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Artificial Neural Network Model for Prediction of Drilling Rate of Penetration and Optimization of Parameters

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According to field data, there are several methods to reduce the drilling cost of new wells. One of these methods is the optimization of drilling parameters to obtain the maximum available rate of penetration (ROP). There are too many parameters affecting on ROP like hole cleaning (including drillstring rotation speed (*N*), mud rheology, weight on bit (WOB) and floundering phenomena), bit tooth wear, formation hardness (including depth and type of formation), differential pressure (including mud weight) and etc. Therefore, developing a logical relationship among them to assist in proper ROP selection is extremely necessary and complicated though. In such a case, Artificial Neural Networks (ANNs) is proven to be helpful in recognizing complex connections between these variables. In literature, there were various applicable models to predict ROP such as Bourgoyne and Young's model, Bingham model and the modified Warren model. It is desired to calculate and predict the proper model of ROP by using the above models and then verify the validity of each by comparing with the field data. To optimize the drilling parameters, it is required that an appropriate ROP model to be selected until the acceptable results are obtained. An optimization program will optimize the drilling parameters which can be used in future works and also leads us to more accurate time estimation. The present study is optimizing the drilling parameters, predicting the proper penetration rate, estimating the drilling time of the well and eventually reducing the drilling cost for future wells.

Keywords
Penetration rate, Drilling optimization, Artificial neural network, ROP correlation

1. Introduction

The rate of penetration (ROP) achieved with the bit has a direct and obvious effect on the cost per foot drilled. There are some variables, which affect the rate of penetration. Lots of experimental work has been done to study the effect of these variables on drilling rate. These factors that affect the rate of penetration are: bit type, weight on bit (WOB), rotary speed (*N*), drilling fluid properties, bit hydraulics and formation properties[1)].

The relationship between ROP and *N* is shown in **Figs. 1** and **2**. In the **Fig. 1**, it is observed that the increases in rotary speed will also enhance ROP (line between points a and b). This improvement continues till hole cleaning problems occurs (line between points b and c). Point "b" is the critical point for the rotary speed. In soft formations, ROP usually increases with increasing *N* but in hard formations it is a reverse relation. This is the primary reason that high rotary speeds (about 150-250 rpm) are usually used in soft formation and low rotary speeds (about 40-75 rpm) are used in hard formations[2)]. In the **Fig. 2**, it is observed that ROP is directly proportional to WOB till a critical point "c." The suitable drilling trend ends in point "c" in the **Fig. 2**. The rate of ROP improvement increase from point "a" to "b." The ROP increses from point "b"

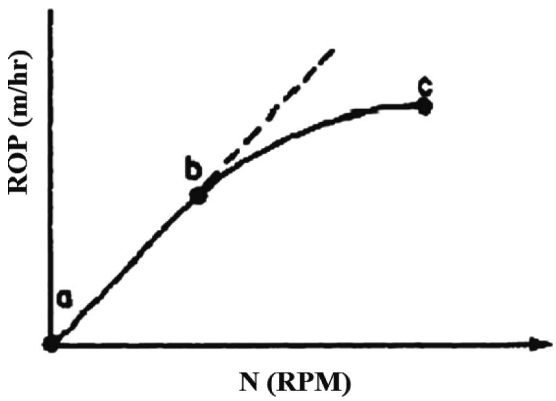

Fig. 1 The Relation of ROP with *N*

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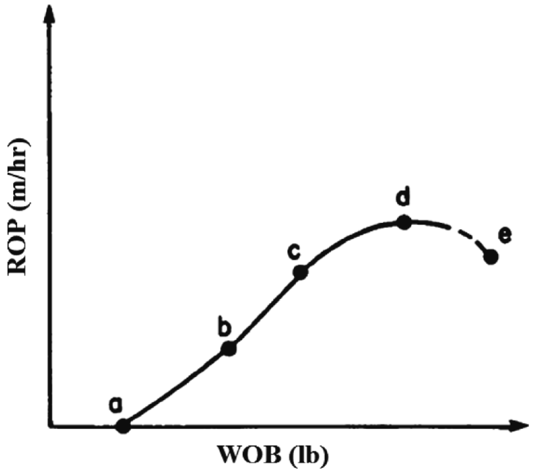

Fig. 2 The Relation of ROP with WOB

to "c" with a constant rate. The rate of increase drops from point "c" to "d." Although the maximum ROP is obtained in point "d," drilling with this weight on bit is not economical. The ROP decreases from point "d" to "e" and the bit fails in point "e."

