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Takagi-Sugeno Integrated Fuzzy System in Subsurface Identification

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***Abstract*:** This study investigates the possibility of using the rule-based fuzzy (FZ) inference method to analyse petrophysical data (DT). Some well logs (WL) DT provided by Shell Producing Development Company (SPDC), Nigeria, were utilised for this study. The exploration WL DT were clustered using an unsupervised neural network. The rule-based lithology (LTG) procedures were established from the training DT sets, and the procedure strength is weighted. The Takagi-Sugeno inference arrangement and the centroid of extent defuzzification technique were employed for the FZ inference. It was observed that FZ inference systems provide fast and comprehensive details of the LTG and fluid content of the subsurface structure of the petrophysical DT that was interpreted.

Keywords: Well log; unsupervised neural network; Takagi- Sugeno system; subsurface; fuzzy inference method.

List of abbreviations/acronyms

Words	Abbreviations/acronyms
Adaptive neuro fuzzy inference system	ANFIS
Artificial Neural Network	ANN
Data	DT
Density log	DEN
Fuzzy	FZ.
Fuzzy logic	FL.
Gamma ray	GR.
Hydrocarbon	HC.
Least means squares algorithm	LMSA
Lithology	LTG
Mamdani FZ inference system	MFIS
Neutron log	NEU
Porosity log	PL.
Reservoir quality	LRQ
Resistivity log	RT
Shell Producing Development Company	SPDC
Takagi-Sugeno Integrated Neuro- Fuzzy System	TSINFS
Well log	WL

1.0 Introduction

Presently, the fuzzy logic FL) investigation of well logs WL) has been used expansively in several reservoir characterisations and description studies. For instance, the study carried out by Fung et al. [1], where they employed a self-producing fuzzy FZ) rule in the withdrawal and inference arrangement for envisaging the petrophysical physiognomies fromWL data DT), and they obtained some useful results. Also, Huang et al. [2] presented a suitableFZ interpolator for envisaging the penetrability or penetrability based onWL DT from the North West Shelf in Australia.FL has also been reportedly employed for the determination of hydrocarbon HC) formation lithofacies [3], and penetrability fromWL DT in the southern North Sea [3]. The results from the study from [3] gave near-perfect distinction among "aeolian, fluvial, and sabkha" rock categories (which are some of the key lithofacies in some North Sea fields) from basicWLs such as "gamma-rayGR) and porosity logs PLs)". The procedures ofFL investigation fromWLs could be applied to both "consolidated and unconsolidated sediments" and for water applications for oil or petroleum exploration and exploitation.

In 2013 Chaki et al. [4] compared "Adaptive NeuroFZ Inference System (ANFIS)" with supervised "Artificial Neural Network (ANN)" for envisaging two reservoir physiognomies; sand fraction and porosity fromWL DT. The predictor parameters were "P-sonic DT),GR content, neutron porosity (NPHI) and density (RHOB) logs". They employed theDT obtained fromHC field which is situated in the Western part of India, and they were able to show that ANFIS has an integral edge over ANN in the description and model uncertainties/reservations. However, the computational complication was high for ANFIS, initiating ANN as a natural or ordinary choice for theDT set under contemplation. Even though an ideal/perfect technique for hydro-geologic studies that have to do with aquifer physiognomies, such as penetrability and hydraulic conductivity is the conventional geophysical well logging, identifying aquifer lithology (LTG) fromWL DT hinges on the ability to differentiate between rocks or soils with grain sizes changing from gravel to clay. Hence, this technique is still mostly subjective in the absence of coreDT [5]. Reportedly, the idea ofFL is beneficial in controlling ambiguity related to non-linear mapping [6-8].

