSE for the validation set is minimum. Moreover, Figure 11 clearly shows that the testing and validation sets have the same MSE characteristics.

Figure 12 shows the actual and predicted mud losses for training (Figure 12a), validation (Figure 12b), testing (Figure 12c), and all (Figure 12d) datasets. The R2 for the training, validation, and testing is 0.96, 0.95, and 0.948, respectively. The network has an overall R2 of 0.956. With this high R2, the network can be used to predict mud losses prior to drilling for natural fractures formations.

Equation 4 can be used to estimate mud losses for natural fractures formations prior to drilling.

$$Losses = \left[\sum_{i=1}^{N} w_{2i}\left(\frac{2}{1+e^{-2\left(\sum_{j=1}^{J} w_{1i,j}x_j+b_{1i}\right)}}-1\right)+b_2\right] \quad \text{Eq. 4}$$

Where N is the number of neurons in the hidden layer which was optimized to be ten, w_1 is the hidden layer's weight, w_2 is the output layer's weight, b_1 is the hidden layer's bias, b_2 is the output layer bias, and x is the input variables. The j's are associated with the input variables such that j=1 is MW, j=2 is ECD, j=3 is PV, j=4 is Yp, j=5 is Q, j=6 is RPM, j=7 is WOB, and j=8 is Nozzles TFA. Table 2 summarizes the coefficients for Equation 4.

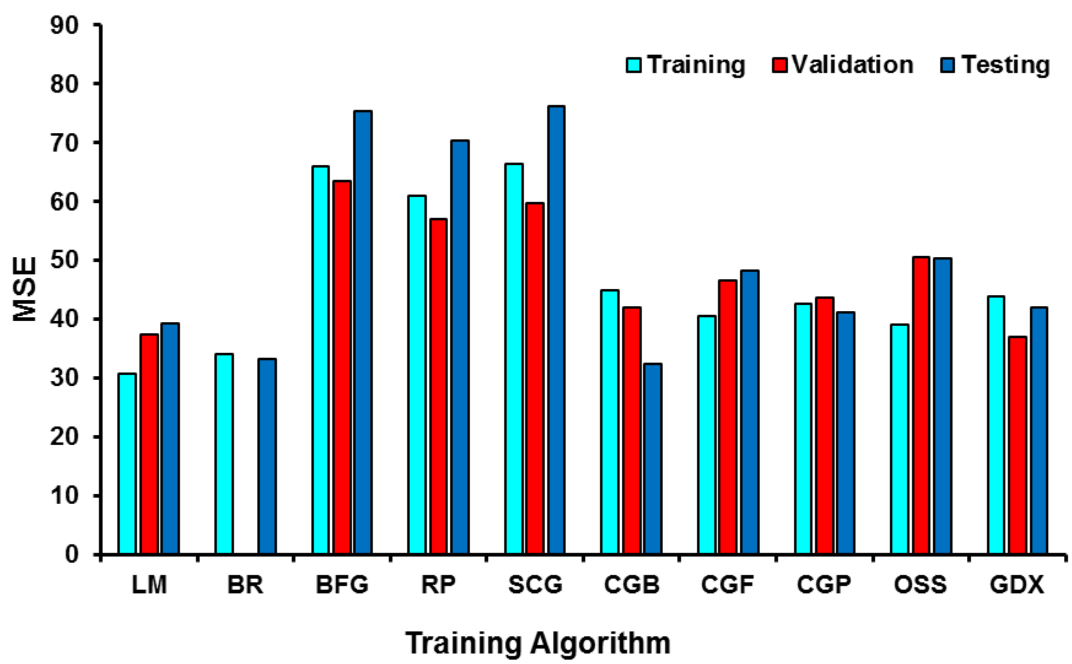

Figure 9. MSE of all Training Functions Examined in this Study (Natural Fractures)

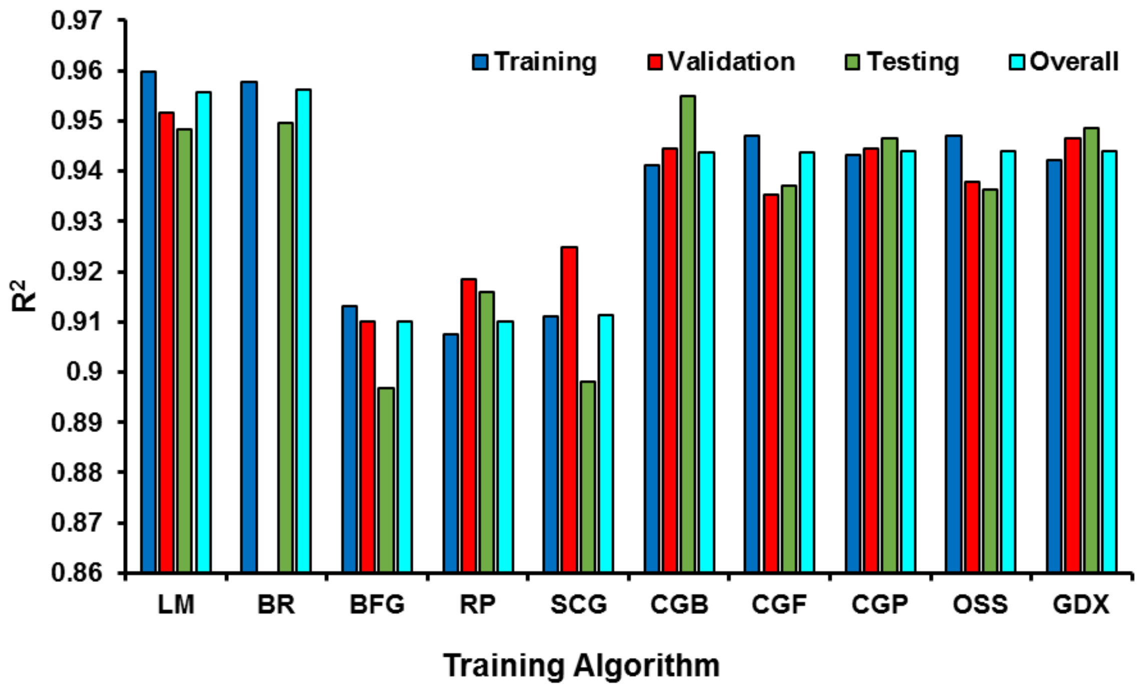

Figure 10. R^2 of all Training Functions Examined in this Study (Natural Fractures)

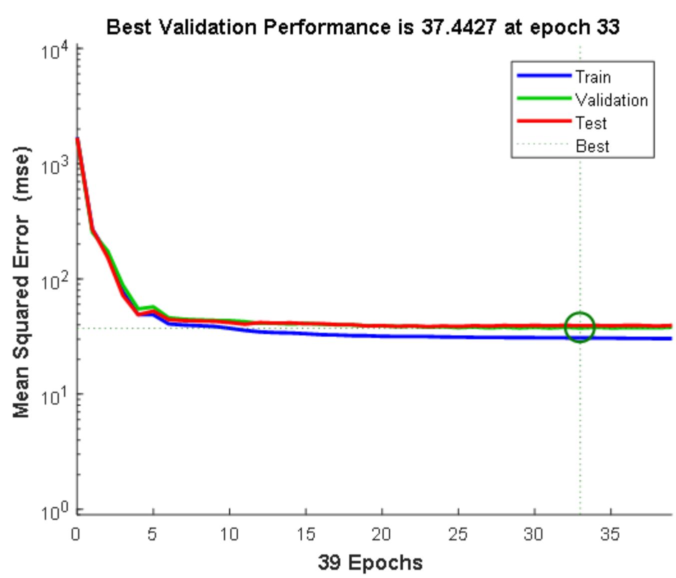

Figure 11. MSE vs Epochs for the LM Training Function (Natural Fractures)