2. ROP Models

2. 1. Overview of ROP Correlation Models

Field history itself can be a good clue to choose some of the important parameters to improve penetration rate, like type of bit, WOB and etc. The approach is to separate field into some sections due to geological likeness; then analyze for each section independently by their performance.

Many mathematical models have been proposed in an effort to describe the relationship of several drilling variables to penetration rate. Most of them depend on the combination of several controllable variables and one combined formation property. Controllable variables are rotary speed, weight on bit, mud weight, pump flow rate, and pump pressure. The models summarize below[2,3].

2. 2. Bingham Model

Bingham model is a simple model which is a modification of Maurer model (an experimental model which is applicable for low value of WOB and N). This model neglects depth of drilling so the answer often has less reliability[4].

$$R = K\left(\frac{W}{d_{\mathrm{b}}}\right)^{a_5} N^{e} \tag{1}$$

2. 3. Bourgoyne and Young's Model

Bourgoyne and Young's model (Bourgoyne *et al.*, 1991) introduces penetration rate as a function of several variables such as sediments compaction and strength, pore pressure, WOB, N, bit hydraulics, teeth wear and etc.[4,6]. The model mathematically is expressed by:

$$R = f_1 \times f_2 \times f_3 \times f_4 \times f_5 \times f_6 \times f_7 \times f_8 \tag{2}$$

which:

$$f_1 = e^{a_1} \tag{3}$$

$$f_2 = e^{a_2(10000-\mathrm{TVD})} \tag{4}$$

$$f_3 = e^{a_3 D^{0.69}(\mathrm{MW}-67.41)} \tag{5}$$

$$f_4 = e^{a_4 \mathrm{TVD}(\mathrm{EMW}_{\mathrm{pore}}-\mathrm{ECD})} \tag{6}$$

$$f_5 = \left[\frac{\left(\dfrac{w}{d_{\mathrm{b}}}\right)-\left(\dfrac{w}{d_{\mathrm{b}}}\right)_t}{4-\left(\dfrac{w}{d_{\mathrm{b}}}\right)_t}\right]^{a_5} \tag{7}$$

$$f_6 = \left(\frac{N}{60}\right)^{a_6} \tag{8}$$

$$f_7 = e^{-a_7 h} \tag{9}$$

$$f_8 = \left(\frac{F_{\mathrm{j}}}{1000}\right)^{a_8} \tag{10}$$

$$R = e^{a_1} e^{a_2(10000-\mathrm{TVD})} e^{a_3 D^{0.69}(\mathrm{MW}-67.41)} \left(\frac{w}{d_{\mathrm{b}}}\right)^{a_5} \left(\frac{N}{60}\right)^{a_6} e^{-a_7 h} \tag{11}$$

2. 4. Warren Model

Warren presented the development of a perfect model for soft formation bits under conditions where cutting removal does not impede ROP. This model relates ROP to WOB, N, rock strength and bit size using dimensional analysis and generalized response curves. It is based on the tests that were designed to provide the basic information about the interrelation between bit and rock, and it accounts for the effect of cutting generation, cutting removal, the "chip hold down effect," and bit wear on penetration rate[8,11].

The perfect-cleaning model (Eq. (12)) is reviewed as a starting point for development of an imperfect-cleaning model:

$$R = \left(\frac{aS^2 d_{\mathrm{b}}^{\,3}}{NW^2} + \frac{c}{Nd_{\mathrm{b}}}\right)^{-1} \tag{12}$$

Dimensional analysis was used to isolate a group of variables consisting of the modified impact force and the mud properties to incorporate into Eq. (12) to account for the cutting removal. These factors were combined with Eq. (12) until an equation was obtained that matched the experimental data[3]. The resultant expression for ROP is:

$$R = d\left(\frac{aS^2 d_{\mathrm{b}}^{\,3}}{NW^2} + \frac{b}{Nd_{\mathrm{b}}} + \frac{cd_{\mathrm{b}}\gamma_{\mathrm{f}}\mu}{F_{\mathrm{jm}}}\right)^{-1} \tag{13}$$

