

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 resistivity will be low. When this same formation contains hydrocarbons, its resistivity will be very high. In this research, deep resistivity and shallow resistivity were studied. Deep resistivity is the resistivity recorded farther away from the inversion core created by the drilling mud. Shallow resistivity log is the resistivity recorded close to the oil well bore. A deep resistivity and shallow resistivity with low gamma ray log is indicative of hydrocarbon (HC) presence. 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.

The neutron log is used mainly for lithology identification, porosity evaluation, and the differentiation between liquids and gases when used in combination with density log. 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.

WELL LOG ANALYSIS PROCEDURE

The procedure adopted for the identification and analysis of the well logs is as follows:

- a. The well logs that were relevant to the research were first identified.
- b. The raw well logs were inspected and erroneous data items such as that which carry negative and null values were removed from the log data.
- c. The raw well logs are subjected to a statistical correlation test, to determine the relationships among the data elements for the purpose of clustering them.
- d. The raw well log values are normalized (in the range 0 to 1) for the purpose of rendering the data dimensionless, and removing the effect of scaling on the values.
- e. The normalized log values are subjected to the clustering algorithm of the SOM neural network for the purpose of generating meaningful clusters.
- f. The mean and standard deviation values of the log data by clusters are computed to determine their fuzzy value which can be considered High, Moderate, or Low. These are important variables desirable for identifying the physical property of each cluster and subsequently generating a chart which shows the distribution of the rocks in the well and location of hydrocarbon and fluid content.

Base Data: 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. The SOM based clustering algorithm, which provides a platform for plotting a multi-dimensional log cross-plot is adopted in this regard.

Data Pre-Processing: A log data set from the Niger Delta Basin was used as for the base data for the research reported in this paper. Only the five lithology logs required were used. A correlation test was carried out 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 result of the correlation test is presented in Table 1.

Self Organizing Map (SOM) Based Clustering: SOM involves competitive learning of one-layer networks with linear processing elements (neurons) organized in one, two or multi-dimensional arrays. Competitive learning is an

adaptive process in which the processing elements in a neural network gradually become sensitive to different input categories or sets of data samples in a specific domain of the input space. In such networks, there is only one winning processing element for every input pattern and only the weights of the winning node are updated. Kohonen (1999) proposes networks which allows the data points that are similar in input space to be mapped to small neighborhoods.

If the input data sets in a Kohonen SOM are arranged logically in an array and are to be mapped onto the output array, it is proposed in Kohonen (1999) that each processing element i of the SOM has an associated d -dimensional reference (also called the weight, codebook, model or prototype) vector $m_i = [m_{i1} \ m_{i2} \ \dots \ m_{id}]$, where d is equal to the dimension of the input vectors. The training of the SOM is carried out by using the following iterative procedure:

The input data (that is the well log data) were first normalized to the range 0 to 1 for the purpose of rendering the data dimensionless, and removing the effect of scaling on the values.

In each training step, one sample vector 'x' from the input data set is chosen randomly and a similarity measure is calculated between it and all the weight vectors of the map. The Best-Matching Unit (BMU), denoted by 'c', is the unit whose weight vector has the greatest similarity with the input sample 'x'. The similarity is usually defined by means of a distance measure, usually the Euclidian distance. The BMU is defined mathematically as the processing element for which the expression:

$$\|x - m_c\| = \min_i\{\|x - m_i\|\}, \quad (1)$$

where $\|\cdot\|$ is the distance measure.

The reference vectors of the BMU and its topological neighbors are moved closer to the input vector in the input space. This adaptation procedure stretches the prototypes of the BMU and its topological neighbors towards the sample vector as shown in Figure 2. The figure illustrates the process of updating BMU and its neighbors towards the input sample marked with 'x'. The solid and dashed lines correspond to situation before and after updating, respectively. The SOM update rule for the weight vector of the unit i is given mathematically as:

$$m_i(t+1) = m_i + a(t) h_{ci}(r(t)) [x(t) - m_i(t)], \quad (2)$$

where t represents time, $a(t)$ represents the learning rate, and $h_{ci}(r(t))$ represents the neighborhood kernel around the winner unit 'c', with neighborhood radius $r(t)$.