Machines that are capable of processing crisp or classicalDT such as either "0 or '1". So as to enable machines to treat vague language input such as "Somehow Satisfied"', the crisp input and output should be transformed to linguistic parameters withFZ mechanisms. Converting crispDT toFZ.DT is known as "fuzzification". Generally,FZ process encompasses the following two processes; "derive the membership functions for input and output variables, and represent them with linguistic variables" [9]. This procedure is comparable to the conversion or mapping of classical sets toFZ sets to changeable degrees. Apparently, membership functions could have several diverse categories, such as the "triangular waveform, trapezoidal waveform, Gaussian category, etc." depends on the definite and genuine applications. For those arrangements that require substantial dynamic distinction in a short duration, a "triangular or trapezoidal waveform" should be employed, and for that arrangement that requires very high control precision, a "Gaussian or S-curve waveform" need to be designated [4].

Hence, this present study investigates the opportunities and prospects of employing the rule-based FZ inference method to investigate some petrophysicalDT from DT obtained from SPDC, Nigeria. The Takagi- Sugeno inference arrangement and the centroid of extent defuzzification technique was employed for the FZ inference. It is believed that the results obtained from the precise combination of techniques as proposed in this paper will provide fast and wide-ranging details of the LTG and fluid content of the subsurface structure of the petrophysical DT that was proposed interpreted. The other sections of this study are structured as follows: Section 2 deliberates on the materials and methods employed for the study, section 3 contains the results and discussion, while section 4 is the concluding section which also encompasses some specifics for the future research direction in the form of recommendations.

2.0 Materials and Methods

The WL DT used for this study consists of GR, deep resistivity, density and neutron logs which were made available by SPDC, Nigeria, in the Niger Delta region of Nigeria located in the utmost parts of southern Nigeria (along a latitude of 5°33'49"N and latitude of 6°31'38"E) [10-21], which is the hallmark of petroleum activities in Nigeria [22]. The logs were acquired WL consisting of GR, resistivity, density and neutron. Sections of the WL used are presented in Appendix 1. The interpretation procedures employed for the petrophysicalDT are as follows:

- Processing ofWL DT
- Cluster analysis of the DT.
- FZ. Inference analysis of the DT.
- Subsurface determination

The first stage of the process was to examine the separate wellbore. The DT type that could be handled, processed or managed with the Matlab (2015a) toolbox is the supposed table DT or spreadsheet after which the DT were cleansed by picking the point where the WL assumed reading. The Matlab toolbox for clustering takes each table row as a sole DT sample. The columns of the table are the parameters of the DT set. The parameters could be a set of measurements measured at a specific time or the properties of an object. First, the information is taken into the Matlab toolbox using the standard Matlab functions "load and fscanf". Also, the function "som_read_ DT" in the toolbox can be used to read "ASCII DT files: sD = som_read_ DT ('DT.txt')". The information is typically put into a supposed DT struct, Matlab struct information related to a DT set.

The cluster analysis was done using the hierarchical approach. The reason for clustering was to reduce the computational load of the system. However, this process could possibly be omitted. It all depends on the choice of the interpreter. The hierarchical method is a clustering method, grounded on the representation of DT as a hierarchy of clusters nested over set-theoretic inclusion or measured physiognomies. It is primarily employed as an instrument for partitioning [2, 8].

2.1 Fuzzy Inference System

The FZ inference method involves the fuzzification procedure, converting crisp DT to FZ. DT. The derivation of the membership function was done [23]. The membership function represents objects or members in a vague or uncertain means, thereby providing a means that is comparable to a human's perceptions and thought procedure to the network.

2.1.1 Takagi-Sugeno Integrated Neuro-FZ System (TSINFS)

TSINFSs use a combination of back proliferation to learn the membership functions and least mean square approximation for determining the coefficients of the linear groupings in the rule's deductions [24]. This technique was employed because of its ability to generate FZ rules from the available DT set compared to other FZ systems. A phase in the learning technique comprises of two portions; in the first portion, the input outlines are proliferated, and the optimum deduction variables are projected by a reiterative least mean square technique, while the precursor variables (membership functions) are presumed to be fixed for the current cycle through the training set. For the second portion, the outlines are proliferated again, and in this epoch, back-proliferation was employed to alter the precursor variables while the deduction variables remain static. This technique is then recapitulated. The complete functioning of each layer, as illustrated in Figure 1, is as follows:

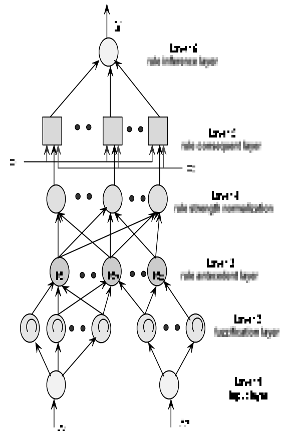

Figure 1. TSINFSs [17].