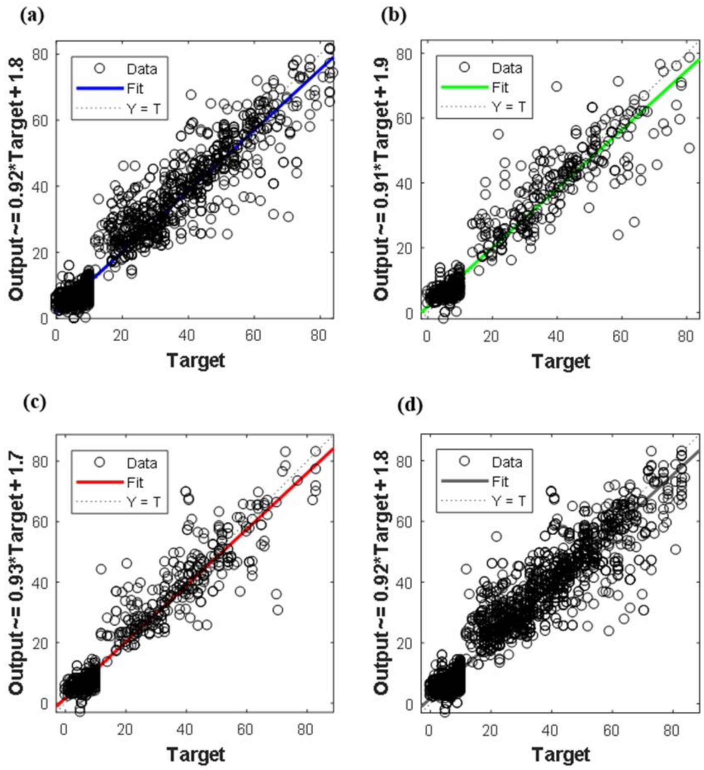

Figure 12. Predicted and Actual Mud Losses (Natural Fractures)

Table 3. Coefficients for Natural Fracture Formations Mud Losses (Eq. (4))

Weights of the Hidden Layer w_{1j}								Bias of the Hidden Layer	Output Layer Weight Matrix	Output Layer Bias
j=1	j=2	j=3	j=4	j=5	j=6	j=7	j=8	b_1	w_2	b_2
-2.2091	2.7249	1.8762	0.6220	-0.0617	-1.7078	-0.7524	-1.0397	-1.7124	0.3750	-0.2793
-6.9222	3.2221	2.1353	-1.7348	1.1825	-0.8590	0.6850	2.7215	3.5206	-0.2016	
-0.4195	-0.7027	-4.4217	1.4298	-1.3663	0.2557	4.9967	1.8083	4.1717	0.2147	
5.5710	1.4180	2.3832	0.8779	-0.7672	-0.1834	-1.0082	-0.0979	-4.8003	0.3362	
-2.3232	-3.2751	1.3330	0.5541	-1.0229	0.9844	-0.6204	-2.8423	-0.5922	2.4752	
1.0026	0.1431	-0.1428	1.4370	0.2717	-1.6094	-0.3796	-1.6778	-2.2784	-0.7235	
1.2600	1.0021	2.5369	-0.1617	5.4880	-0.4228	4.0073	-3.1335	-3.9646	0.1092	
3.2746	3.3977	-2.1981	-0.7570	1.8079	-1.2094	1.2321	3.5979	0.6624	1.8705	
3.3066	0.7451	-0.1552	-0.1148	-0.1447	0.5618	0.3344	-0.0443	2.1266	0.6306	
2.3620	-3.3680	-0.4873	-1.0335	-0.3052	1.7558	-1.8901	1.1824	3.5360	-0.5589	

3.2. INDUCED FRACTURES FORMATIONS NETWORK

ANN with one input layer, one hidden layer with ten neurons, and one output layer was created for the induced fractures dataset. Figure 13 and 14 show the MSE and R2 for all training functions, respectively. Although the BR algorithm has a lower MSE, the LM algorithm was chosen because it has a higher R2.

Figure 15 shows the MSE for the LM algorithm for training, validation, and testing. Figure 15 shows the training stops after 19 iterations which when the MSE for the validation set is minimum. Moreover, Figure 15 clearly shows that the testing and validation sets have the same MSE characteristics. Figure 16 shows the actual and predicted mud losses for training (Figure 16a), validation (Figure 16b), testing (Figure 16c), and all (Figure 16d) datasets. The R2 for the training, validation, and testing is 0.928, 0.925, and 0.91, respectively. The network has an overall R2 of 0.925. With this high R2, the network can be used to predict mud prior to drilling for induced fractures formations.

Equation 5 can be used to estimate mud losses for induced fractures formations prior to drilling.

$$Losses = \left[\sum_{i=1}^{N} w_{2i}\left(\frac{2}{1+e^{-2\left(\sum_{j=1}^{J} w_{1i,j}x_j+b_{1i}\right)}}-1\right)+b_2\right] \qquad \text{Eq. 5}$$

Where N is the number of neurons in the hidden layer which was optimized to be 10, w1 is the hidden layer’s weight, w2 is the output layer’s weight, b1 is the hidden layer’s bias, b2 is the output layer bias, and x is the input variables. The j’s are associated with the input variables such that j=1 is MW, j=2 is ECD, j=3 is PV, j=4 is Yp, j=5 is Q, j=6 is RPM, j=7 is WOB, and j=8 is Nozzles TFA. Table 3 summarizes the coefficients for Equation 5.

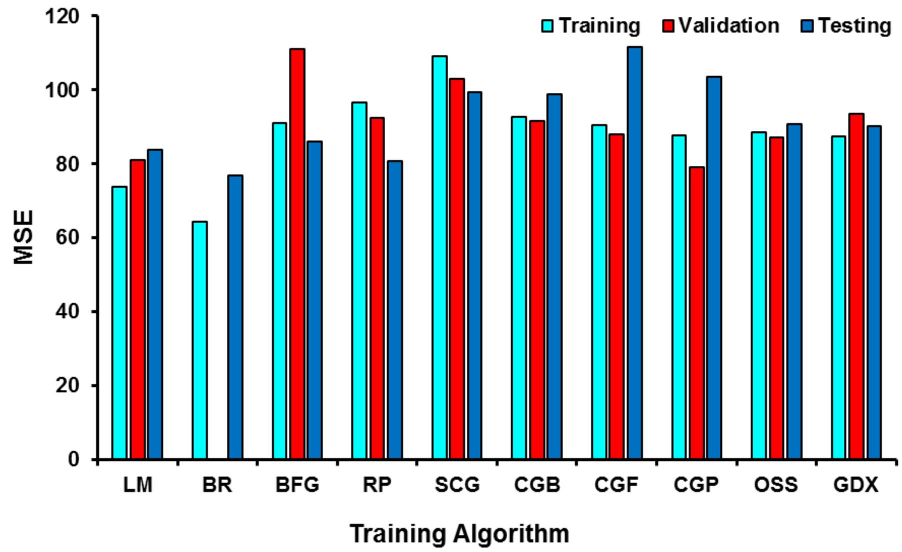

Figure 13. MSE of all Training Functions Examined in this Study (Induced Fractures)