2. 5. Artificial Neural Networks (ANN)

Neural networks are massively parallel-distributed processing units known as neurons. These simple neurons have certain performance characteristics in common with biological neurons. Neural networks

Table 1 Sample of Input Values for Correlations and Neural Network

Depth [m]	WOB [klb]	N [RPM]	MW [pcf]	ROP [m h^{-1}]	Torque [amp]	Pump pressure [psi]	Flow in [g m^{-1}]
3300	55	160	70	5.84	200	850	6500

are capable of learning in order to recognize, classify, and generalize different systems. They are data-driven models which learn by examples presented for them. A typical neural network consists of three layers of neurons called input, hidden and output layers. A neuron takes input values, which are multiplied by connection weights, from the proceeding neurons, adds them up with a value called bias, and feeds them to its transfer function to produce results. The majority of ANNs' solutions have been trained with supervision. In this mode, the output of ANN is compared to the desired output (called target). Weights and biases, which are usually randomly set at the start, are then adjusted by learning function in a manner that the next iteration would result a closer match between the desired and network's output. The learning function works to minimize the current errors of all processing elements. During training process, modifying the weights and biases continues by applying the same training data set until an acceptable network accuracy reaches.

Optimization program will optimize drilling parameters which will be used in future works and also leads us to proper time estimation[5),7),9),10)].

3. Approach of ANN Model

According to the literature, all dominant parameters in ROP estimation have been determined and used in model development. In the present study and modelling process, the proper parameters are selected based on the desired ROP to be achieved. In this model, bit diameter, depth, WOB, RPM and mud weight have been fed as the inputs for ANN while ROP is set to be the output.

In the x-layered network the first layer is the input parameters and the last layer is the target. The other layer/layers are the coefficients for providing the relationship between first and last layer. In developing the networks among 2-layered, 3-layered, and 4-layered networks, the 3-layered had been showed the lowest prediction error. Also, different structures in 3-layered have been tested. Finally, a 3-layered network has been selected which has the best correlation coefficient in testing the models. Back-Propagation algorithm with Levenberg-Marquardt training function has been used for training. So the data from fifteen different offset wells have been used in training and validation of the networks.

About 1810 data-point is used to train this work. Mud weight window and ranges of parameters has been adjusted for optimization. The mud weight should be in defined area to avoid drilling problems, such as mud loss. **Table 1** shows the sample of optimization result. The hole is divided into 100-m parts and adjust result of N and W into 5 steps also MW results into 1 step rounding. As it mentioned, depth and bit size is our constant used parameters like other parameters could be changed.

A brief approach explanation is to produce a model of ROP and use it in optimization to find proper parameters with step of 5 in parameters.

As it shown in **Table 2**, the input ranges of parameters values were used in this field of case study. The limmitation of these parameters is due to application in well. The table of mud window of this field exists in **Table 3**. Mud weight has limit range; not obeying this range leads us drilling problems as lost circulation, well flow, and tight hole.

4. Results and Discussions of Models

Figures 1 and **2** show the effect of WOB and N on ROP. These figures show that high value of (NW) could lead to low penetration rate. All models of ROP are provided by a fitting software. Constants of each method are presented in **Table 4**.

Figure 3 is the result of Bingham model and shows the prediction error; as we see, this model fit the data poorly with high error and high ROP deviation values. Because of lacking the term of depth, Bingham model had high error in this hole.

Figure 4 shows sketched data for Bourgoyne model applied in this well; as it shows, this model fit the data well with lower error and lower ROP deviation values. So it seems that it is a reliable model with respect to other existing models.

Figure 5 shows predicted and real ROP existed in this field by Warren model; as it is shown this model predict a limit range of ROP value and did not show a good result. The predicted values are very close and this is not a reliable model in this field.