The "layers 1, 2 and 3" functions similarly to the Mamdani FZ inference system (MFIS). In "layer 4 (which is the rule strength normalisation)", every node computes the ratio of the i-th rule's firing strength to the summation of the entire rules firing strength (Eqn. 1) [17].

$$\overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1, 2, ... \quad (1)$$

Eqn. 2 [17] is the inference layer for "layer 5 (which is the consequent rule layer)," every node i in this layer is with a node function.

$$w_i f_i = w_i\left(p_i x_1 + q_i x_2 + r_i\right) \quad (2)$$

w_i is the output of layer 4, and (p_i,q_i,r_i) is the variable set. A well-known means is to determine the resulting variables applying the "least means squares algorithm (LMSA). While in "layer 6 (which is the rule inference layer)", the sole node in this layer calculates the complete output as the summation of the entire incoming signals as shown in Eqn. 3 [17].

$$Output(overall) = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (3)$$

2.2 Parameters for Subsurface Identification

The choice of GR logs for LTG determination stem is as a result of the fact that the GR log is intended for measuring the "natural radioactivity of soils and rocks" and is predominantly beneficial in the distinction of shales, sandstones, as WL as for the determination of the depositional surroundings in most cases [25].

The range of GR DT range from 24.197 API to 98.446 API. This was further divided into three (3) sub-ranges or subcategories, viz; if the reading is less than 42 API, then GR is low. If 43 API to 80 API, then the GR is medium and greater than 80 API, GR is high. The subcategories are necessary for identifying the shale, sandstone, carbonates and intermediate regions. Since shale exhibit high GR reading and carbonates is associated with low GR, categorising the log readings will give a proper understanding of what the intermediate region would possibly look like.

The deep-resistivity log was used to determine the presence of any HC. The range of deep resistivity DT was 2.494 Ωm to 146.23 Ωm. Also, this was additionally divided into three (3) subcategories, viz; if the reading is less than 39 Ωm, resistivity is low, for the range 40 Ωm to 110 Ωm, medium and high if it is greater than 110 Ωm.

The neutron and density logs were also be used to ascertain oil, gas and water-bearing regions. The range of neutron DT was 0.1182 FRAC to 0.4219 FRAC. Again, this was further divided into three (3) subcategories viz; if the reading is less than 0.19 FRAC low, medium from 0.2 FRAC to 0.34 FRAC and high when it is greater than 0.034 FRAC.

The range of density DT is 2.013 g/cm^3 to 2.337 g/cm^3. Similarly, this was further separated into three (3) sub-range/subsets: if the reading is less than 2.09 g/cm^3 low, the medium between 2.10 g/cm^3 to 2.26 g/cm^3 and high when it is greater than 2.26 g/cm^3.

The core of an FZ set is the set of variables whose degree of membership (DMS) in that set = 1, which is comparable to a crisp set. The boundary of an FZ set specifies the extent wherein all the parameters whose DMS in that set is between "0 and 1". Figure 2 to 5 shows the Gaussian output of the fuzzification process. Figure 2 is the GR, and Figure 3 is the resistivity log (RT), Figure 4 is the neutron log (NEU), and Figure 5 is the density log (DEN), respectively.

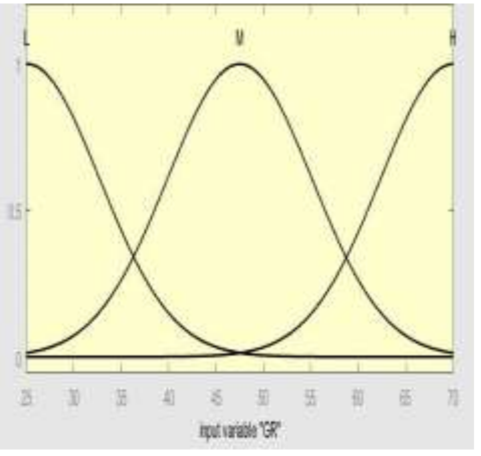

Figure 2. GR.

