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Modeling and Forecasting of Total Dissolved Solids for Irrigation Water Quality Assessment

Ubah J. I[1], Orakwe L.C[1], Awu J.I[2], Chukwuma E.C[1], Okpala C.D[1].
[*1]Department of Agricultural and Bioresources Engineering, Nnamdi Azikiwe University Awka
[2]National Centre for Agricultural Mechanization, Ilorin
*Corresponding Author's E-mail: ji.ubah@unizik.edu.ng

Abstract

Industrial Effluents when discharged into water bodies contain untreated or partially treated substances with an enhanced concentration of nutrient and sediments which poses serious negative impact on the quality and life forms of the receiving water body .Ele River is surrounded by clusters of industries popularly among them which has a direct discharge outlet into the River is Chicason industries Limited. Effluents discharged from these industries contain physico-chemical and heavy metal properties predominantly among them is total dissolved solids (TDS) which comprise inorganic compounds such as salts, heavy metals and some traces of organic compounds that are dissolved in water. The aim of this study is to model and forecast Ele river TDS using artificial neural network for irrigation purposes. Monthly Water samples were collected at ten sampling points of 10m interval for a period of forty-eight months. The water samples were analyzed for TDS concentrations. The results show that during rainy season, The TDS exceeded the FAO permissible standard from point 1 to point 3 and later decreased as the river flows down the river course. Also, the results show that during the dry season, the river TDS concentration values was found to have exceeded the FAO permissible range from point 1 to Point 5 Generally, the river quality from point 1 to point 5 is not safe for agricultural production as the TDS concentration was above FAO guideline for irrigation while from point 6 to 10, the river is safe for agricultural production. The artificial neural network was able to model the River TDS very well as the R^2 value for the model training, testing and forecasting are 0.981 to 0.988, 0.953 to 0.970 and 0.946 to 0.968, respectively. It was recommended that the river water from points 1 to point 5 needs to be treated before use for agricultural production.

Keywords: Irrigation water quality, total dissolved solids, Time series modeling, feed-forward multilayer neural network

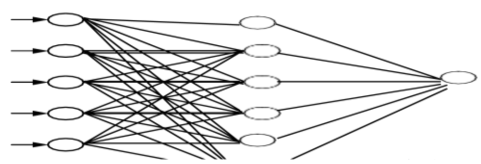
1. Introduction

Water pollution in surface water results from all Human activities such as indiscriminate waste disposal from industries and other pollution sources. Industrial pollution and effluent discharges is becoming a serious environmental issue in many developing countries of Africa (Uzoukwu et al., 2004). These indiscriminate contaminations of the water resources have caused much harm to aquatic animals and have also affected Man in his quest to use water for domestic, drinking and irrigation purposes. Industrial and municipal wastewater discharge can also be considered as a constant pollutant source, but not so for the surface runoff which is seasonal and highly affected by climate (Hafizan et al, 2004). The devastating effects of industrial pollutants have adversely affected most environmental ecosystems. This implies that as a result of Pollution of the aquatic ecosystem, there is a great threat to the lives of aquatic organisms and also the river cannot serve the purpose for dry season irrigation (Ubah et al 2015).

Total dissolved solids comprise inorganic compounds such as salts, heavy metals and some traces of organic compounds that are dissolved in water which has caused serious degradation of surface waters due to its high ionic compounds. Ele River in Nnewi is an important water body as it serves for various purposes including agricultural and domestic needs. The perceived consequences of unregulated waste disposal into water bodies used for portable water sources has stimulated various studies on industrial effluent (Aluyor and Badmus, 2003a; Aluyor and Badmus 2003b). Sequel to this, modeling and forecasting of TDS was done using Artificial Neural Network (ANN) for irrigation water quality assessment for crop production. Artificial intelligence is a technique with a flexible mathematical structure which is capable of identifying complex non-linear relationships between input and output data when compared with other classical modeling techniques (Najah et al., 2011). It comprises methods for analyzing time-series data so as to extract characteristics of data and to forecast future events based on known past. Sahaya and Adish (2018) predicted the water quality index of Paraka Lake, India using artificial neural network.

1.1 Artificial Neural Network as Water Quality Index Prediction Model:

ANN is composed of a large number of simple processing units, each interacting with others via excitatory or inhibitory connections. The ANN technique is flexible enough to accommodate additional constraints that may arise during its application. Moreover, the ANN model can reveal hidden relationships in historical data, thus facilitating the prediction and forecasting of water quality (Najah et al., 2013). In ANN modeling, different layers in the program can be distinguished as follow: The input layer - connecting the input information to the network, Hidden layer-acting as the intermediate computational layer. Multi-layer neural networks contain one or more hidden layer. The Output layer producing the desired output which is in this case the Water Quality Index (WQI).



Input layer Hidden layer Output layer

Fig. 1: Structure of a multi-layer feed forward Artificial Neural Network model

1.1.1 Feed-Forward Multilayer Perceptron (FFMLP)

A feed-forward multilayer perceptron was the ANN architecture that was employed in this study. This structure of an artificial neural network that has been proven to be the best neural network structure for hydrological modeling (Shamseldin, 1997). In the artificial neural network model development, the primary building block was the neuron classification, therefore a neuron class was declared. The neuron class therefore exists in the single neuron and a network of many neurons arranged in layer-by-layer basis.

2.0 Materials And Methods

2.1 Study Area

The study area Nnewi is located on Longitudes 6° 91' E and 6° 55' E and Latitudes 6° 16' N and 6° 55' N. It has an average annual rainfall of 200 mm and mean temperature of 27^{o}C. The months of April to October experience heavy rainfall, while low rainfall, higher temperature and low humidity characterize the months of November to February. Ele River is important surface water since it serves for various purposes including agricultural and domestic needs for the residents. The city spans over 1,076.9 square miles (2,789 km^2) in Nnewi, Anambra State. Ele River is located very close to Industrial Clusters at Umudim Nnewi. Notable among them are, Chicason group of companies, Kotec industries Limited, Innoson Vehicle Manufacturing etc. Effluents from these industries are discharged into Ele River.

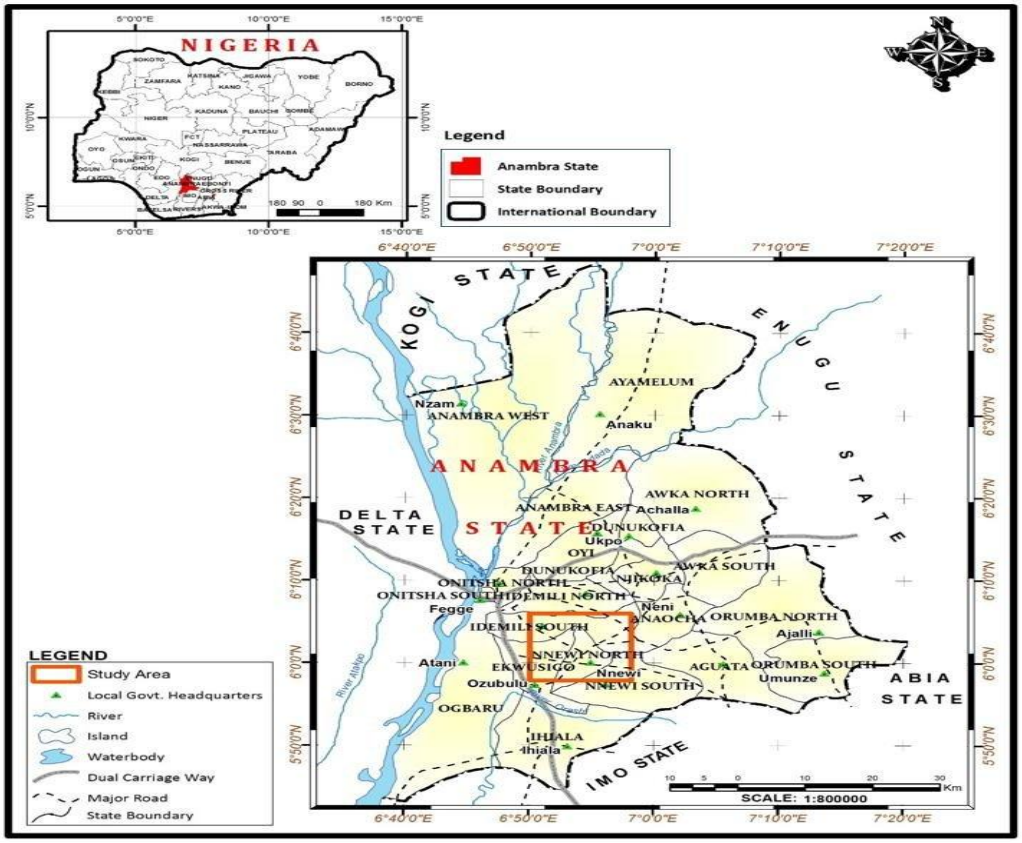


Fig. 1: Nigeria showing Anambra State (top) and Anambra State showing the study area, Nnewi (bottom)