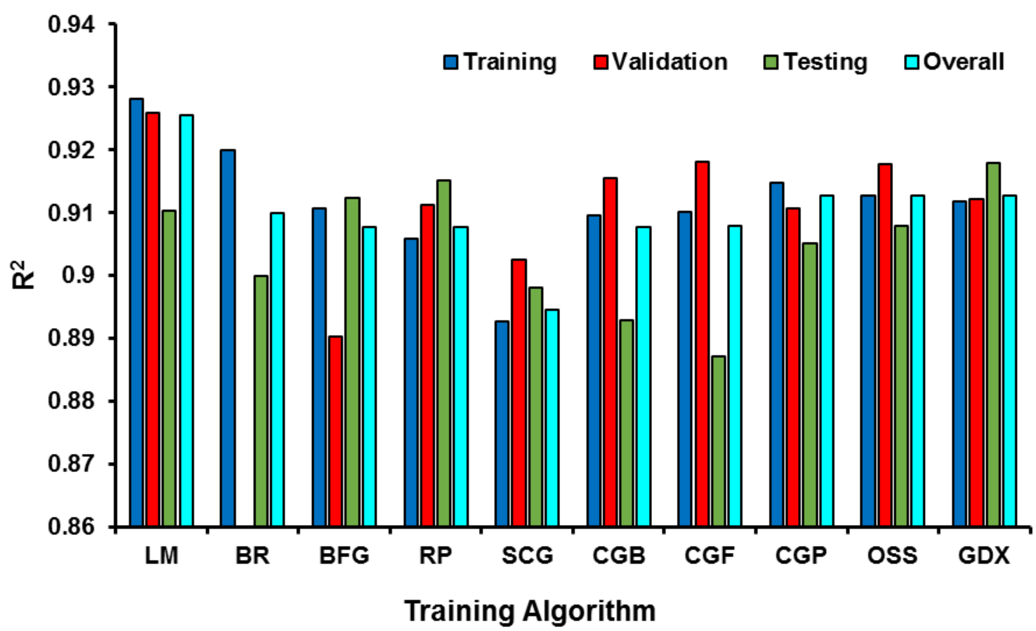

Figure 14. R^2 of all Training Functions Examined (Induced Fractures)

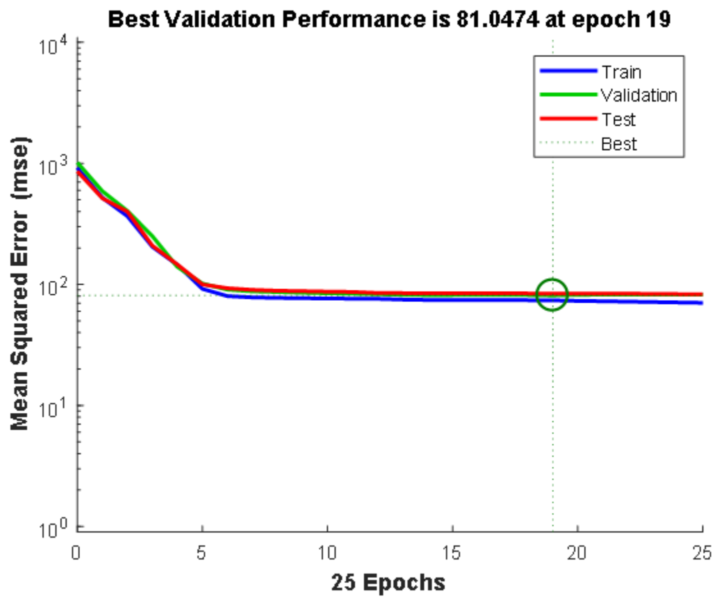

Figure 15. MSE vs Epochs for the LM Training Function (Induced Fractures)

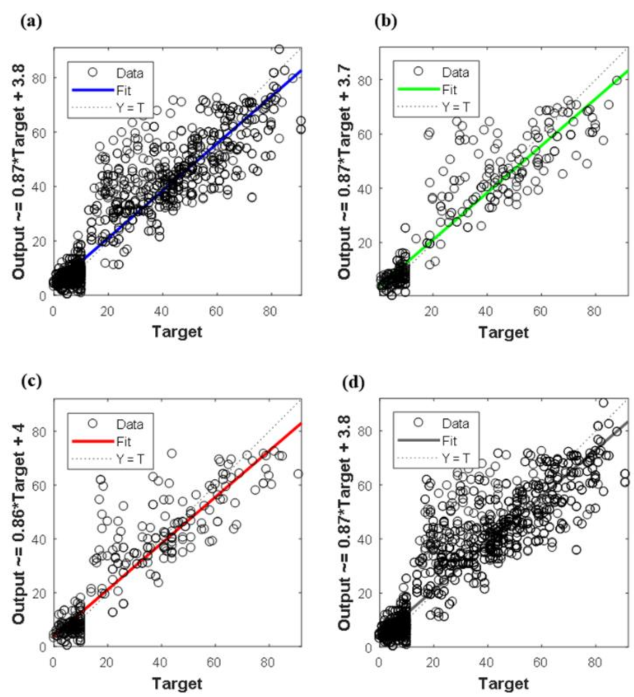

Figure 16. Predicted and Actual Mud Losses (Induced Fractures)

Table 4. Coefficients for Induced Fracture Formations Mud Losses (Eq. (5))

Hidden Layer Weight Matrix w1j								Hidden Layer Bias	Output Layer Weight Matrix	Output Layer Bias
j=1	j=2	j=3	j=4	j=5	j=6	j=7	j=8	b1	w2	b2
-0.0188	0.4299	0.5094	-0.1200	-0.4728	0.9857	-2.2359	-1.5879	-0.9569	-0.8401	-0.0934
-1.2088	0.1555	-0.0515	1.6637	-0.4362	0.3206	-1.9913	-0.5783	2.0514	-0.7485	
-1.4972	1.1058	-0.3683	-0.0899	-0.2342	-1.1991	1.8422	1.4864	0.2953	-0.6208	
0.3541	1.3957	0.9587	-2.0335	0.6458	-0.2935	0.9900	1.7517	-0.5481	0.0843	
1.0827	1.4165	4.9306	0.2243	-0.3265	0.6341	-0.3807	1.2828	-0.9051	0.4399	
-0.6141	-0.9271	0.7023	1.8216	-0.1393	-0.0490	-0.5954	-0.9000	-0.5400	0.7831	
-1.0147	-0.5148	-0.2306	1.0537	-2.5582	0.6457	-0.0649	-3.2413	-1.0419	-1.0123	
-0.5832	-0.2497	-2.6341	-0.6176	0.2716	0.5635	0.4701	-0.5470	1.2409	0.5409	
0.5697	0.3100	-0.3131	0.7437	-2.6053	0.4978	-0.1359	-3.0343	0.7000	1.0956	
1.7660	0.2721	-0.6647	4.0852	-0.5448	0.3596	1.3750	1.0492	2.4765	-0.4157	

4. CONCLUSION

Lost circulation is a complicated problem to be predicted with conventional statistical tools. As the drilling environment is getting more complicated nowadays, more advanced techniques such as artificial neural networks (ANNs) are required to predict mud loss. Huge data of many drilling parameters at the time of mud losses were collected worldwide for natural and induced fractures formations. The goal was to create two ANNs that can be used to predict lost circulation prior to drilling for natural and induced fractures formations. Based on this study, the following conclusions were made:

- Two ANNs were created to be used to predict lost circulation prior to drilling for natural and induced fractures formations worldwide. The networks showed the ability to predict lost circulations prior to drilling within an acceptable range of error.

- After testing a various number of training algorithms, the LM algorithm was chosen to be used since it had the lowest MSE and the highest R^2 which makes it a better predictive model.
- The created neural network can be used in reverse to limit mud loss in induced and natural fractures formations by setting the key drilling parameters and obtaining the target mud loss.
- This work overcame shortcoming in the previous studies about the estimation of mud loss prediction prior to drilling. This is the first study that provides a generalized model to estimate lost circulation prior to drilling that can be used worldwide.