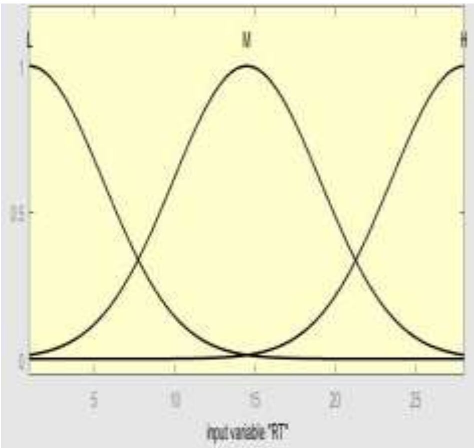

Figure 3. Resistivity log (RT).

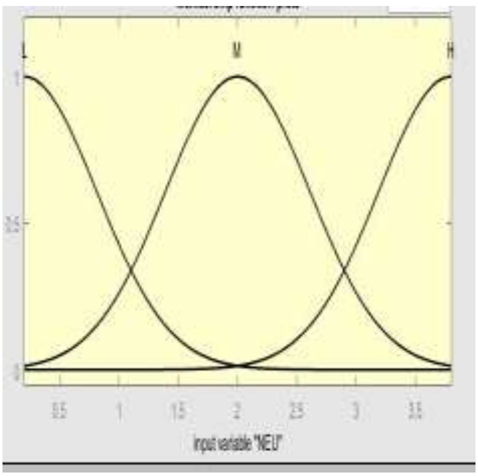

Figure 4. Neutron log (NEU).

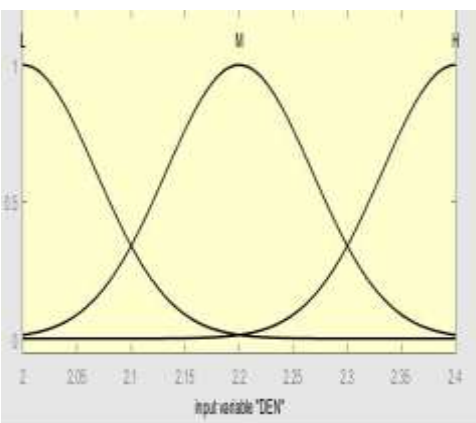

Figure 5. Density log (DEN).

3.0 Results and Discussion

The raw petrophysical DT for each well bore were both acquired logs: GR log, resistivity logs, neutron and density logs, as shown in Table 1. These logs were standardised by removing all the null values from the DT before being fed into the network for clustering. Thereafter, the cluster output of the network was used in setting the FZ inference rules as in Table 2.

Table 1. The selected logs

Depth (ft)	GR (API)	Deep resistivity (Ωm)	Neutron (FRAC)	Density (g/cm^3)
4279.000	93.712	6.250	0.378	2.227
4279.500	96.243	5.750	0.369	2.255
4280.000	96.952	5.490	0.366	2.285
4280.500	97.258	5.700	0.363	2.315
4281.000	96.440	5.860	0.360	2.305
4281.500	93.210	6.140	0.358	2.315
4282.000	93.210	6.310	0.358	2.305
4282.500	92.501	6.190	0.354	2.295
4283.000	92.501	6.190	0.349	2.275

The FZ rules for the TSINFSs are as shown in Table 2. The FZ rule represented by a sequence of IF-THEN form was constructed based on the clusters output of the WL DT, as shown in Table 2. The IF-THEN conditional statement leads to algorithms defining what action/output should be undergone in terms of the recently noticed information, which comprises both input and feedback if a closed-loop control system is employed. However, the law to build or design a set of FZ rules is based on a human's knowledge or/and experience.