Figure 6 shows the error of the ANN model, and as it is expected it shows good results. This model has been used for the optimization of drilling parameters. **Table 5** shows the final result of optimization using the ANN method along the well for the field of study. Low RPM leads in low ROP and high RPM leads in not efficient hole cleaning, stuck pipe drillstring vibration and other drilling problems. Weight on bit if exerts

Table 2 Range of Parameters Used in Optimization

Depth [m]	Bit size [inch]	N_{min} [RPM]	N_{max} [RPM]	WOB_{min} [klb]	WOB_{max} [klb]
0	17.5	45	170	15	50
100	17.5	45	170	15	50
200	17.5	45	170	15	50
300	17.5	45	170	15	50
400	17.5	45	170	15	50
500	17.5	45	170	15	50
600	17.5	45	170	15	50
700	17.5	45	170	15	50
800	17.5	45	170	15	50
900	17.5	45	170	15	50
1000	17.5	45	170	15	50
1100	17.5	45	170	15	50
1200	17.5	45	170	15	50
1300	17.5	45	170	15	50
1400	17.5	45	170	15	50
1500	17.5	45	170	15	50
1600	17.5	45	170	15	50
1700	17.5	45	170	15	50
1800	17.5	45	170	15	50
1900	17.5	45	170	15	50
2000	17.5	45	170	15	50
2100	17.5	45	170	15	50
2200	12.25	35	160	25	60
2300	12.25	35	160	25	60
2400	12.25	35	160	25	60
2500	12.25	35	160	25	60
2600	12.25	35	160	25	60
2700	12.25	35	160	25	60
2800	12.25	35	160	25	60
2900	12.25	35	160	25	60
3000	8.5	45	160	25	50
3100	8.5	45	160	25	50
3200	8.5	45	160	25	50
3300	8.5	45	160	25	50
3400	8.5	45	160	25	50

Table 4 Correlation Constants and Error (all parameters are dimensionless)

Method	a	b	c	d	e	f	R^2 [%]
Bingham	3.73	8.1	1	-	-	-	22.64
Bourgoyne	2.72×10^{-3}	1.77×10^{-4}	5.62	1.37	1.66	-20.78	40.46
Warren	42.73	-1434.65	30.96	9.37	-	-	32.32

Table 3 Range of Mud Weight Used in Optimization

Depth [m]	MW_{min} [pcf]	MW_{max} [pcf]
0-300	62	68
300-600	65	72
600-800	67	74
800-1000	69	75
1000-1400	70	75
1400-1600	77	83
1600-1800	80	85
1800-2200	85	88
2200-2500	128	135
2500-2700	135	142
2700-2900	140	145
2900-3400	65	70

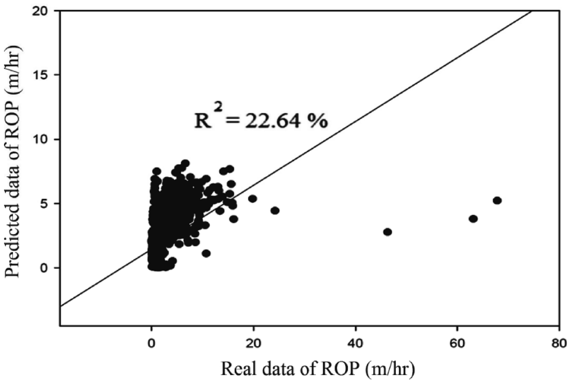

Fig. 3 Bingham Model

over reasonable range may cause bit floundering. In soft formations WOB should start with a small value, get a higher value then stabilized as it shown in tables. Rotary speed should start in a high value and the decreases as it goes deeper. Optimized ROP decreases as the depth increases. Also, mud weights should be checked with a mud weight program to prevent drilling problems, such as mud loss. In hard formations, rotary