The function $h(t)$ is called the neighborhood function. It represents a non-increasing function of time and distance between the winning neuron and its neighbors on the grid. The function consists of two parts: the distance function and the learning rate function of time. If the locations of units c and i on the map grid are denoted by the two-dimensional vectors r_c and r_i , respectively, then the neighborhood function is expressed mathematically as:

$$h_{ci}(t) = h(\|r_c - r_i\|, t) \sigma(t) \quad (3)$$

where r_c represents the location of unit c on the map grid and $\sigma(t)$ represents the neighborhood radius at time t .

Table 1: Correlation Test Result.

	DEP	NEU	DEN	GR	DRS	SRS
DEP	1					
NEU	-0.50854	1				
DEN	0.487547	-0.41668	1			
GR	0.076405	0.466654	0.222112	1		
DRS	0.039717	-0.306	-0.06557	0.34206	1	
SRS	0.253511	-0.40028	-0.05902	0.23694	0.755617	1

Two functions of distance have been reported in the literature. They are:

i. Simple constant defined by:

$$h(d, t) = \begin{cases} \text{const}, & d \leq \sigma(t) \\ 0, & d > \sigma(t) \end{cases} \quad (4)$$

where $\sigma(t)$ is a diminishing function of time.

ii. Gaussian function defined by:

$$h(d, t) = e^{-\frac{d^2}{2\sigma^2(t)}} \dots \dots \dots (5)$$

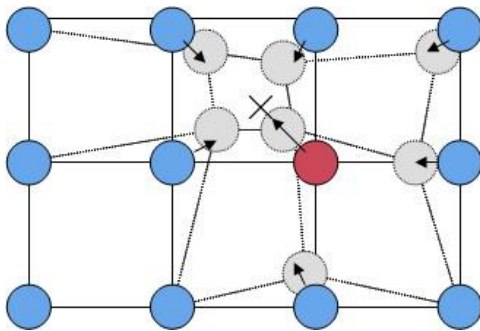


Figure 2: Updating of the Best Matching Unit (BMU) and Its Neighbors.

It is noted that the Gaussian function of distance provides better results. At the beginning of the learning procedure, it is fairly large, but it is made to gradually shrink during learning by using linear diminishing function of time with a view to obtaining a single winning processing element at the end.

The learning process consisting of winner selection by Equation (1) and adaptation of the synaptic weights by Equation (2) can be modeled with a neural network structure, in which the processing elements are coupled by inhibitory connections.

After training the SOM, the neural network would have learned the structure of the input data. The test data file is submitted to the trained SOM network, which then identifies the clusters it had recognized during the training process and the data samples are assigned to cluster groups. An output report typical of the form presented in Table 2 is generated.

The mean of the log values and their standard deviation are then computed. The computed mean of the log values are then 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.

Table 2: SOM Software Output File Format

S/No	DEP	GR	DRS	SRS	NEU	DEN	Clusters
7065	7532	42.37	35.23	22.83	0.29	2.29	20
7066	7532.5	48.43	38.05	24.11	0.28	2.32	20
7067	7533	54.32	41.32	25.73	0.26	2.34	20
7068	7533.5	58.31	44.83	27.58	0.24	2.34	2
7069	7534	59.31	48.08	29.34	0.23	2.34	2
7070	7534.5	56.29	50.5	30.66	0.22	2.33	2
7071	7535	50.15	51.41	31.08	0.22	2.33	2
7072	7535.5	43.88	50.44	30.4	0.22	2.32	2
7073	7536	39.47	48.25	29.08	0.22	2.32	3
7074	7536.5	37.96	46.25	27.89	0.22	2.31	3
7075	7537	38.42	45.11	27.2	0.22	2.3	20
7076	7537.5	38.9	44.95	27.06	0.22	2.29	20
7077	7538	38.59	45.92	27.56	0.22	2.28	20
7078	7538.5	37.39	48.57	29.02	0.22	2.28	3
7079	7539	35.85	53.25	31.54	0.21	2.28	3
7080	7539.5	34.92	58.67	34.35	0.21	2.29	3
7081	7540	34.96	63.17	36.49	0.21	2.3	3
7082	7540.5	35.78	66.68	37.97	0.21	2.3	3
7083	7541	37.24	69.64	39.02	0.21	2.31	3