Fig. 2: Visualized raster image showing Ele River and the industrial zone and major tributary

2.2 Point Sampling

Ele River based on the preliminary survey was divided into ten sampling points putting into consideration the point of discharge which is very close to Chicason Group of Companies discharge outlet**.** These ten (10) sampling points were named P1, P2, P3, P4, P5, P6, P7, P8, P9, and P10 so as to determine the pollution level from the point source to a particular distance considering ion dissolution and sediment transportation from discharge point to sampling point 10. P1 and P2 were located upstream while P3-P10 were located downstream. Distance from each point is 10m, from each sampling points, duplicate water samples were collected using 1.5 litre sterile plastic can. These water samples were collected for 48 months from May 2015 to April 2019.

2.3 Development of Artificial Neural Networ

2.3.1 Feed-Forward Multilayer Perceptron (FFMLP)

Practically, this network architecture contains a number of layers namely; the input, hidden and output layers, respectively. The architecture determines the number of connection weights, also the way information flows through the network. The determination of the best network architecture is one of the difficult tasks in artificial neural network model building process but one of the most important steps that must be taken. A neural network feed-forward multilayer perceptron (FFMLP) was adopted in this study using river quality parameters at times t_{-n} to forecast the river quality parameters at time t_{n+1} . The Neuron class describes an entity with an (x, y) location to manage an array list of neurons, as well as its own location that are drawn relatively to the network's center.

A connection object was also created to connect the neurons from one layer to another. The connection object was made to connect neurons from the preceding layer to the succeeding layer. A new function called 'connect' was therefore added in the neuron class to connect object between the specified neurons.

2.3.2 The Neural Network Training

Supervised Feed-forward Back propagation training algorithm was employed in this study. The supervised back propagation training algorithm endeavours to minimize the error between the desired value and the network output value by changing the values of the synaptic weights in the network through calculating the difference between the network output values and the target values and feeding them back to the network.

The back propagation class created signals from the input layer x_i and multiplies it by a set of fully-connected synaptic weights w_{ji} connecting the input layer to the first hidden layer using the activation function (v_j) . The computation forms the pre-activation signal for the first hidden layer. The pre-activation signal of the hidden layer was transformed using the output function $y(v_j)$ to form the feed-forward activation signals leaving the first hidden layer x_j to the next neuron in the next layer, this process continued to the output layer. The Alyuda network intelligence shield software package was employed in the neural network modelling and forecast.

Input Layer **→Hidden Layer** **→Output Layer**

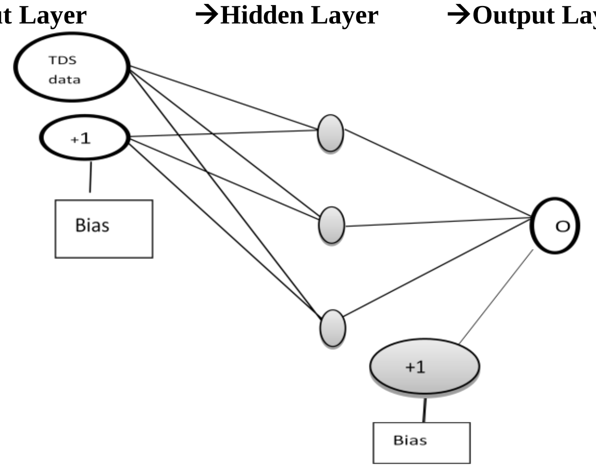


Fig. 3: Schematic diagram of Feed Forward Multilayer Neural Network Architecture used

3.0 Results and Discussions

The result of this study is presented in four categories, namely; the descriptive statistics, the descriptive graph analysis over time, the ANN model and the model evaluation performance, respectively. The descriptive statistics result is presented in Table 1

Table 1: Time Series Descriptive Statistics of TDS

Points	P1	P2	P3	P4	P5	P6
Mean	2458.19	2265.40	2132.88	1956.21	1678.15	1293.94
Median	2439.50	2241.00	2104.0	2010.00	1616.50	1269.00
Max	2742.00	2523.00	2404.0	2286.00	2154.00	2014.00
Min	2199.00	2044.00	1883.0	1367.00	1064.00	922.00
Stadev	127.36	127.07	114.47	213.04	336.42	322.46
Points	**P7**	**P8**	**P9**	**P10**	**FAO Perm. Range**	
Mean	963.23	718.98	494.71	357.98	0 – 2000	
Median	915.00	746.00	499.00	357		
Max	1484.0	940.00	657.00	461		
Min	602.00	429.00	376.00	254		
Stadev	196.20	119.05	66.56	49.312		

The descriptive statistics shows that the TDS mean values ranges from 2458.19 to 357.98, Standard deviation ranges from 127.36 to 49.312, respectively. The low values of standard deviation recorded in this study shows that data set were very close to the mean of the dataset. The descriptive graph analysis of this is shown in Figure 1

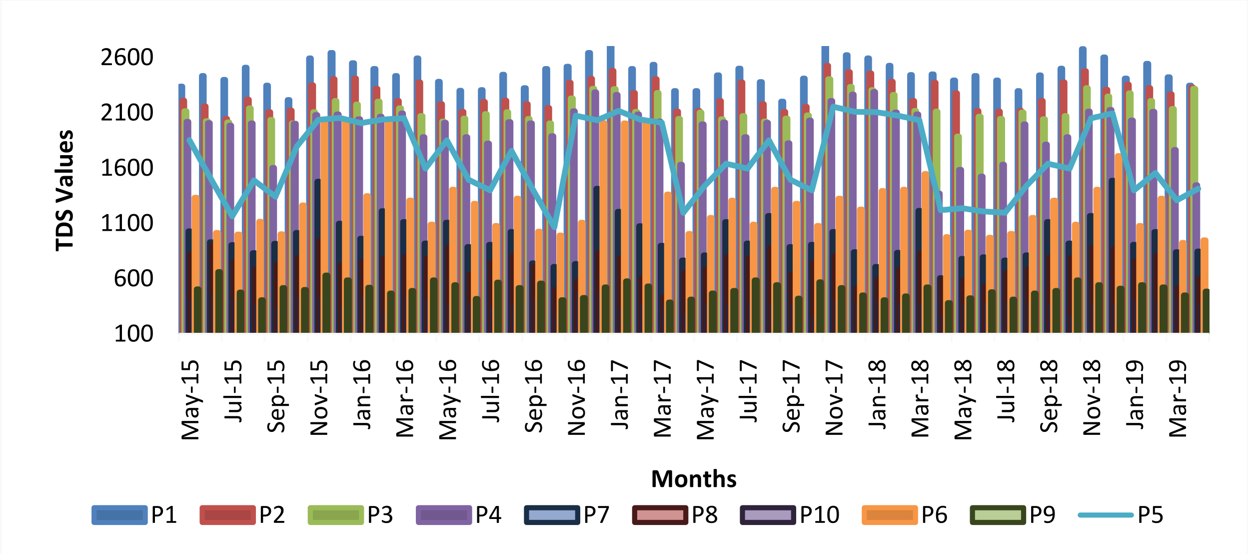


Fig. 1: Descriptive graph of TDS over time

Figure 1 shows a continuous variation of TDS values at different instance. The highest concentrations occurred at Point 1 of November, 2017 and lowest concentration at points 10 of October 2017 and April 2018. It was observed that these high concentrations of TDS were above the FAO permissible range which occurred at the upstream section of the River most especially during dry season over time. These concentrations decrease along the sampling points going downstream. The decrease of the TDS concentration could be as a result of ion dissolutions and rainfall effects.