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V. INTELLIGENT DATA–DRIVEN DECISION–MAKING FOR LOST CIRCULATION TREATMENTS: A MACHINE LEARNING APPROACH

ABSTRACT

Lost circulation is an expensive and critical problem in the drilling operations. Millions of dollars are spent every year to mitigate or stop this problem. In this work, data from over 3000 wells were collected from multiple sources. The data went through a processing step where all outliers are removed and decision rules were set up. Multiple machine learning methods (support vector machine, decision trees, logistic regression, artificial neural networks, and ensemble trees) were used to create a model that can predict the best lost circulation treatment based on the type of loss and reason of loss. 5-fold cross-validation was conducted to ensure no overfitting in the created model. After testing all the aforementioned machine learning methods, the results showed that the support vector machine had the highest accuracy among the other algorithms. Thus, it was selected to train the model. The created model went through quality control/quality assurance (QC/QA) to limit the results of the false negative rate. Two treatments were suggested to treat partial loss, four to treat severe loss, and seven for complete loss, based on the reason of loss. In addition, a formalized methodology to respond to lost circulation was provided to help the drilling personnel handling lost circulation in the field.

1. INTRODUCTION

Lost circulation is an expensive and critical problem at any point in the drilling operations (Xu et al., 2019; Al-Hmaeedi et al., 2017a; Al-Hmaeedi et al., 2017b; Al-

Hmaeedi et al., 2017c; Al-Hmaeedi et al., 2018a). Improper or untimely responses cause loss more drilling fluids, time, and extra cost. It can, also, bring on issues like formation damage caused by plugging of pore throats by mud particles, unsuccessful production tests, borehole instability, well control issues, substandard hydrocarbon production after well completion, and stuck pipe (Yang et al., 2015; Nasiri et al., 2017; Al-Hameedi et al., 2018b). A ton of money is spent every year due to this issue. An average of 10% to 20% of the price of drilling under extreme temperature, extreme pressure wells is spent on mud losses according to the United States Department of Energy in 2010 (Mansour et al., 2017). Drilling fluid materials are very costly. In 2011, companies spent $7.2 billion dollars. The global market for drilling fluids reveals an annual maximize of 10.13% which indicates that in 2018, the cost of drilling fluid materials will reach $12.31 billion dollars (Transparency Market Research, 2013). On average 10% of the total well costs are the cost of drilling mud. The drilling fluid can greatly affect the overall cost as well (Darley and Gray, 1988). Losing drilling fluids into the formation is called lost circulation events, are one of the greatest challenges to be stopped throughout the drilling process. The seriousness of the outcomes depends on loss severity. The outcome could range anywhere from losing drilling fluid to ending up in a blowout (Messenger, 1981). Lost circulation is a major drilling challenge facing the oil and gas industry. Large progress has been made to learn how to combat this issue. However, many items and instructions are available for countering this issue are biased towards announcement for a service company.

A major issue in fractured/cavernous formations, depleted reservoirs, and highly permeable formations is lost circulation (Nayberg and Petty, 1986). There are a couple of conditions required for lost circulation to happen downhole. First, is that the pressure in the wellbore needs to be greater than the pore pressure, and second, when losses happen, there needs to be a flow pathway (Osisanya, 2002). Induced fractures, cavernous formations (crevices and channels), unconsolidated or highly permeable formations, and natural fractures present in the rock formations (as well as not sealed faults) are all examples of subsurface pathways that lead to, or cause lost circulation. Lost circulation is grouped by the quantity of mud or fluid lost per hour (Basra Oil Company, 2007):

- Complete loss (no return)
- Severe loss (loss rate goes up to 15 m^3/hr)
- Partial loss (loss rate goes up 1-10 m^3/hr
- Seepage loss (loss up to 1 m^3/hr)

A good example of complete loss is shown in Figure. The picture in Figure was taken from a downhole camera video taken in offshore United Arab Emirates (UAE). The red arrows show a 3-in channel that caused a complete loss to occur. Treating drilling fluid with standard lost circulation material (LCM) as concentrated pills or background treatments is a practice to diminish seepage or partial losses. Different solutions that need a greater length of time for placement and preparation can be used for extreme or absolute losses such as cement (Messenger and McNiel, 1952; Morita et al., 1990; Fian et al., 2004), cross-linked cement (Mata and Veiga, 2004), dense sand slurries (Saasen et al., 2011; Saasen et al., 2004), chemically initiated cross-linked pills (Caughron et al., 2002; Bruton et al., 2001), gunk squeezes (Bruton et al., 2001; Collins et al., 2010), deformable-viscous-cohesive systems (Wang et al., 2008; Wang et al., 2005; Whitfill and Wang, 2005), and nanocomposite gel (Lecolier et al., 2005).

Figure 1. Downhole Camera Shows a 3-in Channel (Bijjani et al., 2018)

Deciding which lost treatment to use is based on different factors such as type of loss zone, drilling fluid characteristics, the amount of lost circulation, and drilling operation parameters (Alkinani et al., 2019a; Alkinani et al., 2018a). Discovering an analytical solution to this problem is difficult because of the complexity and nonlinear behavior. Due to these complications, machine learning methodologies is an appealing replacement to model this elaborate physical procedure. Computational intelligence methods inquire from past experiences with sets of different learning data can help the decision-making process.

The aim of this work is to use various pattern recognition algorithms (support vector machine, decision trees, logistic regression, artificial neural networks, and ensemble trees) to choose the best lost circulation treatment based on the type of loss and reason for lost circulation using historical data from 3000 wells collected from many sources. In addition, this work will serve as a practical guideline for lost circulation treatment strategies based on data-driven models.

2. MACHINE LEARNING

An easy way to solve a problem is by having a simple and well-defined equation. This is very difficult in real life with so many problems. For example, it is easy for a person to differentiate family members by their looks, but there is no simple equation that can do this (Russell and Norvig, 2010). Artificial intelligence is focused on the ability of computes/machines to act like humans when making decisions. Machine learning is a subset of artificial intelligence. There are many algorithms used to implement machine learning. Examples include, support vector machine, artificial neural network (ANN), nearest neighbor, decision tree, regression, ensemble learning, and Naive Bayes (Russell and Norvig, 2010; Freeman and Chio, 2018). Certain machine learning algorithms have a better learning accuracy, but other factors such as the speed and the difficulty of interpreting results are all critical for considering which machine learning algorithm to use. The following sub-sections will briefly explain the machine learning methods used in this study.

2.1. SUPPORT VECTOR MACHINE

Support vector machine (SVM) represents the state-of-the-art in machine learning due to its, ease of use and performance (Haykin, 2009). The classification in SVM is performed by creating a decision boundary that has the largest distance from the training points. Data that are not linearly separable can be classified in SVM by creating a higher-dimensional hyperspace (Cortes and Vapnik, 1995; Winston, 2010). Wang and Tao (2012) used SVM and ANN as well as analytical models to predict the drilling fluid density in high temperature and pressure environment. The findings showed that the SVM did better than the other algorithms. SVM was utilized for lithology classification and permeability estimation by Al-Anazi and Gates (2010). They used linear discriminant analysis and probabilistic neural network as well as general regression neural network alongside SVM. The results showed that SVM outperformed other methods.

2.2. DECISION TREE

DT is a method used for classification by creating tree structures for the training data. The tree structure can consist of a few nodes for a simple tree, to hundreds for a complex tree. DT was utilized by Perez et al. (2005) to estimate the hydraulic flow units and lithofacies from well logs. Perez et al. (2005) showed that the more nodes the tree has, the better the estimation. However, too many nodes can lead to overfitting and complex interpretation for the influence of the inputs on the outputs. The benefit of DT is that it can present a model that can easily show the influence of the inputs on the outputs. DT can be combined with ANN to have the benefit of ANN and DT by forming a neural decision tree. Alkinani et al. (2019d) provided a summary of the applications of DT in the oil and gas industry.