Table 2. FZ IF THEN rules

IF: (Rule Number)	GR	Deep resistivity	Neutron	Density	THEN: (FZ output)
1	H	L	H	H	3
2	M	L	H	M	2
3	L	L	M	L	6
4	L	L	M	M	1
5	H	L	M	H	3
6	M	L	H	M	2
7	L	M	M	M	5
8	L	H	L	L	4

In Table 2, the linguistic values H, M and L means high, medium and low, respectively, while the crisp values 1- 6 represent the output of FZ. DT If the FZ output is 1, it means the subsurface is sand, 2 indicates that the subsurface is low reservoir quality (LRQ), 3 indicates that the subsurface is non-reservoir, 4 indicates gaseous reservoir, 5 indicates oil reservoir, and 6 indicates water reservoir respectively.

Table 3. A section of Takagi – Sugeno FZ subsurface output

Depth (ft)	GR (API)	Deep resistivity (Ohm m)	NEU (Frac)	DEN (g/cm^3)	FZ output
5819.000	90.777	2.360	0.445	2.348	Shale
5819.500	90.275	2.630	0.443	2.368	Shale
5820.000	84.809	3.160	0.320	2.378	Shale
5820.500	79.452	3.800	0.320	2.368	Shale
5821.000	73.474	4.700	0.320	2.348	Shale
5821.500	66.196	5.490	0.319	2.297	Shale
5822.000	57.588	6.670	0.276	2.197	Shale
5822.500	50.812	9.290	0.233	2.127	Shale
5824.000	39.782	50.120	0.133	2.097	Oil
5824.500	34.927	75.160	0.110	2.087	Oil
5827.500	27.442	86.300	0.042	1.476	Oil
5828.000	26.831	83.180	0.055	1.578	Oil
5828.500	27.136	83.940	0.069	2.148	Oil
5833.000	31.785	110.660	0.138	2.177	Oil
5833.500	29.864	131.820	0.139	2.166	Gas
5834.000	29.155	158.490	0.141	2.166	Gas
5834.500	29.264	169.040	0.142	2.167	Gas
5835.000	28.042	158.490	0.139	2.167	Gas
5835.500	26.930	136.770	0.136	1.870	Gas
5836.000	26.024	112.720	0.138	2.217	Oil

Table 3 is the Takagi-Sugeno FZ output of the interpreted well. The result indicates the presence of shale at 5822.5 (ft). On the same well, it is observed that the predominant feature is HC at a depth of about 5833.0.

To ascertain the result's credibility from the FZ analysis of the WL, Petrel E&P software platform, version 2013.2 was used to interpret the WL DT. The Petrel interpretation of a section of the exploration is well examined, and arrows indicate the zone of interest in Figure 6. Logs experts have employed this application to delineate WL zones that possess a unique curve shape. Each curve shape often corresponds to a geologic contact containing lithological information extracted from WL based on log magnitude, log curve shape and stratigraphic position. The log magnitude of the log interpreted in Figure 6 gives a clue as to the LTG type of a particular unit. For example, the high conductivity of the gamma-ray log often indicates that the LTG is shale. The log curve shape patterns in the log zone provide more detailed information as each lithologic unit exhibit curve patterns, such as fining upward trends.

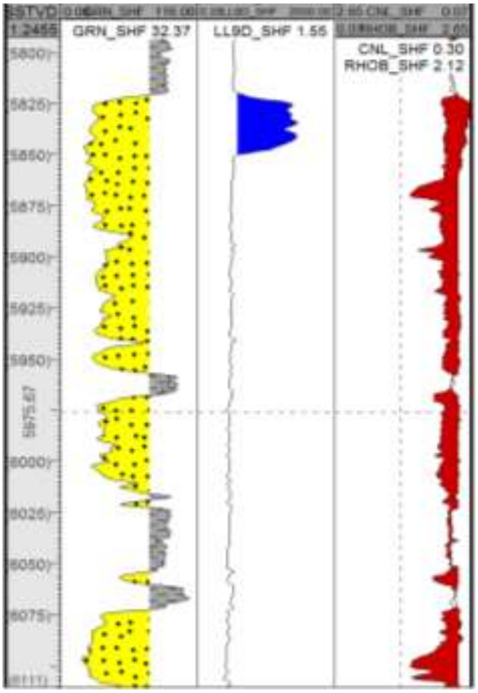

Figure 6: Petrel output of a section of the WL.