Considering the water quality permissible range, River quality modeling and forecast shows different variations seasonally such that the pollution level during dry season was higher than the rainy season since the TDS values during wet season were high from the point of discharge from points 3 to 4 due the presence of dissolved solids, ions and inorganic salts in the water at the entry points of the River which gradually decreases as the flow goes downstream due to ion dissolution which increases with the flow rate and presence of rainfall. The presence of total dissolved solids was higher during dry season due to decrease in flow rate and absence of rainfall, thus increasing the TDS level so high beyond the permissible standard along the sampling points down to points 4 to 5. It is noteworthy that at several sampling points, there were insignificant deviations in values between the ANN model and actual. The ANN Training, Validation and forecast model of the TDS is shown from Figure 2 to 31:

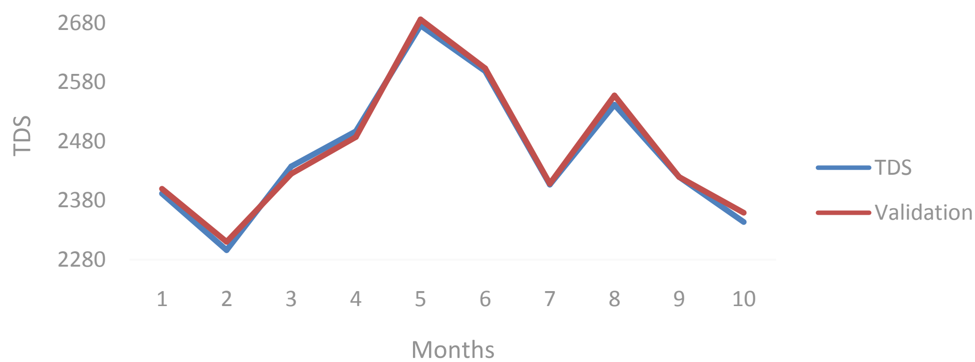


Fig. 2: TDS and Training model graph at point 1

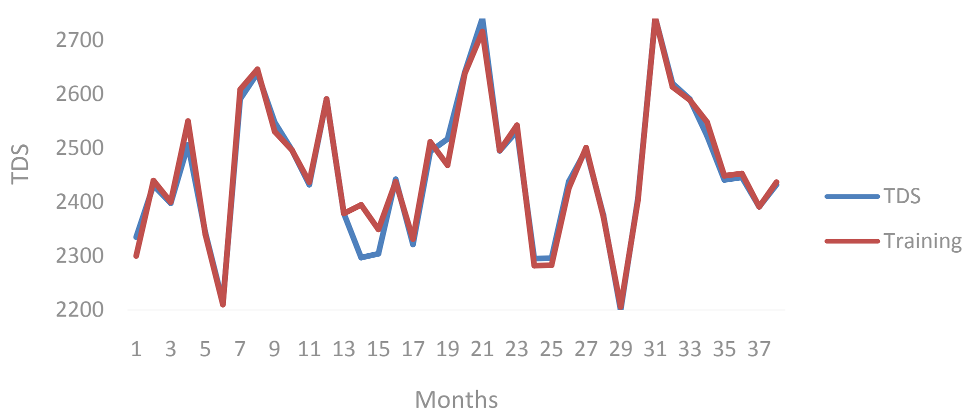


Fig. 3: TDS and Validation model graph at point 1

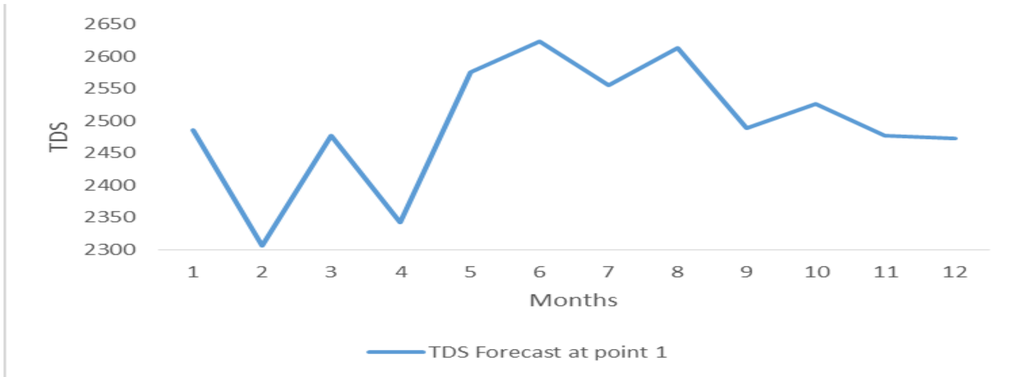


Fig. 4: TDS forecast at point

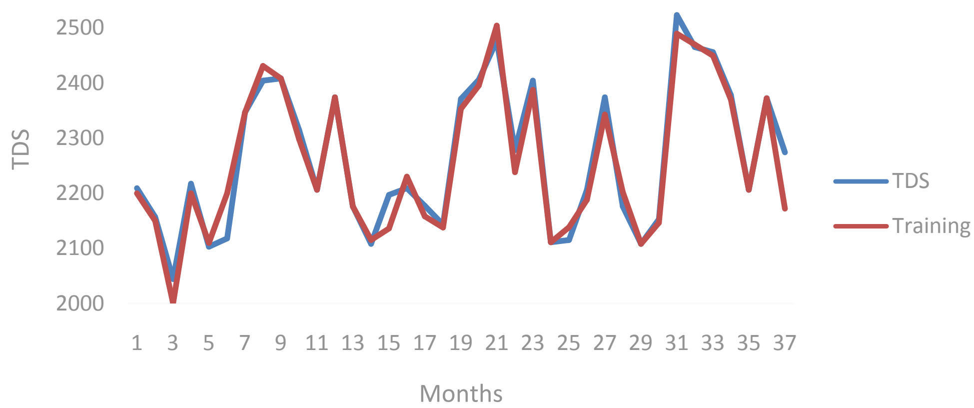


Fig. 5: TDS and Training model graph at point 2

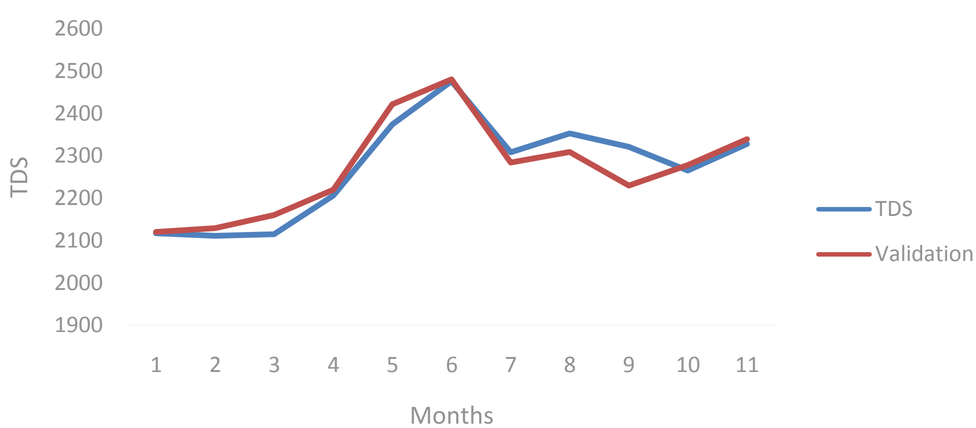


Fig. 6: TDS and Validation model graph at point 2

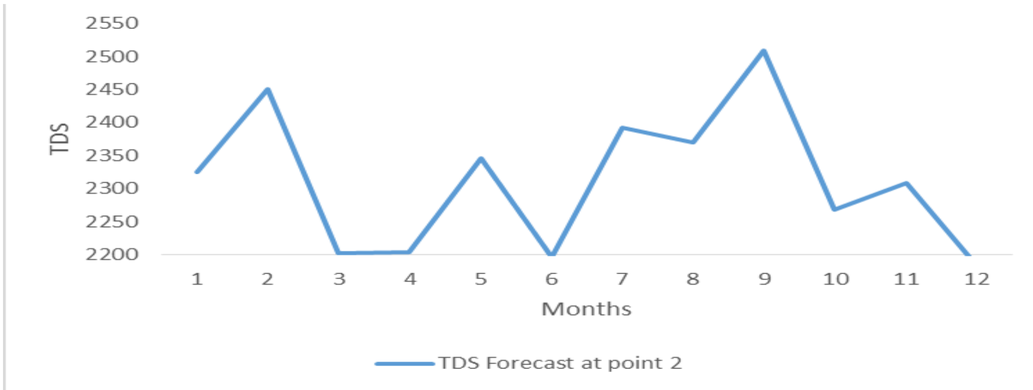


Fig. 7: TDS and forecast at point 2

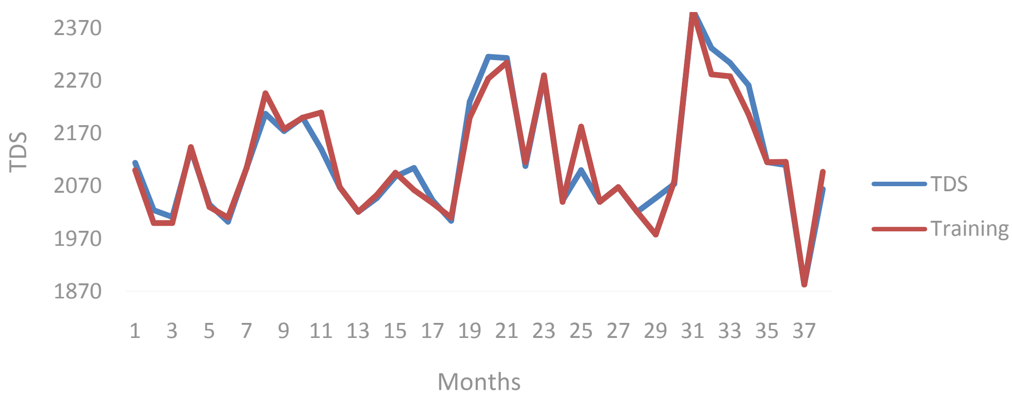