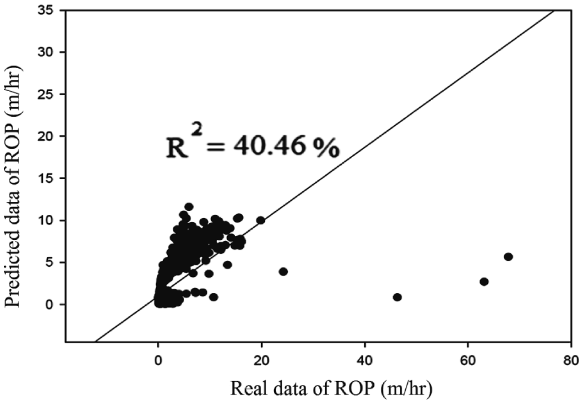

Fig. 4 Bourgoyne Model

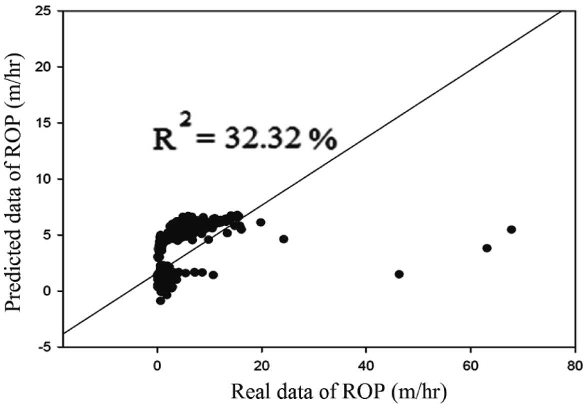

Fig. 5 Warren Model

Table 5 Result of Optimization Applying Roundation of 5 for *N* and W and 1 for MW for Each 100 m

Depth [m]	WOB [klb]	*N* [RPM]	MW [pcf]	ROP [m h^{-1}]
0	50	125	62	31.5051
100	50	125	62	30.3562
200	50	125	62	29.1363
300	15	165	65	34.8352
400	15	165	65	32.9356
500	15	165	65	31.13
600	15	165	67	34.3098
700	15	165	67	31.9165
800	15	165	69	32.9425
900	15	125	69	29.7956
1000	15	125	70	28.7502
1100	15	125	70	25.7209
1200	50	65	70	24.0006
1300	50	65	70	22.9681
1400	15	45	77	24.7313
1500	15	45	77	23.5856
1600	15	45	80	24.0669
1700	15	45	80	22.5436
1800	15	45	85	24.0005
1900	15	45	85	22.515
2000	15	45	85	20.9734
2100	15	45	85	19.3991
2200	25	155	128	39.7086
2300	25	155	128	39.6838
2400	25	155	128	39.5944
2500	25	155	135	43.1674
2600	25	155	135	43.1745
2700	25	155	140	45.6986
2800	25	155	140	45.6056
2900	25	155	140	45.4314
3000	50	45	65	21.6657
3100	50	45	65	19.208
3200	50	45	65	16.7201
3300	25	125	65	14.6483
3400	25	125	65	14.0026

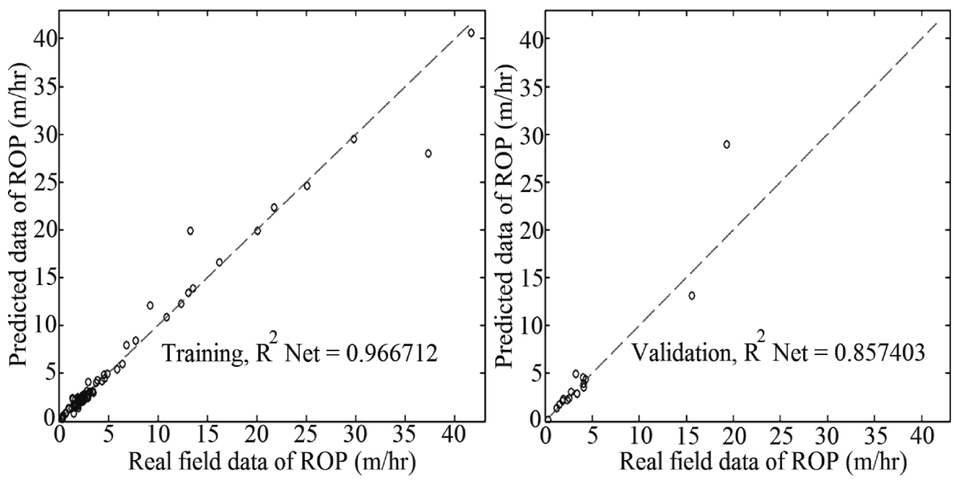

Fig. 6 ANN Model, Errors of Training and Validation

speed should start in low value and increases as the depth increases. Optimized ROP also decreases as the depth increases. PDC bits' performance changes with rock type so recommended drilling parameters also should be adapted with rock type.

5. Conclusions

Increasing WOB or rotary speed does not always increases ROP. This study shows in some parts which the driller exerts high WOB and N, the ROP value decreases due to cleaning problem and bit floundering. **Figure 3** shows bad result of these effects, so optimization program recommend using less WOB and N in these parts.