2.3. ENSEMBLE LEARNING (ESL)

ESL has proven to be successful in image classification, face recognition, and medical image analysis. This is due to its ability to combine multiple classifiers which will lead to mitigating the weaknesses in those classifiers (Mao et al., 2019). There are many algorithms used for ESL, including but not limited to, boosted tree, bagged tree, and random undersampling boosting (RUSBoost). More information about these algorithms and other ESL algorithms can be found in MATLAB (2019). Anifowose et al. (2017) used ESL in reservoir characterization modeling. Anifowose et al. (2017) showed that the incorrect decision from a classifier is a binomial distribution. Thus, Anifowose et al. (2017) showed that the uncorrelated errors from the classification can be minimized by averaging.

2.4. LOGISTIC REGRESSION

A very reliable classification technique is logistic regression. A commonly used instrument by most statisticians. It has an S-shaped distribution which is seen in many areas such as banking, marketing, demographics, psychology, and epidemiology. Because of its qualities, the technique is being used in supervised classification problems (Tufféry, 2011). It is used to show categorical dependent variables that acquire discrete outcomes. Independent variables can be quantitative or qualitative. It can have qualitative variables with more than two responses. When the response variable has 2, ≥3 nominal, ≥3 ordered categories, it can be categorized as ordinal logistic regression, multinomial and binary. Logistic regression was used for EOR applications, drilling, and rock type identification (Ahdaheri et al., 2017; Hegde et al., 2019; Klyuchnikov et al., 2019).

2.5. ARTIFICIAL NEURAL NETWORKS (ANNS)

An artificial neural network is “an information-processing system that has certain performance characteristics in common with biological neural network” (Mohaghegh, 2000). The idea of neural networks is to mimic the biological neurons. An artificial neural network consists of three layers; one input layer where are the inputs are fed, one or multiple hidden layers where the information is processed and features are extracted from the data, and one output layer where the results are given. ANNs can be very simple consist of one hidden layer, or very complex with many hidden layers. More hidden layers require more computational power. Alkinani et al. (2019b) used ANN to predict lost circulation prior to drilling. Alkinani et al. (2019c) provided a summary of ANN applications in the oil and gas industry.

3. DATA AND METHODS

In this section, the process of data collection and processing, as well as the SVM algorithm, will be explained in details since it is the algorithm that was selected among the others. The other algorithms tested in this study (decision tree, ensemble learning, ANN, and logistic regression) will not be explained in this paper since that is beyond the scope of the paper.

3.1. DATA COLLECTION

The data used in this study was collected from many resources including daily drilling report, mud logging reports, final drilling report, etc. In addition, data from the literature were collected. More than 3000 wells were used in this study. Rod dots in Figure show the location where the data were collected. Lost circulation treatment data used in this study are shown in the Appendix. It is worth mentioning that the data used for this study are up to data (up to the beginning of 2019).

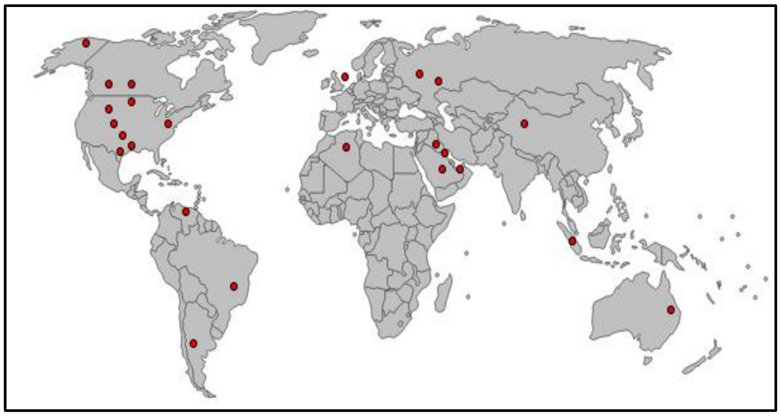

Figure 2. Data Collection Locations

3.2. DATA PROCESSING, ALGORITHMS TESTING, AND INPUT DATA SELECTION

The data were cleaned from any outliers using box plots such that any data point falls outside the whiskers of the box plot was eliminated (Alkinani et al., 2018b). Once the data were cleaned, the data were classified based on the type of loss as partial, severe, and complete loss. In addition, the data were classified based on the reason for lost circulation as induced fractures and natural fractures as well as vugs and caves.

To set up the data for the classification algorithms, any lost circulation treatment that was utilized less than 50 times was ignored. In addition, the classification problem was set up to predict success or fail based on the type of loss and reason of lost circulation. The probability cut off for success was set to be >=75%. Thus, when the model predicts success, it means the probability is >=75%. Otherwise, the treatment is considered a failed treatment. The inputs for the models were selected based on the trial and error to meet two goals, the first one is to have the highest accuracy, and the second one is to minimize the number of predictors. Table 1 summarizes the predictors (inputs) and the response (output). The algorithms tested for this study are summarized in Table 2.

Table 1. Predictors and Response

Predictors				Response
Reason	**Treatment Number (NO)**	**Type of Loss**	**Well Type**	**Results**
Vugs and Caves	1 to 46	Partial	Vertical	Fail
Natural Fractures	/	Severe	Deviated	Success
Induced Fractures	/	Complete	/	/

Table 2. Summary of the Classifiers Used in This Study (MATLAB, 2019)

Classifier	Classifier Type	Prediction Speed	Memory Usage
Tree	Fine	Fast	Small
	Medium		
	Coarse		
SVM	Linear	Binary: Fast Multiclass: Medium	Medium
	Quadratic	Binary: Fast Multiclass: Slow	Binary: Medium Multiclass: Large
	Cubic		
	Fine Gaussian		
	Medium Gaussian		
	Coarse Gaussian		
ANN		Vary depends on the training algorithm	Vary depends on the training algorithm
Logistic Regression (LR)		Fast	Medium
Ensemble	Boosted Tree	Fast	Low
	Bagged Tree	Medium	High
	RUSBoosted Tree	Fast	Low

The accuracy (ACC) of each classifier was measured by the following Eq. (1) (Pomares et al., 2018):

$$ACC = 100 \times \frac{TP+TN}{TP+FP+TN+FN} \qquad \text{Eq.1}$$

Where *TP* is the true positive, *TN* is the true negative, *FP* is the false negative, and *FN* is the false negative.

3.3. SVM ALGORITHM

Support vector machine (SVM) is the state-of-the-art machine learning. SVM performs classification by creating a decision boundary with the largest distance to the data point (Winston, 2010). Figure shows the theory of the SVM algorithm. Assume there are two classes " $\times$ " and " $-$ ". The goal is to maximize the margin between those two classes.

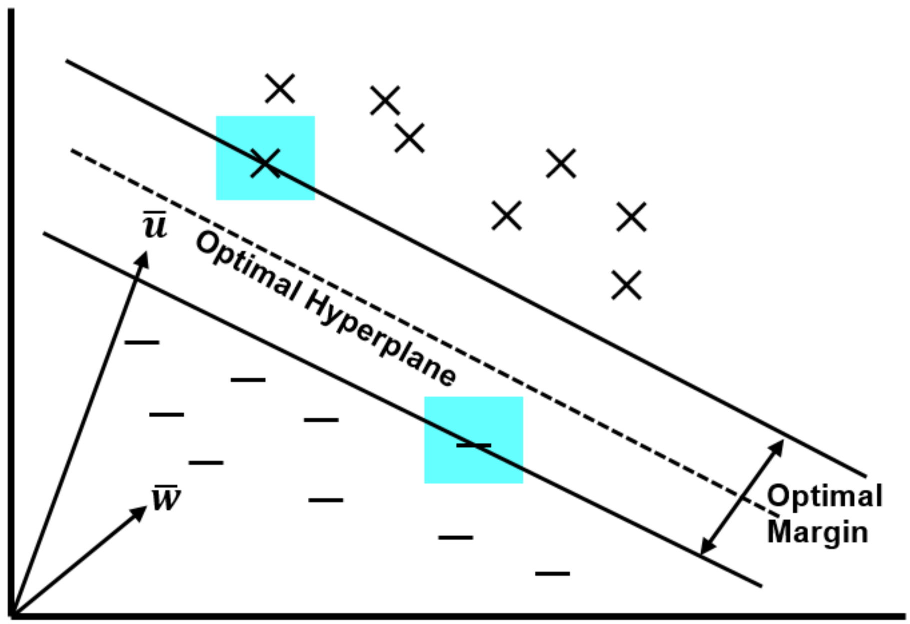

Figure 3. SVM Algorithm

Assume w is a vector perpendicular to the optimal hyperplane and u is an unknown vector. Then u classified as " $\times$ " if (Cortes and Vapnik, 1995; Winston, 2010):