Fig. 8: TDS and Training model graph at point 3

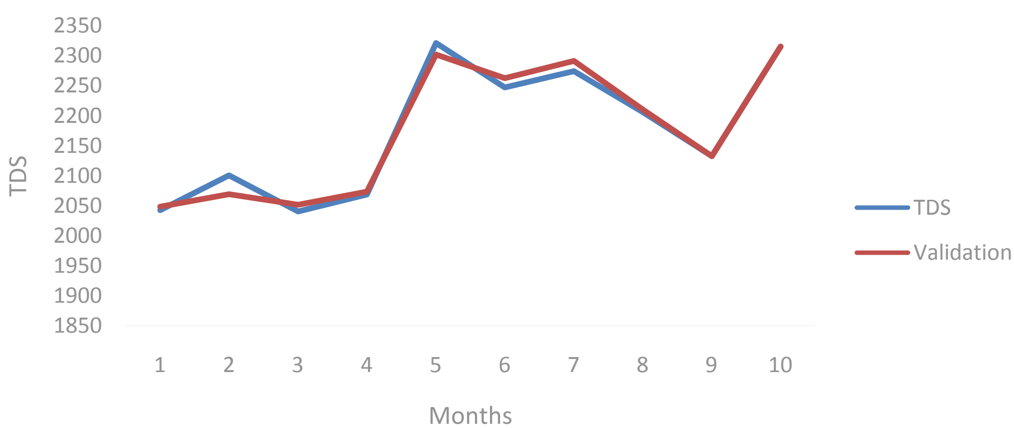


Fig. 9: TDS and Validation model graph at point 3

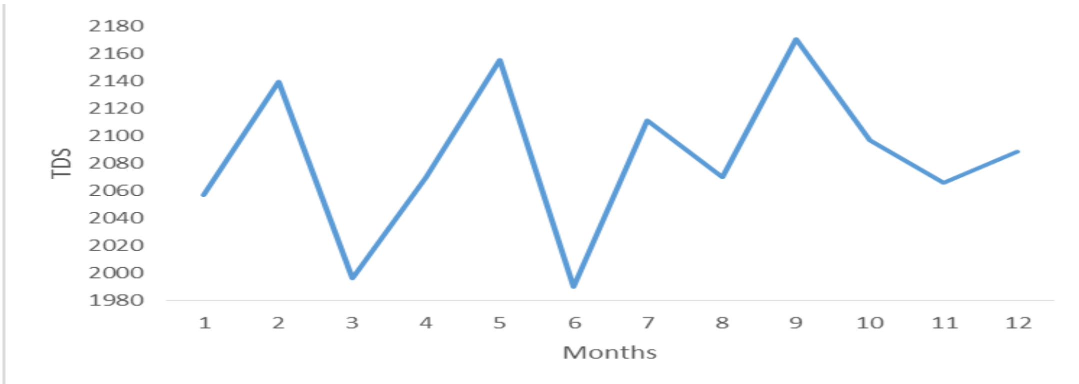


Fig. 10: TDS Forecast at point 3

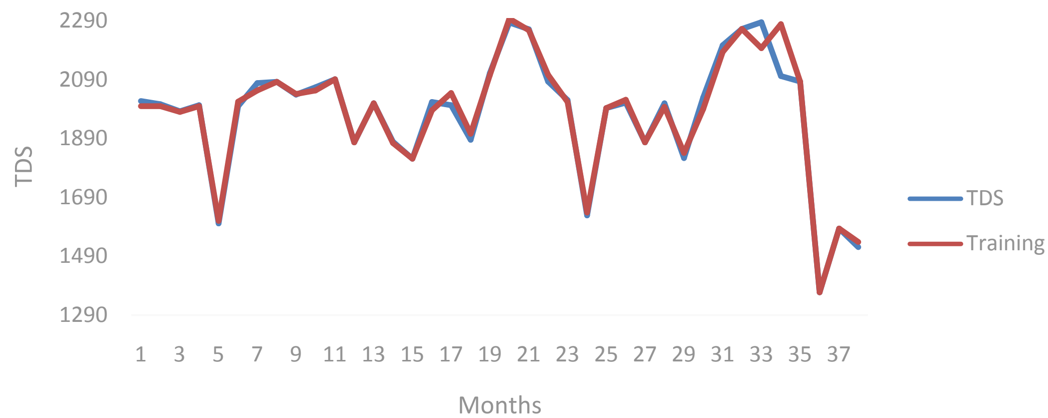


Fig. 11: TDS and Training model graph at point 4

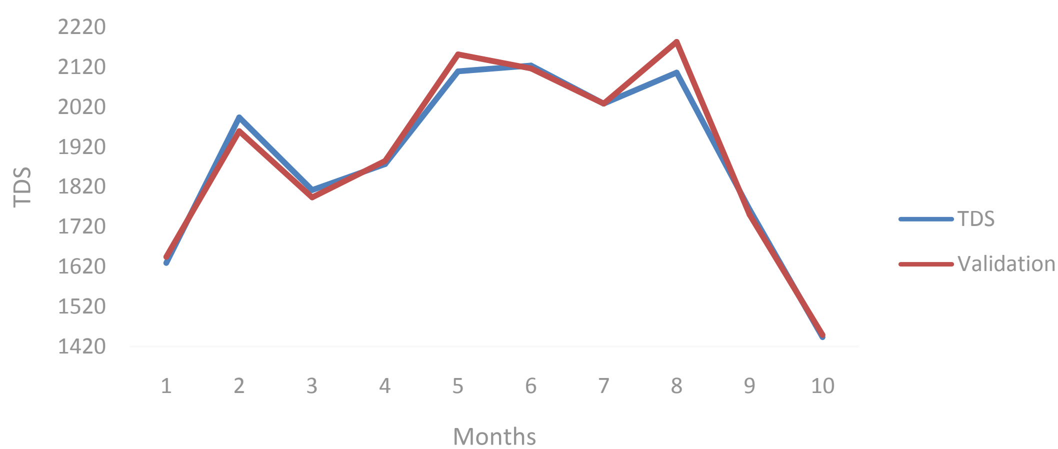


Fig. 12: TDS and Validation model graph at point 4

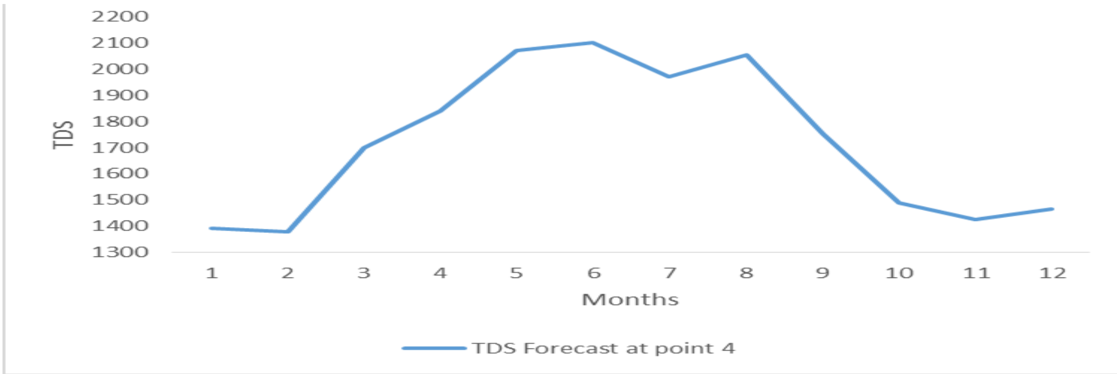


Fig.13: TDS forecast at point 4

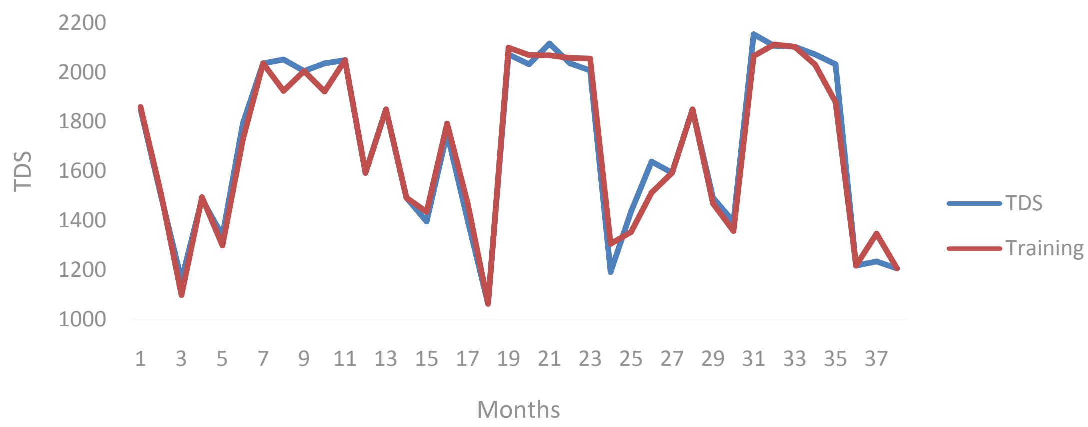


Fig. 14: TDS and Training model graph at point 5

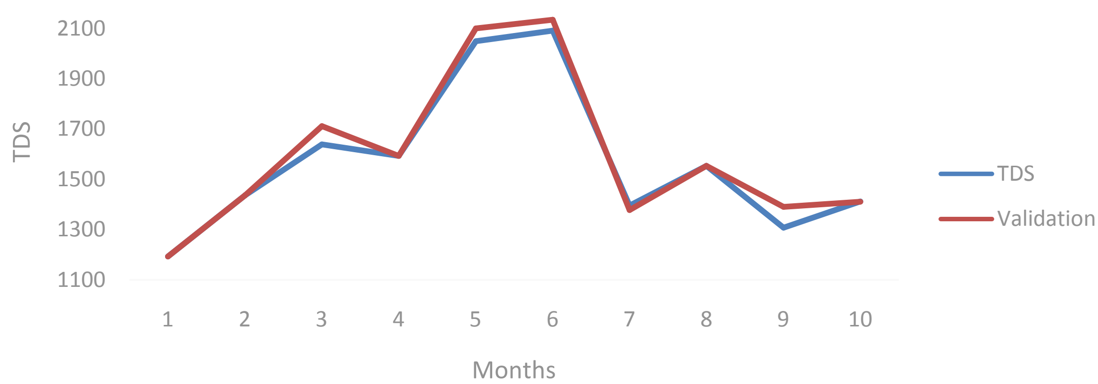


Fig. 15: TDS and Validation model graph at point 5

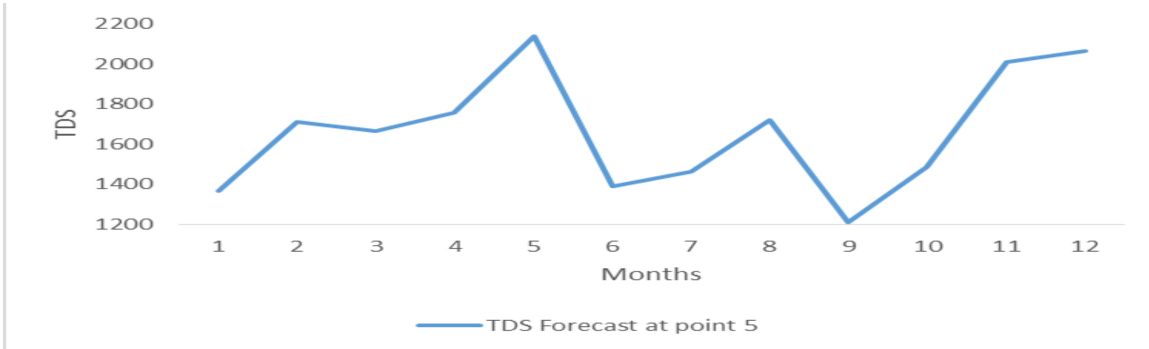


Fig. 16: TDS Forecast at point 5

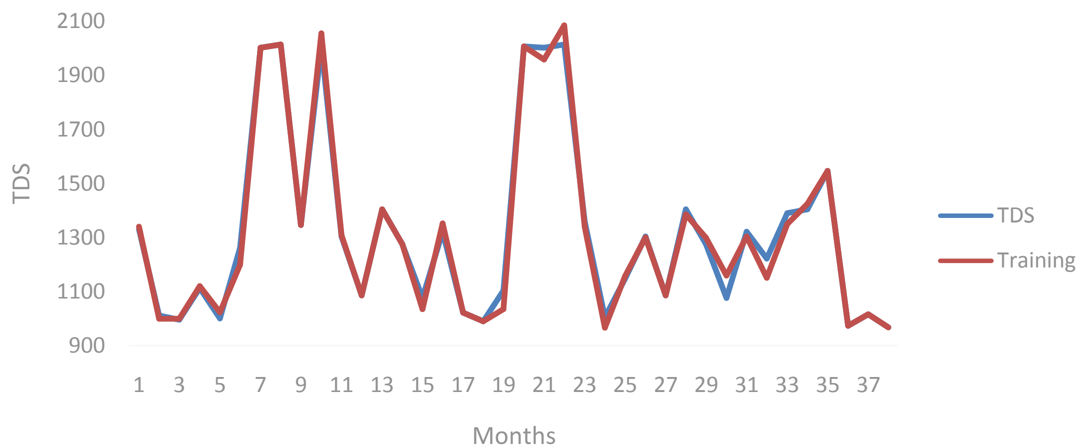


Fig. 17: TDS and Training model graph at point 6

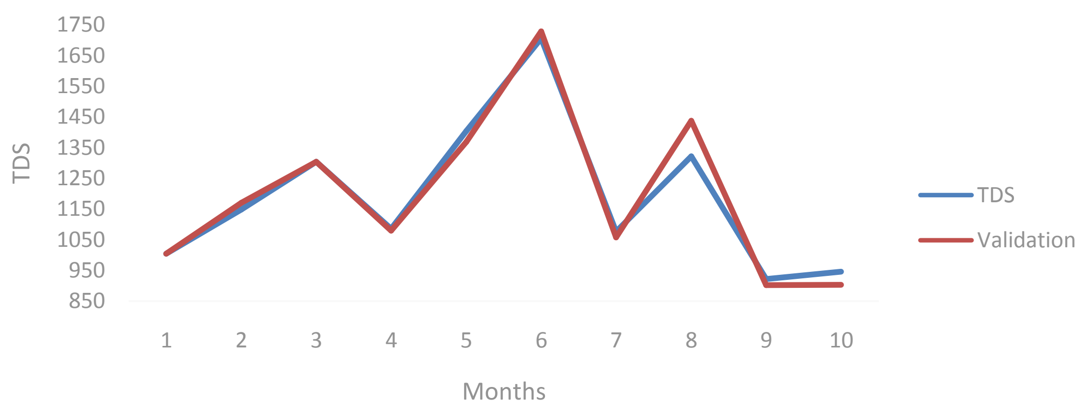


Fig. 18: TDS and Validation model graph at point 6

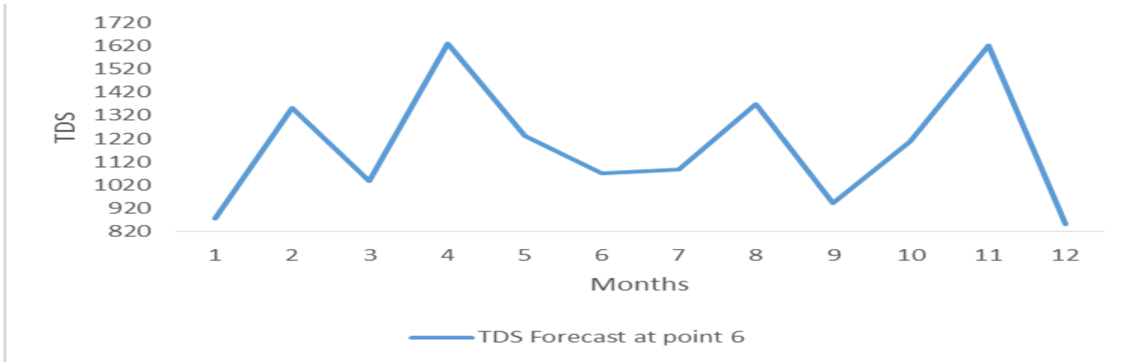


Fig. 19: TDS Forecast at point 6

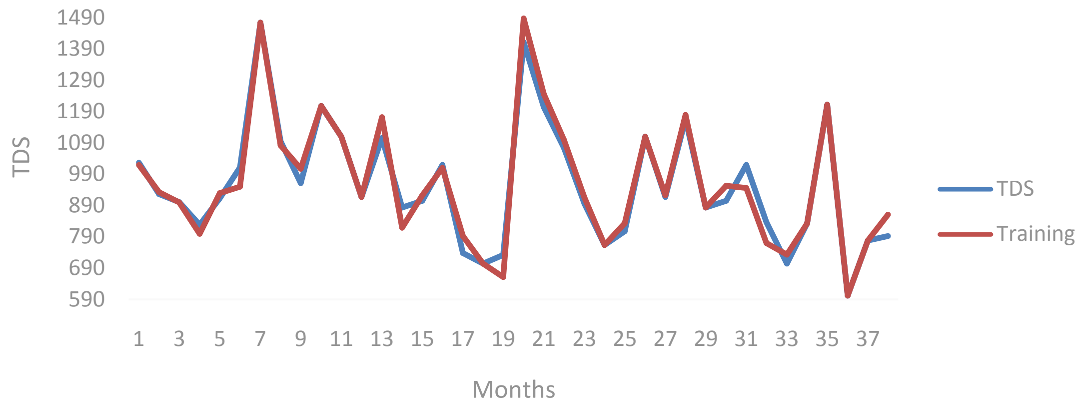


Fig. 20: TDS and Training model graph at point 7

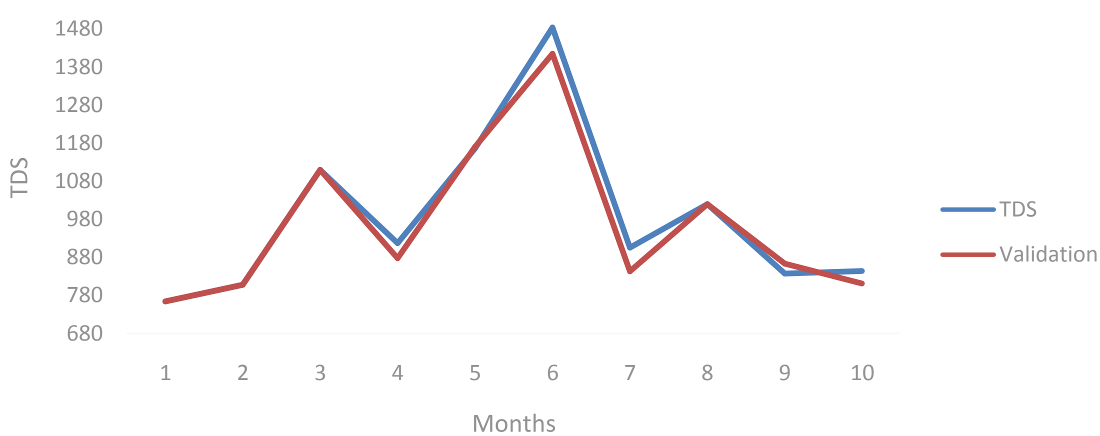


Fig. 21: TDS and Validation model graph at point 7

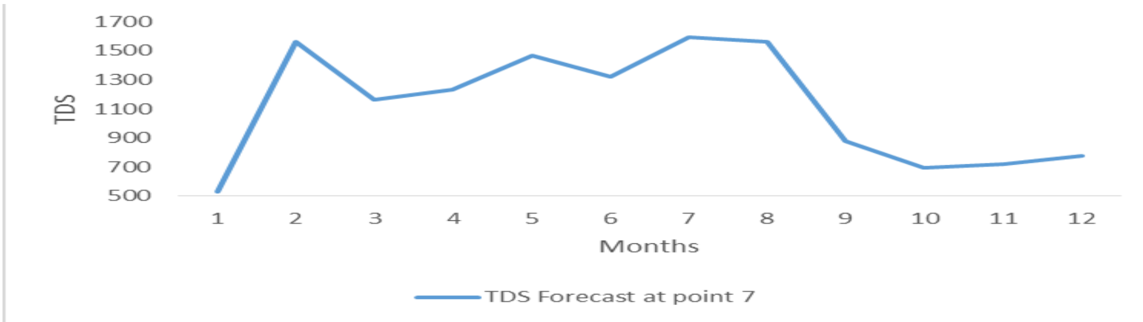


Fig. 22: TDS Forecast at point 7

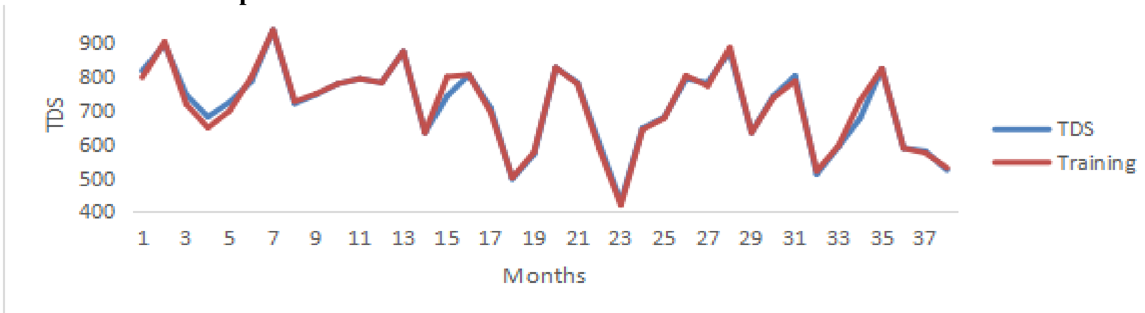


Fig. 23: TDS and Training model graph at point 8

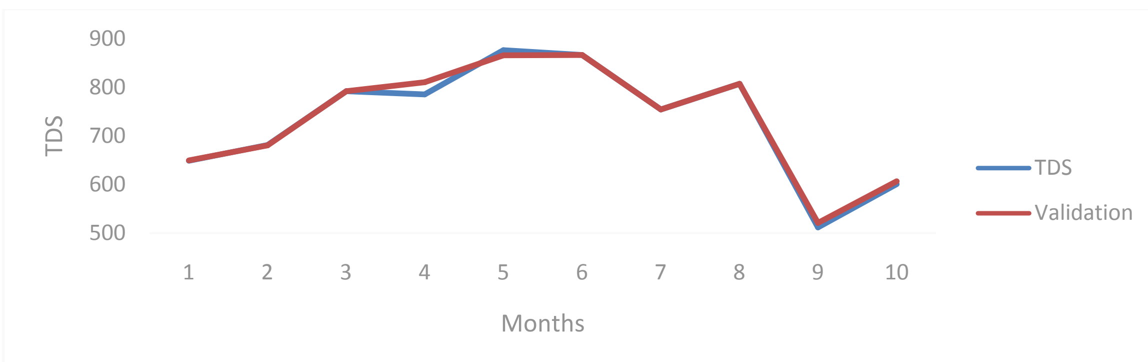


Fig. 24: TDS and Validation model graph at point 8

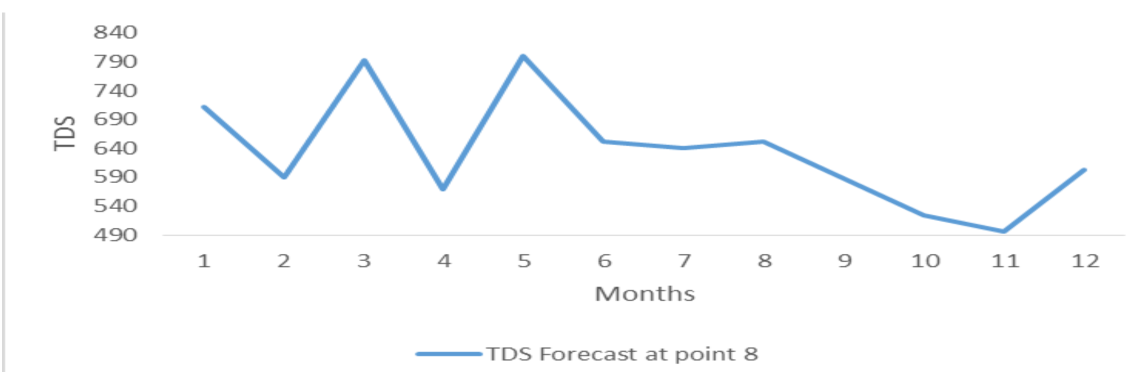


Fig. 25: TDS Forecast at point 8

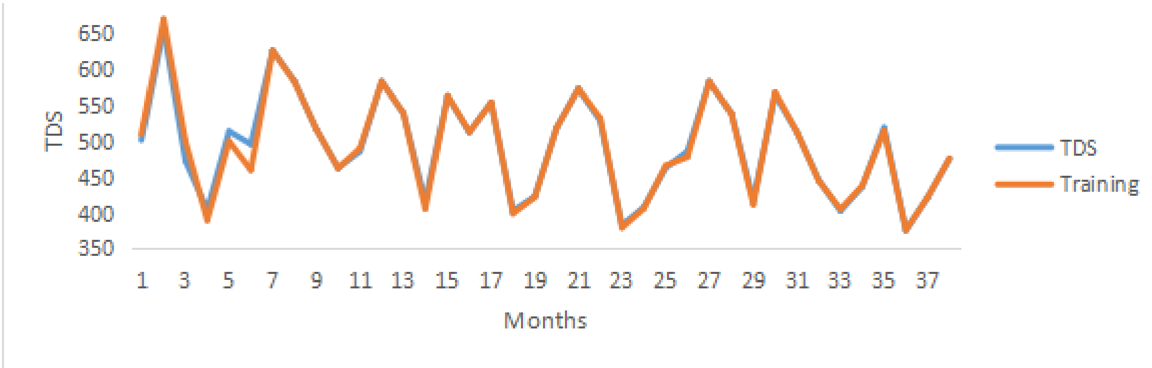


