

Well Logs Analysis Using Neuro-Fuzzy Technology (Case Study of Niger-Delta Region of Nigeria)

¹A.B. Adeyemo, ²O.C. Akinyokun and ³A. Adesida

¹Department of Computer Science, University of Ibadan, Ibadan, Nigeria

²Department of Computer Science, ³Department of Applied Geophysics,
Federal University of Technology, Akure, Nigeria

Abstract: Petrophysical log interpretation is one of the most useful and important tools available to a petroleum geologist. Well logs help to define physical rock characteristics such as lithology, porosity, permeability and to identify productive zones, to determine depth and thickness of zones, to distinguish between oil, gas, or water in a reservoir and to estimate hydrocarbon reserves. This study presents the results of a study that used unsupervised Self Organizing Map (SOM) artificial neural networks and fuzzy rules derived from log characteristics for the determination of oil well lithology from open-hole geophysical well logs. The methodology proposed for the identification of oil well lithology was tested with case data obtained from an oil well located in the Niger delta region of Nigeria. The result shows that the fuzzy logic based log interpretation model used for the analysis of the clusters (log-facies) generated from the well logs can be used to identify and classify the lithology of oil wells without the use of core sample data.

Key words: Log facies, SOM neural networks, fuzzy logic, Niger-delta region

INTRODUCTION

Artificial Neural Networks are non-linear, sophisticated modeling techniques capable of modeling extremely complex functions (Statsoft, 2002). Artificial Neural Networks can transform a linearly inseparable problem into a linearly separable one. They learn by example and can be applied in virtually every situation in which a relationship between the predictor variables (independents, inputs) and predicted variables (dependents, outputs) exists. They are applicable even when the relationship may be very complex and not easy to articulate in the usual terms of "correlations" or differences between groups.

Artificial Neural Networks can be trained using either the supervised or the unsupervised learning or training techniques (Statsoft, 2002). In supervised learning, the correct results (target values, desired outputs) are known and are given to the network during training. The network can adjust its weights to match its outputs to the target values and the network learns to infer the relationship between the two. Training data is usually taken from historical records. The network is trained using one of the supervised learning algorithms of which the best-known example is the back propagation method.

Artificial Neural Networks that use the unsupervised learning paradigms are very simple, one-layer networks. In unsupervised learning there is no teacher and the network must self-organize according to some internal rules in response to the environment. A number of unsupervised learning algorithms exist. Some of these are the Hebbian and the Competitive learning methods (Statsoft, 2002). The Hebbian learning is the most common variety of unsupervised learning. The Oja's and Sangers unsupervised learning are variants of plain Hebbian learning that can be used for principal component analysis. The Sanger's learning procedure can also extract the principal components with respect to the output unit ordering.

The Kohonen Self-Organizing (feature) Map (SOM) network (Kohonen, 1995) uses the competitive learning method. The SOM network has only two layers of processing elements (or neurons). These are the input layer and an output layer of radial units (also known as the topological map layer). The units in the topological map layer are laid out in space, usually in two dimensions. The SOM artificial neural network which combines competitive learning with dimensionality reduction can be used for exploratory data analysis, classification tasks and novelty detection.

The basic theory of fuzzy sets was first introduced by Zadeh (1965). Unlike classical logic, which is based on crisp sets of "true and false", fuzzy logic views problems as a degree of "truth", or "fuzzy sets of true and false". It is a methodology that was developed to obtain an approximate solution where the problems are subject to vague description. The major concept of fuzzy logic is the use of a linguistic variable which is a variable whose values are words or sentences in a natural or synthetic language. This also leads to the use of fuzzy if-then rules, in which the antecedent and consequents are propositions containing linguistic variables.