Fuzzy Inference System: The fuzzy value of the logs can be modeled by three fuzzy membership functions, which correspond to the linguistic values High (H), Moderate (M), or Low (L). The fuzzy values are used to generate fuzzy rules for the determination of rock lithology and fluid content. The fuzzy sets are presented in Figures 3 - 7. Figure 8 shows the output fuzzy sets.

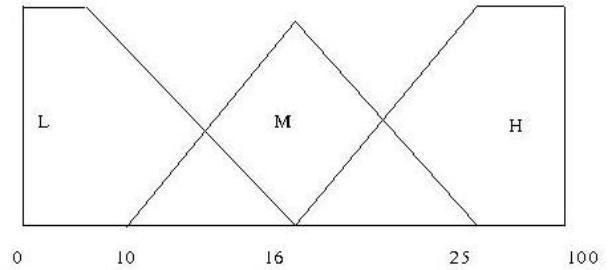


Figure 7: NEU Log Membership Functions.

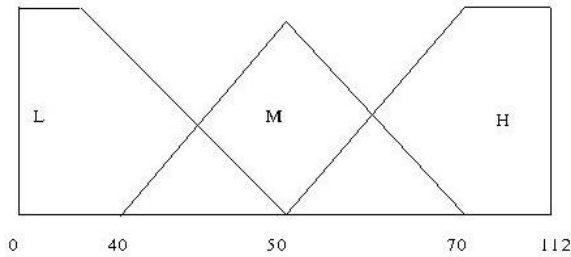


Figure 3: GR Log Membership Functions.

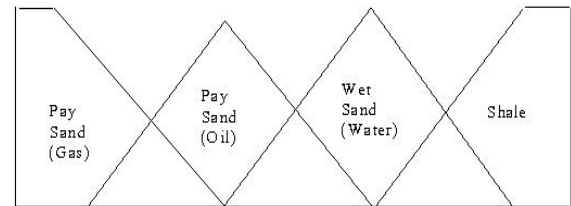


Figure 8: Output Membership Functions.

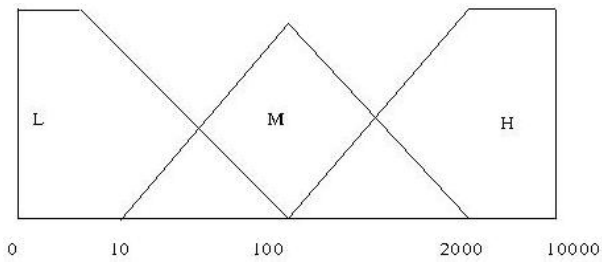


Figure 4: DRS Log Membership Functions.

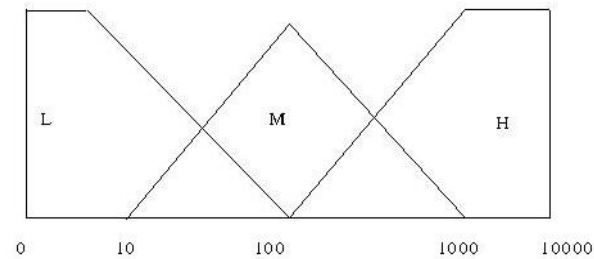


Figure 5: SRS Log Membership Function.

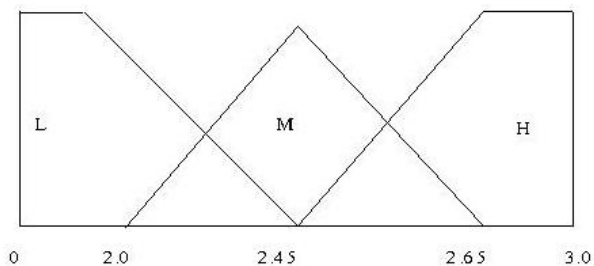


Figure 6: DEN Log Membership Functions.