Fig. 26: TDS and Training model graph at point 9

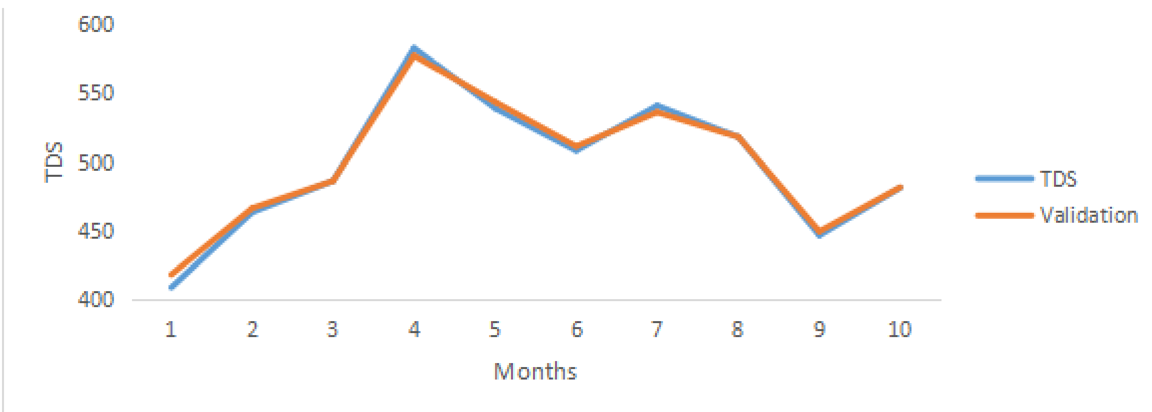


Fig. 27: TDS and Training model graph at point 9

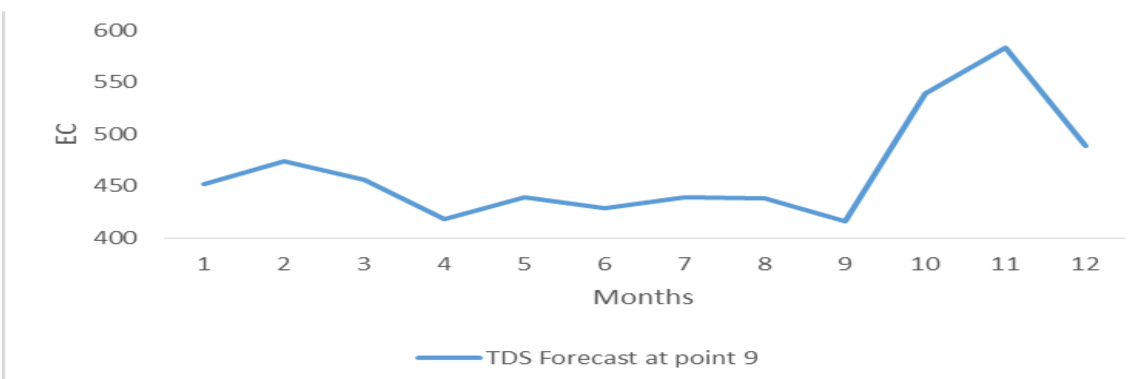


Fig. 28: TDS Forecast at point 9

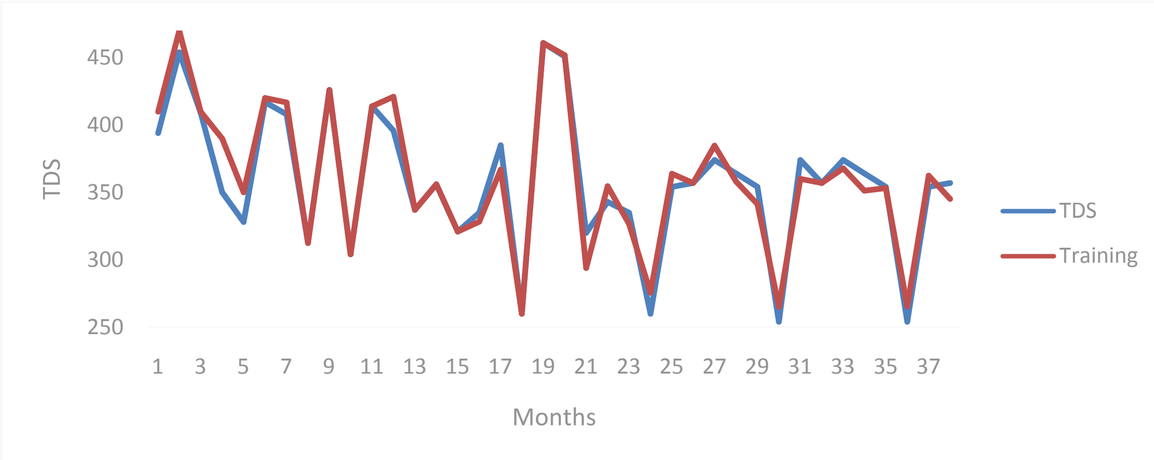


Fig. 29: TDS and Training model graph at point 10

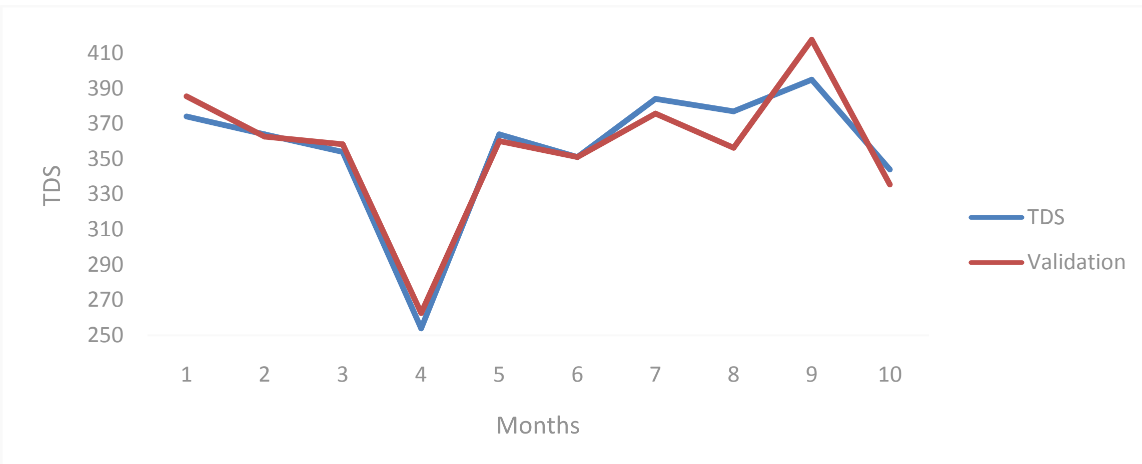


Fig. 30: TDS and Validation model graph at point 10

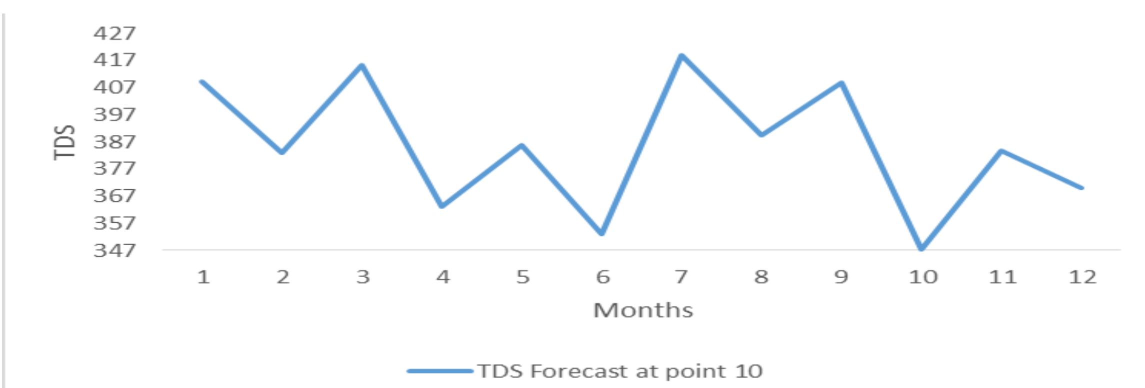


Fig. 31: TDS Forecast at point 10

These high concentrations of TDS at the entry points towards the mid-point of the River are likely to increases the salinity of the surface water, changes the taste of the Water, increases the electrical conductivity of the River system and as well decreases the dissolved oxygen level of the surface water making it difficult for survival of aquatic organisms. These high concentrations of TDS at the entry points towards the mid-point of the River are likely to increases the salinity of the surface water, changes the taste of the Water, increases the electrical conductivity of the River system and as well decreases the dissolved oxygen level of the surface water making it difficult for survival of aquatic organisms.

Moreover, these anions and cations which increase the electric conductivity in water affect irrigation adversely since salts settle at crop root zones making it difficult for infiltration, absorption of moisture and nutrients necessary for crop production. Thus the manageable source of water supply for irrigation can be at the last sampling