Neuro-fuzzy modeling is a technique for describing the behavior of a system using fuzzy inference rules within a neural network structure. The model has a unique feature in that it can express linguistically the characteristics of a complex nonlinear system. In recent years, fuzzy logic, or more generally, fuzzy set theory, has been applied extensively in many reservoir characterization studies (Nikravesh and Aminzadeh, 2002). This is mainly due to the fact that reservoir geology is mainly a descriptive science which uses mostly uncertain, imprecise, ambiguous and linguistic information. Fuzzy set theory has the ability to deal with such information and to combine them with the quantitative observations.

The prediction of lithofacies (that is, rock type identification) is important for many geological and engineering disciplines. The conventional method used for the identification of lithofacies is by direct observation of underground cores (Chang *et al.*, 2002). These are small cylindrical rock samples, retrieved from oil wells at selected well depths. The recovery of cores is an expensive process and is not always total. In addition, different geologists may provide different interpretations for the retrieved core samples. This is why a lower-cost method providing similar or higher accuracy is desirable (Chang *et al.*, 2002). In an attempt to solve such reservoir characterization problems using differed well logging measurements, some researchers in geosciences have employed statistical methods and the use of artificial neural networks. Some published research using some of these techniques to solve reservoir characterization and lithology determination or prediction problems include: Soto and Holditch (1999), Mohaghegh (2000), Chang *et al.* (2000), Ford and Kelly (2001), Barlai (2002) and Chikhi *et al.* (2004). Most of the researches used supervised neural networks trained with core samples to recognize rock types present in a fresh data set previously unseen by the neural network. Chang *et al.* (2002) reported the use of an unsupervised SOM network to generate clusters in log data and used classified core data for the lithology identification program.

From studies of well log characteristics the well logs that can be used for lithology determination are Gamma Ray (GR) log, Density (DEN) log, Neutron (NEU) log, Electrical Resistivity (RES) log. Gamma ray logs measure natural radioactivity in formations. Shale-free sandstones and carbonates give low gamma ray readings. As shale content increases, the gamma ray log response also increases. The resistivity log is a measure of a formation's resistivity. Most rock materials are essentially insulators, while their enclosed fluids are conductors. When a formation is porous and contains salty water, the overall resistivity will be low. When this same formation contains hydrocarbons, its resistivity will be very high. Shales show low resistivity values with high gamma ray values. The density log is a continuous record of a formation's bulk density. It is used mainly for the determination of porosity and the differentiation between liquids and gases (when used in combination with neutron log). When organic content is present, density is low. Variation of density indicates porosity changes. For example, low density indicates high porosity and vice-versa. On cross-plot of neutron and density logs, pure shale can be recognized by the high neutron value relative to the density value which gives a large positive separation to the logs while gas stands out distinctly giving a large negative separation.

This study presents the result of a study that proposed a methodology for the identification and classification of oil well lithology and fluid content using a SOM neural network to generate log-facies or electro-facies (Rider, 1996) from geophysical well logs and fuzzy rules generated from the known physical properties of the well logs. With the fuzzy rules the lithology of the wells can be determined without the use of core sample data. A case study program was implemented using case data from the Niger Delta region of Nigeria. The Niger Delta is situated in the Gulf of Guinea and extends throughout the Niger Delta Province. It contains only one identified petroleum system referred to as the Tertiary Niger Delta (Akata-Agbada) Petroleum System (Tuttle *et al.*, 1999). It is composed of mainly sedimentary rock and divided into three formations. These are Benin formation, Agbada formation and Akata formation. The Benin formation consists of mainly sand, the Agbada formation consists of sand and shale, while the Akata formation consists of shale. Limestone and salts are not found in the Niger Delta region. The depth of the Benin formation is about 6,000 ft, the Agbada formation about 17,000 ft and Akata formation about 6,000 ft. The source rocks for the petroleum system are located in the Akata formation while the petroleum reservoirs are located in the Agabda formation.