It was found that Bingham model does not predict ROP accurately; it is due to that model does not consider the depth effect.

In soft formations WOB should start with a small value, get a higher value then stabilized. Rotary speed should start in a high value and the decreases as it goes deeper. Optimized ROP decreases as the depth increases. In hard formations, rotary speed should start in low value and increases as the depth increases. Optimized ROP also decreases as the depth increases. PDC bits' performance changes with rock type so recommended drilling parameters also should be adapted with rock type.

This is the ability of ANN analysis whether no equation can find the actual amounts of parameters which maximize penetration rate. As results show, always less mud weight used leads in higher ROP value which is a correct concept. Great range for N and WOB is used and observed that best one was neither the maximum nor the minimum value. Increasing WOB or rotary speed not always increases ROP. This study shows in some parts which the driller exerts high WOB and N, and consequently the ROP value decreases due to cleaning problem and bit floundering.

An appropriate ROP was selected based on the previous ROP to be achieved by using the modelled function and applying the corresponding drilling bit parameters.

Nomenclatures

a	: constant	[-]
b	: constant	[-]
c	: constant	[-]
d	: constant	[-]
D	: depth	[m]
d_b	: bit diameter	[inch]
e	: constant	[-]
ECD	: equivalent circulating density	[pcf]
EMW	: equivalent mud weight	[pcf]
F_j	: impact force	[kN]
F_{jm}	: modified impact force for bit nozzles	[kN]
h	: eroded height of bit in portion of 8	[-]
k	: constant	[-]
MW	: mud weight	[pcf]
N	: rotary speed	[rpm]
PDC	: polycrystalline diamond compact	[-]
ROP	: rate of penetration	[m h^{-1}]
RPM	: rotation per minute	[-]
S	: confined rock strength	[kPa]
t	: threshold	[-]
TVD	: true vertical depth	[-]
W, WOB	: weight on bit	[klb]
<Greeks>		
γ_f	: fluid specific gravity	[-]
μ	: mud viscosity	[cP]

References

1) Adam, N., Charrier, T., "Drilling Engineering: A Complete Well Planning Handbook," Pennwell Corp., Oklahama, USA ISBN-13: 978-0878142651 (1985).
2) Bataee, M., Kamyab, M., Ashena, R., International Oil and Gas Conference and Exhibition in China, ISBN : 978-1-55563-295-3 (2010).
3) Bilgesu, H. I., Tetrick, L. T., Mohaghegh, S., Ameri, S., SPE Eastern Regional Meeting, Lexington, Kentucky, USA, ISBN : 978-1-55563-398-1 (1997).
4) Bourgoyne, A. T., Millheim, K. K., Chenevert, M. E., Young Jr., F. S., "Applied Drilling Engineering (SPE Textbook Series, Vol. 2)," Society of Petroleum Engineers, ISBN-13: 978-1555630010 (1986).
5) Edalatkhah, S., Arabjamaloei, R., Hashemi, A., *Journal of Petroleum Science and Technology*, **28**, (18), 1946 (2010).
6) Nygaard, R., Hareland, G., Latin American & Caribbean Petroleum Engineering Conference Buenos Aires, Argentina, ISBN : 978-1-55563-185-7 (2007).
7) Paes, P., Aragao, A., Chen, D. C., SPE Latin American and Caribbean Petroleum Engineering Conference Rio de Janeiro, Brazil, ISBN : 978-1-61399-006-3 (2005).
8) Rastegar, M., Hareland, G., Nygaard, R., Bashari, A., IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition, Jakarta, Indonesia, ISBN : 978-1-55563-174-1 (2008).
9) Remmert, S. M., Witt, J. W., Dupriest, F. E., SPE/IADC Drilling Conference, Amsterdam, The Netherlands, ISBN : 978-1-55563-158-1 (2007).
10) Roehrlich, M., Belohlavek, K. U., IADC/SPE Drilling Conference, Miami, Florida, USA, ISBN : 978-1-55563-238-0 (2006).
11) Walker, B. H., Black, A. D., Klauber, W. P., Little, T., Khodaverdian, M., SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, USA, ISBN : 978-1-55563-607-4 (1986).