points downstream which are not close to the bank of the River. In order to select the most suitable input or input combination of the model, correlation analysis was carried out between the input and output as the model performance evaluation is shown in Table 2

The R^2 value were generally observed to have varied in the second decimal place for the training, testing and forecast model, respectively. The training performance evaluation shows that R^2 values ranges from 0.981 to 0.988 which indicated a satisfactory performance. Also, the testing performance shows that the R^2 value ranges from 0.953 to 0.970. The forecast performance evaluation shows that the R^2 values ranges from 0.946 to 0.968 which indicates a satisfactory performance. The water quality forecast performance was further evaluated using the Root Mean Squared Error (RMSE) which ranges from 0.012 to 0.087.

Generally, the ANN model performed very well as their coefficient of multiple determination R^2 were very close 1 this is in agreement with the study of AWU et al. (2017). It shows that the training set performed better than the testing set followed by the forecast as its coefficient of multiple determination, R^2, was closer to 1.

Table 2: Model Performance Evaluation

Water Quality Parameter	Statistical Measurement	P1	P2	P3	P4	P5
TDS	**R^2 TRAIN.**	0.981	0.985	0.982	0.981	0.988
	R^2 TEST	0.959	0.970	0.964	0.954	0.962
	R^2 FORECAST	0.947	0.965	0.949	0.945	0.967
	RMSE	0.043	0.046	0.011	0.055	0.077
		P6	**P7**	**P8**	**P8**	**P10**
	R^2 TRAIN.	0.984	0.986	0.986	0.980	0.988