The fuzzy rules matrix presented in Table 3 was derived from the characteristic response of the lithology logs to the logging tools in different rock materials. 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.
- The resistivity logs were inspected to determine if there is any hydrocarbon presence indicated by an inversion of the deep resistivity logs and the shallow resistivity logs.
- The density and neutron logs are used to confirm either the presence of oil, gas or water in the rock materials matrix.

CASE STUDY OF LOG DATA OF NIGER DELTA OF NIGERIA

A case study was carried out using geophysical well log data from the Niger-Delta region of Nigeria. Twelve cluster groups were identified in the well log data. The cluster groups (denoted by their cluster numbers), their mean values and computed standard deviations are presented in Table 4.

Table 3: Fuzzy Rules Matrix.

Rule	GR value	DRS value	SRS value	DEN value	NEU value	Primary Lithology	Final Lithology	Fluid content
1	H or M	L	L	H or M	H or M	Shale	Shale	None
2	L	L	L	M	H or M	Sandstone	Sandy-shale	None
3	L	H	H	M	M	Sandstone	Pay Sand	Oil
4	L	H	H	L	L	Sandstone	Pay Sand	Gas
5	L	M	M	M	M	Sandstone	Pay Sand	Oil
6	L	M	M	L	L	Sandstone	Pay Sand	Gas
8	L	L	L	L	M	Sandstone	Wet Sand	Water

Table 4: Identified Cluster Groups.

Cluster No.	No. of samples	Value	GR	DRS	SRS	DEN	NEU
1	44	Mean	34.78091	1797.661	646.9207	2.122727	0.1025
		SD	4.098724	640.3153	133.0228	0.020839	0.016861
2	525	Mean	101.152	25.47221	20.02962	2.364	0.286533
		SD	17.74415	52.78437	34.29039	0.108893	0.068276
3	52	Mean	33.15673	36.47615	31.785	2.255	0.186538
		SD	4.954649	28.36702	26.73754	0.045092	0.052239
4	149	Mean	27.66638	636.7572	324.199	2.136443	0.102483
		SD	6.193327	655.1077	179.5119	0.035165	0.026276
5	302	Mean	73.72493	20.83497	17.96874	2.253543	0.362252
		SD	20.10554	31.77368	26.70736	0.101342	0.135341
6	3	Mean	73.27	44.35667	38.19	1.466667	0.543333
		SD	10.6865	29.90384	23.00508	0.030551	0.055076
7	11	Mean	22.45636	6663.72	916.8719	2.185455	0.079091
		SD	1.111362	989.4961	24.25633	0.005222	0.009439
8	46	Mean	108.5622	21.68348	16.45804	2.386304	0.471087
		SD	13.26835	9.696412	6.700888	0.107442	0.050519
9	668	Mean	31.14049	64.80641	33.6712	2.229701	0.227695
		SD	5.427909	20.89779	11.143	0.06483	0.039719
10	425	Mean	30.38256	209.0674	115.5055	2.194635	0.173882
		SD	5.412735	107.8224	91.93481	0.049334	0.058011
11	68	Mean	26.47603	994.1869	262.3741	2.147059	0.122647
		SD	4.332712	536.3986	110.8691	0.034471	0.019518
12	1630	Mean	70.93486	64.38815	40.78978	2.294018	0.26716
		SD	22.56937	49.62646	33.97884	0.115673	0.070795

In a fuzzy system, the general inference process proceeds in the following steps (Krause et al., 1994; Akinyokun, 2002):

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

The fuzzy inference process started with the fuzzification sub-process 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 rule premise has a non-zero degree of truth, then the rule fires. In the inference sub-process, 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 after which the output was defuzzified. The results after carrying out the inference procedure showing the lithology and fluid contents inferred from the cluster groups are presented in Table 5.