MATERIALS AND METHODS

The base data used for the lithology determination are the open-hole wireline subsurface well log data. Cross-plot techniques are employed in the analysis of well log data. The log data models the response of the subsurface rocks to the measuring instrument according to the rock properties. The cross-plots allow the nature of the rocks properties to be inferred from the logs. However, due to visualization problems, the cross-plots cannot handle more than 3-dimensional data. It was observed that the operation of the SOM based clustering algorithm is similar to plotting a multi-dimensional log cross-plot. It is noted that in the conventional cross-plot chart, if the dimensions of the chart are more than three dimensions, the visualization and interpretation of the cross-plot chart becomes more complex. The SOM based clustering algorithm has the advantage of not being limited to three dimensions.

The analysis of the well logs begins by first cleaning the log data. Erroneous data items and outliers were removed from the raw well log data. A correlation test was performed on the log values to determine if there was any relationship between the log data values. Knowing the nature of the relationships also helps in the selection of the appropriate log variables when similar data items are present in the data records. The data elements were normalized (between the range 0 and 1) to renders the input data dimensionless and remove the effect of scaling. The neural network was then trained using a training data set.

After training the SOM, the neural network would have learned the structure of the input data. The testing data file, which contains the data that is to be clustered, is now submitted to the trained SOM network, which then identifies the clusters it has recognized during the training process. The test data file may be the same as the training data file or any other data file, which is to be classified, based on the clusters identified by the training data set. The data samples are assigned to cluster groups by the SOM software and the result saved in either a spreadsheet file or an ASCII text file. Each data sample is assigned a label (number) showing the cluster to which it has been assigned. The output file is imported into a spreadsheet file, sorted to group data samples belonging to the same clusters together and then the mean and standard deviation of each cluster group computed.

The computed mean of the log values were used to infer the lithology and fluid content of the rock species that characterize the geological formation of the oil well being investigated by determining their fuzzy value. In a fuzzy system, the general inference process proceeds in the following steps.

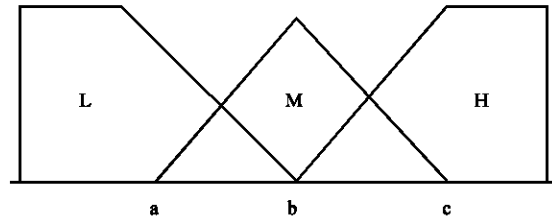


Fig. 1: Fuzzy membership functions

- Fuzzification which involves the conversion of numeric data in real world domain to fuzzy numbers in fuzzy domain.
- Fuzzy inference which involves the computation of the truth value of each rule and its application to the conclusion part of the rule.
- Composition of the output variables of sub rules which can fire in parallel for the purpose of drawing a global conclusion.
- Defuzzification, which is optional, involves the conversion of the derived fuzzy number to the numeric data in real world domain.

The fuzzy value of the logs can be modeled by four fuzzy membership functions which correspond to the linguistic values High (H), Moderate (M), or Low (L) as shown in Fig. 1.

The fuzzy values are used to generate fuzzy rules for the identification of rock lithologies represented by log data clusters generated by the SOM software. Mathematically this can be represented by Eq. 1 as:

$$x_j = \begin{cases} \{ H \text{ if } b \geq x \leq c \\ \{ M \text{ if } a > x < b \\ \{ L \text{ if } x \leq a \end{cases} \quad (1)$$

Where,

x_j represents mean value of subset j (of log reading)
 a, b and c represents threshold values

In determining, the threshold value a, b and c used in this work the following were noted:

- The gamma ray log value in shales varies enormously in any one area or well and it ranges between 40 and 112 API and in sandstones ranges between 10 and 50 API (Rider, 1996). The threshold values used for the Gamma Ray log (GR) are:

$$a = 40 \text{ API, } b = 50 \text{ API, } c = 112 \text{ API}$$

- There are no characteristic resistivity limits for shales, limestone and sandstone (Rider, 1996).