	R^2 TEST	0.954	0.955	0.956	0.953	0.954
	R^2 FORECAST	0.948	0.956	0.962	0.969	0.952
	RMSE	0.064	0.048	0.087	0.086	0.071

4.0. Conclusion

Artificial Neural Network is a notable forecasting tool in water quality assessment. This study was on modeling and forecasting of Total dissolved solids using feed-forward back propagation neural network for irrigation water quality assessment in Ele River, Nnewi. This was accomplished using readily available input data of TDS obtained from laboratory analysis results. The results obtained from the modeling and prediction indicated that there was insignificant deviation of values between the actual and model confirming a good fit. Also, it was observed that the TDS concentration was too high at the upstream to certain points mid-stream at most instances especially in the dry season. The forecast also predicted same results showing that TDS increased the River pollution index which perhaps increased the electrical conductivity of the River system. If the River must be used for irrigation at the farmer's risk, the source should be at the downstream, specifically towards sampling points 8 to 10 due to lower concentration of TDS. Besides, it is recommended that the irrigation water must be subjected to wastewater treatment before use so as to reduce the level of salt contamination at the crop root zones.

5.0 Recommendations

i. Environmental Regulatory Agencies in Nigeria should device mechanisms to enforce existing environmental laws on the discharge of effluents into nearby surface waters.