$f(u) = w \cdot u + b > 0$ Eq.2

Then, constrain for all " $\times$ " samples vectors is:

$f(x_\times) = w \cdot x_\times + b \geq 1$ Eq.3

And constrain for all " $-$ " samples vectors is:

$f(x_-) = w \cdot x_- + b \leq -1$ Eq.4

Subtracting Eq. (3) and Eq. (4) will give:

$w \cdot (x_\times - x_-) = 2$ Eq.5

Dividing by the length of the vector w will give the distance between the decision lines:

$$\frac{w}{\|w\|} \cdot (x_{\times} - x_{-}) = \frac{2}{\|w\|} \qquad \text{Eq.6}$$

To maximize the optimal margin (distance between the lines), Eq. (6) has to be maximized (length of vector w should be minimized), while still honoring constrains (Eq. (3) and Eq. (4)). A possible solution is to use Lagrange's method, to maximize the optimal margin, the following should be minimized:

$$\frac{1}{2}\|w\|^2 \qquad \text{Eq.7}$$

The transformation from Eq. (6) into Eq. (7) with ½ and squaring, is for mathematical convenience. The constrains in Eq. (3) and Eq. (4) can be written as:

$$y_i(w \cdot x_i + b) \geq 1 \qquad \text{Eq.8}$$

Where y_i is 1 for " $\times$ " class, and -1 for " $-$ " class. The Lagrange's multipliers can be written as:

$$L = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i (y_i(x_i \cdot w + b) - 1) \qquad \text{Eq.9}$$

Where α_i is the multipliers for the constrains. The derivative of Eq. (9) with respect to w will give:

Table 3. Values of γ for Radial Basis Kernel (MATLAB, 2019)

Radial Basis Kernel	**γ**
Fine Gaussian SVM	sqrt(P)/4, where P is the number of predictors
Medium Gaussian SVM	sqrt(P)
Coarse Gaussian SVM	sqrt(P)*4

3.4. CROSS-VALIDATION

Cross-validation is important to ensure the robustness of the created model. The problem associated with dividing the data to training and testing is that some representative samples may be missing during the training process. Cross-validation ensures a better representation of the data in the training set. In this study, 5-fold cross-validation was utilized to ensure a robust model. The idea of 5-fold cross-validation is that the data will be randomly divided into 5 equal-sized sets (5-folds). Then, in the training process, one of the pairs will be used for testing (the other 4 will be used for training). This is done five times, each time leaving another fold out of the training and used for testing. Finally, the average of those iterations will be taken to calculate the accuracy of the model (Alpaydin, 2014). This will ensure that every data point is represented in the training process. Furthermore, cross-validation will ensure no overfitting will be presented in the model and generalization for new data can be achieved.

4. RESULTS

Multiple machine learning classification algorithms were tested and the algorithm with the highest accuracy (ACC) was selected. Figure shows the tested algorithms with their accuracy. Quadratic SVM showed the best performance among the other algorithms with an accuracy of 74%. Thus, the quadratic SVM was selected to train the model. All the results from the other algorithms will not be shown in this paper.

Figure (a) and (b) show a scatter plot of the classification of the treatments based on reason for loss and type of loss, respectively. Orange points indicate successful results and blue points show failed treatments. In the same vein, dots indicate successful classification and crosses show incorrect classification. Figure can be utilized to select the best treatments based on the type of loss and reason for loss. For example, treatment 23 was correctly classified as a successful treatment used to treat naturally fractured formations (Figurea). In the same vein, treatment 23 was correctly classified as a successful treatment used to treat partial loss (Figureb). Thus, it can be concluded that treatment 23 can be used to treat partial loss in naturally fractured formations.

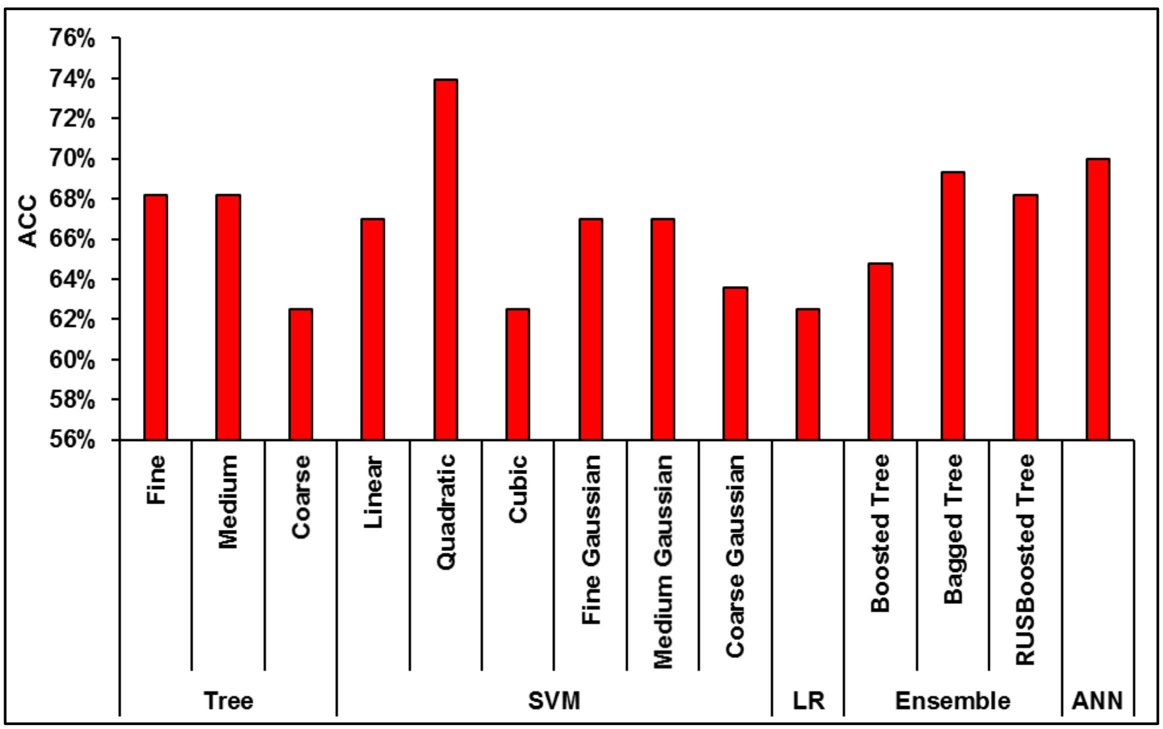

Figure 4. Comparison between Different Classification Methods

Figure shows the confusion matrix for the quadratic SVM. Confusion matrix green boxes show successful classification while red boxes show incorrect classification. The model shows a 79% successful classification rate for the fail class, and 66% successful rate for the success class. Figure also shows the true positive rate and the false negative rate.