However, it is noted that resistivity values are low for shales, sandstone and water. It is high for hydrocarbons (oil/gas). The threshold values used for the un-invaded resistivity log (RES) are:

$$a = 10 \text{ ohm-m, } b = 100 \text{ ohm-m, } c = 300 \text{ ohm-m}$$

- In shales the density log value ranges between 1.18 and 2.75 g cm⁻³, while in sandstones it ranges between 1.9 and 2.65 g cm⁻³. Since oilfield densities are usually between 2.0 and 3.0 g cm⁻³ and the mean apparent dry bulk density for shales is 2.45 g cm⁻³ (Rider, 1996). The threshold values used for the Density (DEN) log are:

$$a = 2.45 \text{ g cm}^{-3}, b = 2.65 \text{ g cm}^{-3}, c = 3.0 \text{ g cm}^{-3}$$

In order to generate the fuzzy rules to be used for the analysis of the clusters a rock properties determination matrix was created using the known log properties. Using three fuzzy membership functions and three logs gave 27 unique combinations. Not all the rules are physically feasible. However, since the known primary lithology is sand and shale, this provides a way for reducing the number of rules generated to a more manageable and effective number by selecting only the rules relevant to the objective of the study. These are the rules for determining the well lithology which is classified as being shale, sandy-shale, pay sand and wet sand. The relevant combinations are presented in Table 1. In deriving the rules, the following were considered:

- The gamma ray log, which is the primary lithology log, was used to determine the primary lithology of the rock type.
- Next, the resistivity log was used to determine if there is any hydrocarbon presence indicated by a high resistivity log value.
- Finally, the density log was used to further characterize the lithofacies.

The fuzzy rules inferred from the rules determination matrix are:

- If (GR = H) and (RES = L) and (DEN = H or M)
Then (Lithology = Shale)
- (GR = L) and (RES = L) and (DEN = H or M)
Then (Lithology = Sandy-shale)
- If (GR = L) and (RES = H) and (DEN = M)
Then (Lithology = Pay Sand)
- If (GR = L) and (RES = H) and (DEN = L)
Then (Lithology = Pay Sand)

- If (GR = L) and (RES = M) and (DEN = M)
Then (Lithology = Pay Sand)
- If (GR = L) and (RES = M) and (DEN = L)
Then (Lithology = Pay Sand)
- If (GR = L) and (RES = L) and (DEN = L)
Then (Lithology = Wet sand)

RESULTS AND DISCUSSION

Case studies using well log data from the Niger Delta region of Nigeria (obtained from Shell Petroleum Development Corporation with the permission of the Department of Petroleum Resources, Nigeria) were carried out. The log data contains the Depth (DEP), the True Vertical Depth (TVD), Gamma Ray log (GR), Resistivity log (RES) and Density log (DEN). The log had 3941 data elements which ranged from 7000-11870 ft. A correlation test was carried out on the input data. The result showed that the Depth (DEP) and True Vertical Depth (TVD) were highly correlated hence, only the Depth (DEP) values were used. The well logs were then normalized. The data was then used to train the SOM software and clusters were generated. The mean log value

Table 1: Fuzzy rules determination matrix

	GR value	RES value	DEN value	Indicated lithology
1	H or M	L	H or M	Shale
2	L	L	H or M	Sandy-shale
3	L	H	M	Pay sand
4	L	H	L	Pay sand
5	L	M	M	Pay sand
5	L	M	L	Pay sand
6	L	L	L	Wet sands

Table 2: Clusters generated by SOM software

Cluster	No. of samples		GR	RES	DEN
1	18	Mean	33.01778	493.666668	2.375
		SD	3.345639	120.187046	0.025029394
2	3	Mean	40.89333	567.64331	2.33666667
		SD	1.247812	4.1311504	0.04163332
3	56	Mean	35.73875	91.053929	2.43821429
		SD	3.162037	54.191674	0.02249098
4	599	Mean	85.81002	21.328431	2.53435726
		SD	22.72294	27.803078	0.04879703
5	6	Mean	39.42667	1441.0467	2.30666667
		SD	1.456896	250.23838	0.01966384
6	92	Mean	32.23467	5.61130435	2.428695652
		SD	4.573356	0.5782566	0.022833241
7	64	Mean	36.40203	49.0335937	2.41921875
		SD	3.837196	30.0236259	0.046369965
8	94	Mean	34.19521	225.854576	2.372765957
		SD	3.162344	88.2995406	0.029924789
9	162	Mean	91.79079	18.2691089	2.499517327
		SD	28.73966	35.3942291	0.082534254
10	578	Mean	114.4018	4.80583045	2.621557093
		SD	12.52467	1.71185725	0.040848849
11	3	Mean	34.08	54.753334	2.406666667
		SD	3.016768	6.50432495	0.015275252
12	812	Mean	104.117	9.53756159	2.483054187
		SD	24.15951	10.3751173	0.044311775

DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP
10560	10616	10670	10725	10780	10835	10890	10945	11000	11055	11110	11165	11220	11275	11330
10561	10617	10671	10726	10781	10836	10891	10946	11001	11056	11111	11166	11221	11276	11331
10562	10618	10672	10727	10782	10837	10892	10947	11002	11057	11112	11167	11222	11277	11332
10563	10619	10673	10728	10783	10838	10893	10948	11003	11058	11113	11168	11223	11278	11333
10564	10620	10674	10729	10784	10839	10894	10949	11004	11059	11114	11169	11224	11279	11334
10565	10621	10675	10730	10785	10840	10895	10950	11005	11060	11115	11170	11225	11280	11335
10566	10622	10676	10731	10786	10841	10896	10951	11006	11061	11116	11171	11226	11281	11336
10567	10623	10677	10732	10787	10842	10897	10952	11007	11062	11117	11172	11227	11282	11337
10568	10624	10678	10733	10788	10843	10898	10953	11008	11063	11118	11173	11228	11283	11338
10569	10625	10679	10734	10789	10844	10899	10954	11009	11064	11119	11174	11229	11284	11339
10570	10626	10680	10735	10790	10845	10899	10955	11010	11065	11120	11175	11230	11285	11340
10571	10627	10681	10736	10791	10846	10900	10956	11011	11066	11121	11176	11231	11286	11341
10572	10628	10682	10737	10792	10847	10901	10957	11012	11067	11122	11177	11232	11287	11342
10573	10629	10683	10738	10793	10848	10902	10958	11013	11068	11123	11178	11233	11288	11343
10574	10630	10684	10739	10794	10849	10903	10959	11014	11069	11124	11179	11234	11289	11344
10575	10631	10685	10740	10795	10850	10904	10960	11015	11070	11125	11180	11235	11290	11345
10576	10632	10686	10741	10796	10851	10905	10961	11016	11071	11126	11181	11236	11291	11346
10577	10633	10687	10742	10797	10852	10906	10962	11017	11072	11127	11182	11237	11292	11347
10578	10634	10688	10743	10798	10853	10907	10963	11018	11073	11128	11183	11238	11293	11348
10579	10635	10689	10744	10799	10854	10908	10964	11019	11074	11129	11184	11239	11294	11349
10580	10636	10690	10745	10800	10855	10909	10965	11020	11075	11130	11185	11240	11295	11350
10581	10637	10691	10746	10801	10856	10910	10966	11021	11076	11131	11186	11241	11296	11351
10582	10638	10692	10747	10802	10857	10911	10967	11022	11077	11132	11187	11242	11297	11352
10583	10639	10693	10748	10803	10858	10912	10968	11023	11078	11133	11188	11243	11298	11353
10584	10640	10694	10749	10804	10859	10913	10969	11024	11079	11134	11189	11244	11299	11354
10585	10641	10695	10750	10805	10860	10914	10970	11025	11080	11135	11190	11245	11300	11355
10586	10642	10696	10751	10806	10861	10915	10971	11026	11081	11136	11191	11246	11301	11356
10587	10643	10697	10752	10807	10862	10916	10972	11027	11082	11137	11192	11247	11302	11357