Comparing this output with the FZ output in Table 3 and Figure 6, it was observed that at a depth of about 5825 feet to 5850 feet, the indicated LTG from petrel output is a reservoir. From a depth of about 6025 feet to 6075 feet, the indicated LTG is shale which is a non-reservoir due to the high conductivity of the gamma-ray log and low conductivity of the deep resistivity log. Hence, the comparison of the results from FZ LTG, petrel interpretation and the descriptive LTG obtained from SPDC are discussed below:

The LTG results of the exploration WL from Petrel analysis, Shell descriptive core analysis and Neuro-FZ LTG are summarised in Table 4. The three primary columns represent LTG from the three procedures.

Table 4: Comparison of the results from Petrel, descriptive core and FZ analysis of the WL.

Depth (feet)	Petrel interpretation	Depth (feet)	Descriptive core analysis	Depth (feet)	FZ LTG
5825-5830	reservoir	5825-5830	no available result	5825-5830	reservoir
5840-5870	reservoir	5840-5870	reservoir	5840-5870	reservoir
5957-5968	non-reservoir	5957-5968	no available result	5957-5968	non-reservoir

From the Petrel output of the DT analysed in Figure 6, the region (5826 feet– 5870 feet) is probably a reservoir of HC, water or gas. The FZ output of the same well, Table 3 also indicated a reservoir corresponding to the Petrel output. From SPDC's descriptive LTG in Table 4, it is clear that the reservoir region, as indicated by FZ system analysis, is in conformity and agrees very well with the expert analysis of SPDC, as can be seen from the descriptive core made available.

4.0 Conclusion and Future Prospects

This study investigated the possibility of using the rule-based FZ inference method to analyse some petrophysical DT. The general LTG of the Niger-Delta of Nigeria is mainly shale and sand. The results obtained in this study are comparable to that of the conventional methods (such as the Archie method, ratio method, bulk volume water, etc.) of petrophysical DT analysis of the LTG in the studied area. However, conventional log interpretation methods were used to set the FZ inference rules. However, it is noteworthy that the TSINFSs used in the interpretation of the DT would enhance the speed of DT analysis. Therefore, it is recommended that future research studies focus on employing this precise combination of techniques as proposed in this paper to improve its accessibility and theoretical framework to close the knowledge gap and attain more convincing and beneficial results.

Acknowledgments
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Appendix 1. Section of the WL used

-9999	24.3985	67.3	10.8	-9999	2.14027	-9999	-9999
-9999	23.5909	71.12	10.8	-9999	2.15068	-9999	-9999
-9999	23.1871	73.11	10.8	-9999	2.15002	-9999	-9999
-9999	22.3795	72.44	10.9	-9999	2.14892	-9999	-9999
-9999	21.7689	71.78	10.9	-9999	2.14865	-9999	-9999
-9999	21.572	71.12	10.8	-9999	2.15842	-9999	-9999
-9999	21.1682	71.12	10.8	-9999	2.11793	-9999	-9999
-9999	20.8629	71.12	10.8	-9999	2.11786	-9999	-9999
-9999	21.1682	72.44	10.8	-9999	2.12796	-9999	-9999
-9999	21.1682	75.86	11.2	-9999	2.13814	-9999	-9999
-9999	21.572	77.98	11.41	-9999	2.13814	-9999	-9999
-9999	21.6705	75.16	11.2	-9999	2.15835	-9999	-9999

-9999	21.572	69.18	10.8	-9999	2.18864	-9999	-9999
-9999	21.9758	62.52	10.7	-9999	2.18874	-9999	-9999
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-9999	22.2811	67.3	10.5	-9999	2.13843	-9999	-9999
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