Figure 7 and Figure 8 show the receiver operating characteristics (ROC) curve for the positive class being the success class and fail class being a positive class, respectively. A perfect ROC curve will have an area under the curve to be 1. The area under the ROC curve of this model is 0.77 which is considered good.

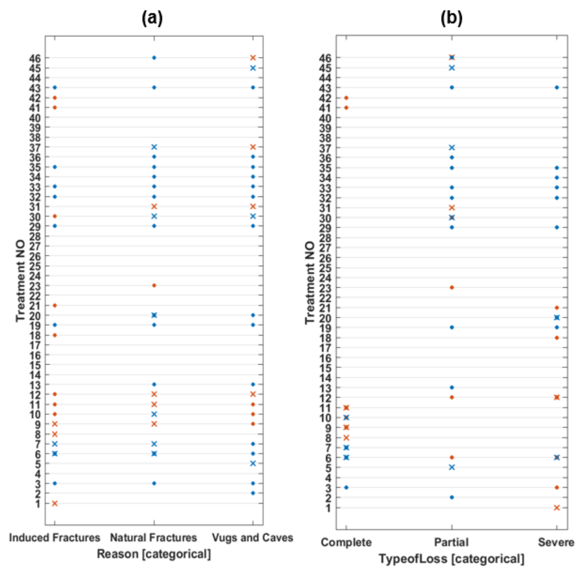

Figure 5. Quadratic SVM Training Scatter Plot Based on (a) Reason of Loss and (b) Type of Loss

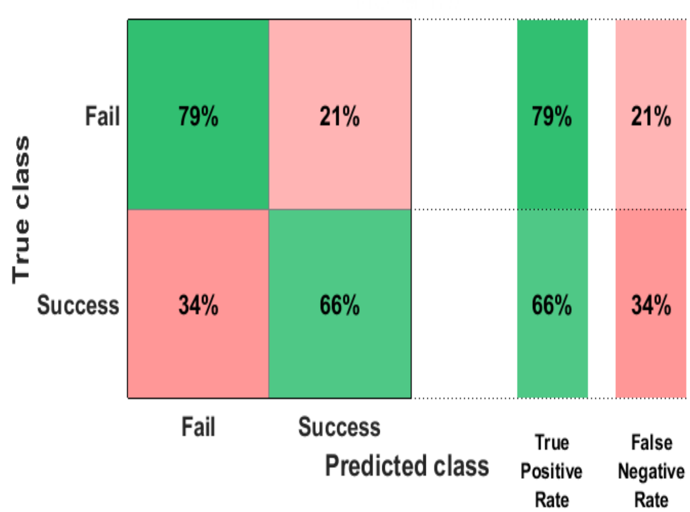

Figure 6. Confusion Matrix

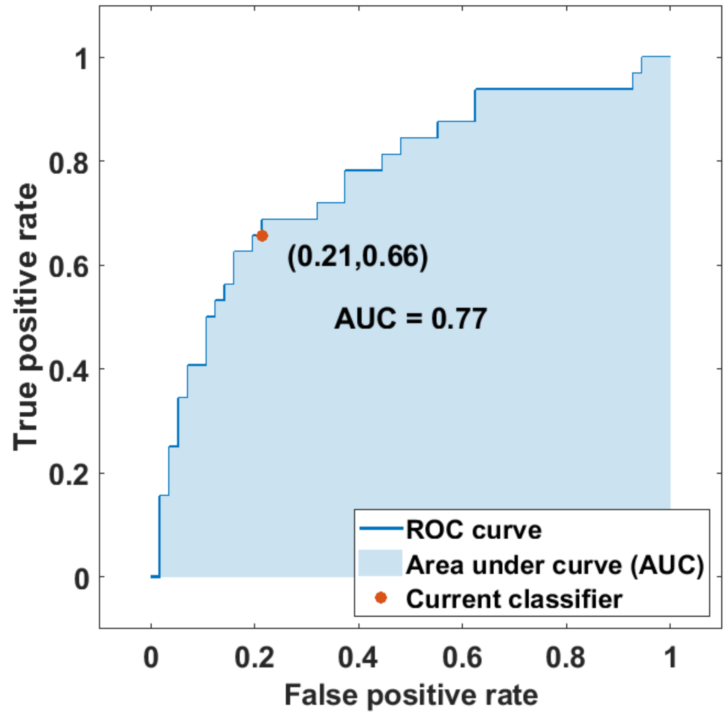

Figure 7. ROC Curve (Positive Class =Success Class)

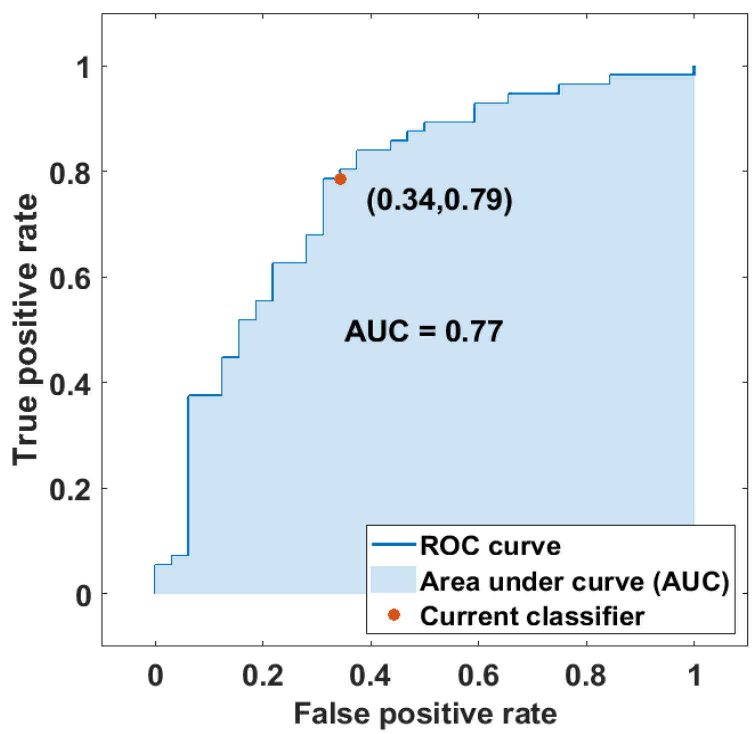

Figure 8. ROC Curve (Positive Class =Fail Class)

5. DISCUSSION

Quadratic SVM gave the best accuracy (74%) among the other models. The closest model to the quadratic SVM was the ANN with an accuracy of 70%. However, the quadratic SVM was selected since it gave the highest accuracy. The model was cross-validated using 5-fold cross-validation to avoid overfitting and poor generalization. Thus, the model is reliable and can be used for new data.

An argument can be made about the false negative rate which is 34% for success class and 21% for fail class. However, quality control/ quality assurance (QC/QA) in the process of selecting the treatments that will prevent or minimize this false negative rate. This is done using the scatter plot in Figure. The way the treatments selection work is by looking at the correctly classified treatments (shown in dots) and recommend these treatments based on the type of loss and reason for loss. On the other hand, the incorrectly classified treatments (shown in crosses) will be avoided since the model was unable to classify them correctly. By doing this, the false negative rate can be minimized. Thus, QC/QA is very important in the process of selecting the best lost circulation treatments and avoiding the false negative rate. Using this criterion, Figure 9 was created that shows the results of the model after applying the QC/QA process.

For severe loss due to vugs and caves, treatment 3 (Blend of Fibers in Cement) resulted in success. For induced fractures, there were three treatments showed successful results; treatment 12 (H.V Mud + Blend of LCM (High Concentration)), treatment 18 (High Concentration Acid Soluble LCM), and treatment 21 (High Fluid Loss Squeeze Resilient Graphitic Carbon + Blend of (Granules, Flakes and Fibers) (High Concentration)). All those treatments have proven successful results and can be used to treat severe mud loss due to induced fractures. It is very hard to obtain cost data from the companies and even if it is available, it will be limited. The data used for this study had a total average cost for treatment 12 that was applied in Iraq, close to $13,000. The other two treatments costs are not available (Alkinani et al., 2018c). However, it will not be significant which treatment to choose since the cost will be close. It is recommended to use any of them and if one fails for some reason, then the other two treatment should be given priority in the application after the first one fails.