Appendix A presents a chart of the oil well showing the location of the fluid content (that is whether there is oil, gas, or water) that is contained in the rock matrix (sandstone) of the oil well. On the chart, the depth intervals containing pay sand with gas content is represented by the yellow colored regions, depth intervals containing pay sand with oil content is represented by the green 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 2, 5, 6, 8 and 12 represent shales. Cluster 7 represents a pay sand cluster containing gas while clusters 1, 4, 10 and 11 represents pay sand clusters containing oil. Cluster 3 and 9 represent wet sand clusters containing water. The

results were verified by a log analyst that was familiar with the dataset used.

Table 5: Identified Clusters.

Cluster	Lithology	Fluid Content	Legend
1	Pay Sand	Oil	1
2	Shale		2
3	Wet Sand	Water	3
4	Pay Sand	Oil	4
5	Shale		5
6	Shale		6
7	Pay Sand	Gas	7
8	Shale		8
9	Wet Sand	Water	9
10	Pay Sand	Oil	10
11	Pay Sand	Oil	11
12	Shale		12

CONCLUSION

In this work, the SOM neural network had 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 was derived from the methods used in the interpretation of traditional graphical cross-plots by log analysts.

There are generally two types of petroleum reservoirs: carbonates and siliciclastics. The former is composed chiefly of limestone or dolomite and the latter sand or sandstone. In the Niger Delta Region (of the Niger Delta province) of Nigeria, the general lithology is mainly sand and shale (Tuttle et al., 1999). This is consistent with the result obtained in this work. The result not only gives the oil well lithology, it also gives an indication of the fluid content of the oil well and rock materials identified. The SOM based clustering and the fuzzy inference rules developed in this paper can form the basis for the development of a neuro-fuzzy expert system that can be used for the detection of fluid content in oil wells.