10588	10644	10698	10753	10808	10863	10917	10973	11028	11083	11138	11193	11248	11303	11358
10589	10645	10699	10754	10809	10864	10918	10974	11029	11084	11139	11194	11249	11304	11359
10590	10646	10700	10755	10810	10865	10919	10975	11030	11085	11140	11195	11250	11305	11360
10591	10647	10701	10756	10811	10866	10920	10976	11031	11086	11141	11196	11251	11306	11361
10592	10648	10702	10757	10812	10867	10921	10977	11032	11087	11142	11197	11252	11307	11362
10593	10649	10703	10758	10813	10868	10922	10978	11033	11088	11143	11198	11253	11308	11363
10594	10650	10704	10759	10814	10869	10923	10979	11034	11089	11144	11199	11254	11309	11364
10595	10651	10705	10760	10815	10870	10924	10980	11035	11090	11145	11200	11255	11310	11365
10596	10652	10706	10761	10816	10871	10925	10981	11036	11091	11146	11201	11256	11311	11366
10597	10653	10707	10762	10817	10872	10926	10982	11037	11092	11147	11202	11257	11312	11367
10598	10654	10708	10763	10818	10873	10927	10983	11038	11093	11148	11203	11258	11313	11368
10599	10655	10709	10764	10819	10874	10928	10984	11039	11094	11149	11204	11259	11314	11369
10600	10656	10710	10765	10820	10875	10929	10985	11040	11095	11150	11205	11260	11315	11370
10601	10657	10711	10766	10821	10876	10930	10986	11041	11096	11151	11206	11261	11316	11371
10602	10658	10712	10767	10822	10877	10931	10987	11042	11097	11152	11207	11262	11317	11372
10603	10659	10713	10768	10823	10878	10932	10988	11043	11098	11153	11208	11263	11318	11373
10604	10660	10714	10769	10824	10879	10933	10989	11044	11099	11154	11209	11264	11319	11374
10605	10661	10715	10770	10825	10880	10934	10990	11045	11100	11155	11210	11265	11320	11375
10606	10662	10716	10771	10826	10881	10935	10991	11046	11101	11156	11211	11266	11321	11376
10607	10663	10717	10772	10827	10882	10936	10992	11047	11102	11157	11212	11267	11322	11377
10608	10664	10718	10773	10828	10883	10937	10993	11048	11103	11158	11213	11268	11323	11378
10609	10665	10719	10774	10829	10884	10938	10994	11049	11104	11159	11214	11269	11324	11379
10610	10666	10720	10775	10830	10885	10939	10995	11050	11105	11160	11215	11270	11325	11380
10611	10667	10721	10776	10831	10886	10940	10996	11051	11106	11161	11216	11271	11326	11381
10612	10668	10722	10777	10832	10887	10941	10997	11052	11107	11162	11217	11272	11327	11382
10613	10669	10723	10778	10833	10888	10942	10998	11053	11108	11163	11218	11273	11328	11383
10614	10670	10724	10779	10834	10889	10943	10999	11054	11109	11164	11219	11274	11329	11384
10615	10671	10725	10780	10835	10890	10944	11000	11055	11110	11165	11220	11275	11330	11385

DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP
11220	11275	11300	11305	11440	11485	11500	11605	11690	11715	11720	11825			
11221	11276	11301	11306	11441	11486	11501	11606	11691	11716	11721	11826			
11222	11277	11302	11307	11442	11487	11502	11607	11692	11717	11722	11827			
11223	11278	11303	11308	11443	11488	11503	11608	11693	11718	11723	11828			
11224	11279	11304	11309	11444	11489	11504	11609	11694	11719	11724	11829			
11225	11280	11305	11310	11445	11490	11505	11610	11695	11720	11725	11830			
11226	11281	11306	11311	11446	11491	11506	11611	11696	11721	11726	11831			
11227	11282	11307	11312	11447	11492	11507	11612	11697	11722	11727	11832			
11228	11283	11308	11313	11448	11493	11508	11613	11698	11723	11728	11833			
11229	11284	11309	11314	11449	11494	11509	11614	11699	11724	11729	11834			
11230	11285	11310	11315	11450	11495	11510	11615	11700	11725	11730	11835			
11231	11286	11311	11316	11451	11496	11511	11616	11701	11726	11731	11836			
11232	11287	11312	11317	11452	11497	11512	11617	11702	11727	11732	11837			
11233	11288	11313	11318	11453	11498	11513	11618	11703	11728	11733	11838			
11234	11289	11314	11319	11454	11499	11514	11619	11704	11729	11734	11839			
11235	11290	11315	11320	11455	11500	11515	11620	11705	11730	11735	11840			
11236	11291	11316	11321	11456	11501	11516	11621	11706	11731	11736	11841			
11237	11292	11317	11322	11457	11502	11517	11622	11707	11732	11737	11842			
11238	11293	11318	11323	11458	11503	11518	11623	11708	11733	11738	11843			
11239	11294	11319	11324	11459	11504	11519	11624	11709	11734	11739	11844			
11240	11295	11320	11325	11460	11505	11520	11625	11710	11735	11740	11845			
11241	11296	11321	11326	11461	11506	11521	11626	11711	11736	11741	11846			
11242	11297	11322	11327	11462	11507	11522	11627	11712	11737	11742	11847			
11243	11298	11323	11328	11463	11508	11523	11628	11713	11738	11743	11848			
11244	11299	11324	11329	11464	11509	11524	11629	11714	11739	11744	11849			
11245	11300	11325	11330	11465	11510	11525	11630	11715	11740	11745	11850			
11246	11301	11326	11331	11466	11511	11526	11631	11716	11741	11746	11851			
11247	11302	11327	11332	11467	11512	11527	11632	11717	11742	11747	11852			
11248	11303	11328	11333	11468	11513	11528	11633	11718	11743	11748	11853			
11249	11304	11329	11334	11469	11514	11529	11634	11719	11744	11749	11854			
11250	11305	11330	11335	11470	11515	11530	11635	11720	11745	11750	11855			
11251	11306	11331	11336	11471	11516	11531	11636	11721	11746	11751	11856			
11252	11307	11332	11337	11472	11517	11532	11637	11722	11747	11752	11857			
11253	11308	11333	11338	11473	11518	11533	11638	11723	11748	11753	11858			
11254	11309	11334	11339	11474	11519	11534	11639	11724	11749	11754	11859			
11255	11310	11335	11340	11475	11520	11535	11640	11725	11750	11755	11860			
11256	11311	11336	11341	11476	11521	11536	11641	11726	11751	11756	11861			
11257	11312	11337	11342	11477	11522	11537	11642	11727	11752	11757	11862			
11258	11313	11338	11343	11478	11523	11538	11643	11728	11753	11758	11863			
11259	11314	11339	11344	11479	11524	11539	11644	11729	11754	11759	11864			
11260	11315	11340	11345	11480	11525	11540	11645	11730	11755	11760	11865			
11261	11316	11341	11346	11481	11526	11541	11646	11731	11756	11761	11866			
11262	11317	11342	11347	11482	11527	11542	11647	11732	11757	11762	11867			
11263	11318	11343	11348	11483	11528	11543	11648	11733	11758	11763	11868			
11264	11319	11344	11349	11484	11529	11544	11649	11734	11759	11764	11869			
11265	11320	11345	11350	11485	11530	11545	11650	11735	11760	11765	11870			
11266	11321	11346	11351	11486	11531	11546	11651	11736	11761	11766	11871			
11267	11322	11347	11352	11487	11532	11547	11652	11737	11762	11767	11872			
11268	11323	11348	11353	11488	11533	11548	11653	11738	11763	11768	11873			
11269	11324	11349	11354	11489	11534	11549	11654	11739	11764	11769	11874			
11270	11325	11350	11355	11490	11535	11550	11655	11740	11765	11770	11875			
11271	11326	11351	11356	11491	11536	11551	11656	11741	11766	11771	11876			
11272	11327	11352	11357	11492	11537	11552	11657	11742	11767	11772	11877			
11273	11328	11353	11358	11493	11538	11553	11658	11743	11768	11773	11878			
11274	11329	11354	11359	11494	11539	11554	11659	11744	11769	11774	11879			
11275	11330	11355	11360	11495	11540	11555	11660	11745	11770	11775	11880			