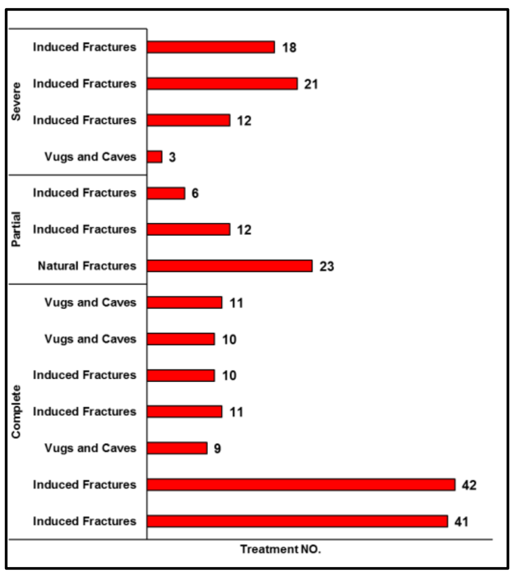

Figure 9. Treatments Selection

In the case of complete loss, three treatments resulted in success for complete loss due to vugs and caves; treatment 9 (Diesel Oil Bentonite (DOB) Plug), treatment 10 (Diesel Oil Bentonite Cement (DOBC) Plug), and treatment 11 (Gilsonite Cement). Treatments 9 and 10 are difficult to be applied and they need a specialized crew to conduct the treatments. Cost-wise, the cost difference is not significant comparing to the entire drilling operations. For instance, treatment 9 total average cost is $49,500, and treatment 10 total average cost is $53,000, while treatment 11 total average cost is $48,000. A couple of thousand dollars is not significant in comparison with the total cost of the drilling operation (Alkinani et al., 2018c). On the other hand, the results showed complete loss due to induced fractures has four successful treatments; treatment 10 (Diesel Oil Bentonite Cement (DOBC) Plug), treatment number 11 (Gilsonite Cement), treatment number 41 (Right Angle Set Polymers Cement), and treatment number 42 (Soft and Hard Plugs Special Fibers Cement). Once again, the cost difference is not significant and all four those treatments have shown successful results. Table 4 summarizes the treatments recommended for each type of loss.

Table 4. Summary of the Recommended Treatments

Type of Loss	Reason of Loss	Treatment
Partial	Induced Fractures	H.V Mud + Blend of LCM (High Concentration)
	Natural Fractures	High Fluid Loss Squeeze Resilient Graphitic Carbon + Blend of (Granules, Flakes and Fibers) (Low Concentration)
Severe	Vugs and caves	Blend of Fibers in Cement
	Induced Fractures	H.V Mud + Blend of LCM (High Concentration)
		High Concentration Acid Soluble LCM
		High Fluid Loss Squeeze Resilient Graphitic Carbon + Blend of (Granules, Flakes and Fibers) (High Concentration)
Complete	Vugs and caves	Diesel Oil Bentonite (DOB) Plug
		Diesel Oil Bentonite Cement (DOBC) Plug
		Gilsonite Cement
	Induced Fractures	Diesel Oil Bentonite Cement (DOBC) Plug
		Gilsonite Cement
		Right Angle Set Polymers Cement
		Soft and Hard Plugs Special Fibers Cement

6. CONCLUSION

Lost circulation is a difficult problem that has been encountering the drilling operation. Choosing the best treatment for lost circulation is not a straightforward process and requires a high level of knowledge and experience. Large data set of 3000 wells was collected from many sources. Machine learning was implemented to assist in the decision-making process. Based on this study, the following conclusions were made:

1. After testing multiple machine learning methods, quadratic SVM was selected to train the model since it gave the highest accuracy. SVM has a history of great performance in pattern recognition problems. 5-fold cross-validation was used to avoid overfitting and poor generalization.
2. QC/QA was implemented in the process of selecting the lost circulation treatments to limit the error due to incorrect classification. This ensures more accuracy in selecting the best treatment for lost circulation.
3. The main decision-making criteria were based on whether the treatment will be successful or not. The cost is a pivotal parameter in the decision-making process. However, a couple of thousand dollars is not significant compared to the cost of the entire drilling operations to choose between the treatments.
4. Two treatments recommended to stop partial loss, four for severe loss, and seven for complete loss, depending on the reason of loss.
5. With the large historical data available in the oil and gas industry, machine learning can be utilized to make better future decisions that will optimize the drilling operations and save time and money.

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SECTION

2. CONCLUSION

Based on this study, the following conclusions were made:

- A detailed summary of the different DTA and EMV, ANNs applications from the literature was provided in this work.
- EMV and DTA were utilized to select the best lost circulation treatments based on the type of loss for three formations; Dammam, Hartha, and Shuaiba.
- Two supervised ANNs were created to be used to predict lost circulation prior to drilling for natural and induced fractured formations worldwide. The networks showed the ability to predict lost circulations prior to drilling within an acceptable range of error.
- After testing a various number of training algorithms to train the ANN, the LM algorithm was chosen to be used since it had the lowest MSE and the highest R^2 which makes it a better predictive model.
- The created neural networks can be used in reverse to limit mud loss in induced and natural fractured formations by setting the key drilling parameters and obtaining the target mud loss.
- This work overcomes the shortcoming in the previous studies about mud loss prediction prior to drilling. This is the first study that provides a generalized model to estimate lost circulation prior to drilling that can be used worldwide.
- After testing multiple machine learning methods to help to select the best classifier, quadratic SVM was selected to train the model since it gave the highest accuracy.

SVM has a history of great performance in pattern recognition problems. 5-fold cross-validation was used to avoid overfitting and poor generalization.

- QC/QA was implemented in the process of selecting the lost circulation treatments to limit the error due to incorrect classification. This ensures more accuracy in selecting the best treatment for lost circulation.
- The main decision-making criteria were based on whether the treatment will be successful or not. The cost is a pivotal parameter in the decision-making process. However, a couple of thousand dollars is not significant compared to the cost of the entire drilling operations to choose between the treatments.
- Two treatments recommended to stop partial loss, four for severe loss, and seven for complete loss, depending on the reason of loss.
- With the large historical data available in the oil and gas industry, machine learning can be utilized to make better future decisions that will optimize the drilling operations and save time and money.

VITA

Husam Hasan Alkinani was born in November 1992, in Baghdad, Iraq. He was in the top of his high school graduates. Due to his excellent performance in high school, he received a fully-funded scholarship from the prime minister office of Iraq/Higher Committee of Education Development in Iraq (HCED) to study engineering in the United States. He started as a freshman at Missouri University of Science and Technology in fall 2012. He received his Bachelor of Science in Petroleum Engineering and a minor in Geology in December 2016 with 3.9/4 GPA. Then, he started with master's degree at Missouri University of Science and Technology directly after he finished his bachelor's degree. He received his Master of Science in Petroleum Engineering in December 2017. Afterward, he directly started his PhD program and received the Doctor of Philosophy in Petroleum Engineering from Missouri University of Science and Technology in December 2019

He researched a variety of subjects such as data analytics, machine learning, artificial intelligence, drilling and completion fluids, drilling economics, wellbore stability, wellbore integrity, and hydraulic fracturing. He published 50+ scholarly publications during his study at Missouri University of Science and Technology. He was part of a team who was able to obtain a huge data set of more than 3000 wells drilled in Iraq with official approval to use this data for research.