APPENDIX A - Well Stratigraphy Chart

DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP	DEP
7000	10	7050	12	7100	12	7150	10	7200	10	7250	9	7300	9	7350	12
7001	10	7051	9	7101	12	7151	10	7201	10	7251	9	7301	9	7351	12
7002	10	7052	9	7102	12	7152	10	7202	10	7252	9	7302	12	7352	12
7003	10	7053	9	7103	12	7153	10	7203	10	7253	10	7303	12	7353	12
7004	10	7054	9	7104	12	7154	10	7204	10	7254	10	7304	12	7354	12
7005	10	7055	9	7105	12	7155	10	7205	10	7255	10	7305	9	7355	12
7006	10	7056	9	7106	12	7156	10	7206	10	7256	10	7306	12	7356	12
7007	10	7057	9	7107	12	7157	10	7207	10	7257	10	7307	12	7357	12
7008	10	7058	9	7108	12	7158	10	7208	10	7258	10	7308	12	7358	12
7009	10	7059	9	7109	12	7159	10	7209	10	7259	10	7309	12	7359	12
7010	10	7060	9	7110	12	7160	10	7210	10	7260	10	7310	12	7360	12
7011	10	7061	12	7111	12	7161	10	7211	10	7261	10	7311	12	7361	12
7012	10	7062	12	7112	12	7162	10	7212	9	7262	10	7312	12	7362	12
7013	10	7063	12	7113	12	7163	10	7213	9	7263	10	7313	12	7363	12
7014	10	7064	12	7114	12	7164	12	7214	10	7264	10	7314	12	7364	12
7015	10	7065	12	7115	12	7165	12	7215	10	7265	10	7315	9	7365	12
7016	10	7066	12	7116	12	7166	12	7216	10	7266	10	7316	9	7366	12
7017	9	7067	12	7117	12	7167	12	7217	10	7267	10	7317	10	7367	12
7018	9	7068	12	7118	12	7168	12	7218	9	7268	9	7318	9	7368	12
7019	12	7069	12	7119	12	7169	12	7219	9	7269	9	7319	12	7369	12
7020	12	7070	8	7120	12	7170	12	7220	10	7270	9	7320	12	7370	12
7021	12	7071	12	7121	12	7171	12	7221	10	7271	9	7321	12	7371	12
7022	12	7072	12	7122	12	7172	12	7222	10	7272	9	7322	12	7372	12
7023	12	7073	12	7123	12	7173	12	7223	10	7273	9	7323	12	7373	12
7024	12	7074	12	7124	12	7174	12	7224	10	7274	12	7324	12	7374	12
7025	12	7075	12	7125	12	7175	12	7225	10	7275	12	7325	12	7375	12
7026	12	7076	12	7126	12	7176	12	7226	10	7276	12	7326	12	7376	12
7027	12	7077	12	7127	12	7177	12	7227	10	7277	12	7327	12	7377	12
7028	12	7078	12	7128	12	7178	12	7228	10	7278	12	7328	12	7378	12
7029	12	7079	12	7129	12	7179	12	7229	10	7279	12	7329	12	7379	12
7030	12	7080	12	7130	12	7180	12	7230	10	7280	10	7330	10	7380	12
7031	12	7081	12	7131	12	7181	12	7231	9	7281	10	7331	10	7381	12
7032	12	7082	12	7132	12	7182	12	7232	9	7282	10	7332	10	7382	12
7033	12	7083	12	7133	12	7183	12	7233	9	7283	10	7333	12	7383	12
7034	12	7084	12	7134	12	7184	12	7234	12	7284	10	7334	12	7384	12
7035	12	7085	12	7135	12	7185	12	7235	12	7285	10	7335	12	7385	12
7036	12	7086	12	7136	12	7186	12	7236	12	7286	10	7336	12	7386	12
7037	12	7087	12	7137	12	7187	12	7237	12	7287	10	7337	12	7387	12
7038	12	7088	12	7138	12	7188	12	7238	12	7288	10	7338	12	7388	12
7039	12	7089	12	7139	12	7189	10	7239	12	7289	10	7339	12	7389	12
7040	12	7090	12	7140	12	7190	10	7240	12	7290	9	7340	12	7390	12
7041	12	7091	12	7141	12	7191	10	7241	12	7291	9	7341	10	7391	12
7042	12	7092	12	7142	12	7192	10	7242	12	7292	9	7342	12	7392	12
7043	12	7093	12	7143	9	7193	10	7243	12	7293	9	7343	12	7393	12
7044	12	7094	8	7144	9	7194	10	7244	12	7294	9	7344	12	7394	12
7045	12	7095	12	7145	9	7195	10	7245	12	7295	12	7345	12	7395	12
7046	12	7096	12	7146	9	7196	9	7246	12	7296	12	7346	12	7396	12
7047	9	7097	12	7147	9	7197	10	7247	12	7297	12	7347	12	7397	12
7048	12	7098	12	7148	9	7198	10	7248	12	7298	12	7348	12	7398	12
7049	12	7099	12	7149	10	7199	10	7249	10	7299	12	7349	12	7399	12
7050	12	7100	12	7150	10	7200	10	7250	9	7300	9	7350	12	7400	12
7500	9	7501	9	7502	9	7503	9	7504	9	7505	9	7506	9	7507	9
7550	12	7551	12	7552	12	7553	12	7554	12	7555	12	7556	12	7557	12
7600	8	7601	8	7602	8	7603	8	7604	12	7605	9	7606	8	7607	8
7650	12	7651	12	7652	12	7653	12	7654	12	7655	12	7656	12	7657	12
7700	12	7701	12	7702	12	7703	12	7704	12	7705	12	7706	12	7707	12
7750	12	7751	12	7752	12	7753	12	7754	12	7755	12	7756	12	7757	12
7800	8	7801	8	7802	8	7803	8	7804	12	7805	9	7806	8	7807	8
7850	12	7851	12	7852	12	7853	12	7854	12	7855	12	7856	12	7857	12
7900	12	7901	12	7902	12	7903	12	7904	12	7905	12	7906	12	7907	12
7950	12	7951	12	7952	12	7953	12	7954	12	7955	12	7956	12	7957	12
8000	12	8001	12	8002	12	8003	12	8004	12	8005	12	8006	12	8007	12

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