Cluster No	Lithology	Legend
1	Pay sand	1
2	Pay sand	2
3	Pay sand	3
4	Shale	4
5	Pay sand	5
6	Wet sand	6
7	Pay sand	7
8	Pay sand	8
9	Shale	9
10	Shale	10
11	Pay sand	11
12	Shale	12

Fig. 2: Well stratigraphy chart

Table 3: Interpretation of SOM software clusters

Cluster No	Lithology
1	Pay sand
2	Pay sand
3	Pay sand
4	Shale
5	Pay sand
6	Wet sand
7	Pay sand
8	Pay sand
9	Shale
10	Shale
11	Pay sand
12	Shale

and standard deviation of the cluster groups were computed. The standard deviation measures the spread of the data about the mean value gives an indication of the effectiveness of the clusters generated. Table 2 presents the clusters (represented by a number label) identified in the log data, their mean values and their standard deviation.

The fuzzy inference process started with the fuzzification subprocess where the membership functions defined on the input variables were applied to their actual values to determine the degree of truth for each rule premise. If a rules premise has a non-zero degree of truth, then the rule fires. In the inference subprocess, the truth-value of each rule was computed and applied to its conclusion part. The fuzzy ‘max’ rule of composition of inferences was then applied. The results showing the lithology of the well inferred from the cluster groups is presented in Table 3.

Figure 2 presents a chart of the oil well showing the location of the different types of rock materials in the well. On the chart, the depth intervals containing pay sand is represented by the yellow colored regions, depth intervals containing wet sand with water content is represented by the blue colored regions. Regions where shales (or shaly rock materials) can be found are shown in ochre. Clusters 4, 9, 10 and 12 represent shales. It can be observed that the difference between these shale clusters is a progressive increase in the shale density. Clusters 1, 2, 3, 5, 7, 8 and 11 represents pay

sand clusters. It can also be observed that there is a reduction in pay sand density with increase in pay sand resistivity values. Cluster 6 represents a wet sand cluster. A log analyst that was familiar with the data set used verified the result of the case study program. The chart shows relatively thin layers of sand interbedded within thick and expansive shale units (Adesida *et al.*, 2006).

CONCLUSION

In this study, the SOM neural network has been used to analyze well log data obtained from the Niger-Delta region of Nigeria in order to extract knowledge from the well log data. The fuzzy inference methodology adopted in the interpretation of the clusters were derived from the methods used in the interpretation of traditional graphical cross-plots by log analysts. Well logs characteristic response in different rock materials were used to formulate fuzzy rules, which were used to identify the lithology represented by the clusters generated by the SOM from well log data.

While it is only the fuzzy rules relevant to the lithology determination program that have been extracted in this research, it is noted that the rule base actually accommodates all possible rock materials that may be of further interest in future research work. With the three logs used that is gamma ray log, resistivity log and density log, lithology discrimination has been achieved. However, better resolution could still be obtained with associated fluid content determination carried out by using logs that can be used to discriminate between fluids like the neutron log, although this tends to increase the number of fuzzy rule that can be derived from the logs.

The fuzzy rules can form the basis for the development of a software tool. A neuro-fuzzy expert system which can use the SOM neural networks clustering algorithm as a pre-processor for a fuzzy classification module. Or a fuzzy logic expert system since the fuzzy rule can also be incorporated into a software

application that can directly classify the log values by fuzzify them, analyzing them and then classifying the individual log elements using the fuzzy rules. The software tool can be used by log analyst to determine the lithology and fluid content of an oil well prior to further processing of the log data in absence of core data.

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