ii. Wastewater treatment plants should be installed in the surrounding industries to reduce pollutants in Ele River and by so doing will also promote Waste Management practices in Nigeria.

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APPENDIX 1: Tables of Data Used in the Model Training

SN	PARAMETERS	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
1	May-15	2335	2209	2114	2017	1852	1331	1027	819	502	394
2	Jun-15	2431	2157	2024	2007	1501	1011	927	898	657	454
3	Jul-15	2398	2044	2011	1983	1162	996	901	748	473	409
4	Aug-15	2506	2217	2139	2003	1488	1113	828	682	404	350
5	Sep-15	2344	2103	2035	1601	1339	1001	913	726	514	328
6	Oct-15	2214	2118	2002	2000	1795	1262	1012	787	496	417
7	Nov-15	2591	2347	2104	2079	2036	2003	1474	940	626	408
8	Dec-15	2639	2404	2207	2083	2052	2014	1095	722	583	313
9	Jan-16	2548	2408	2174	2039	2006	1346	961	749	517	426
10	Feb-16	2496	2315	2200	2064	2037	2008	1208	781	463	304
11	Mar-16	2432	2206	2140	2092	2049	1304	1110	795	486	414
12	Apr-16	2591	2374	2068	1877	1594	1086	917	784	583	396
13	May-16	2379	2176	2021	2010	1850	1404	1106	876	539	337
14	Jun-16	2297	2108	2047	1879	1493	1276	884	636	416	356
15	Jul-16	2304	2197	2088	1821	1397	1076	905	744	563	321
16	Aug-16	2442	2209	2104	2014	1754	1322	1020	807	513	335
17	Sept-16	2321	2177	2043	2003	1403	1022	738	709	554	385
18	Oct-16	2494	2143	2004	1886	1064	990	704	498	403	260
19	Nov-16	2517	2371	2230	2112	2073	1104	732	571	423	461
20	Dec-16	2641	2406	2315	2284	2033	2007	1412	828	519	451
21	Jan-17	2741	2477	2313	2262	2117	2002	1204	784	573	320
22	Feb-17	2495	2278	2108	2084	2037	2014	1074	604	529	343
23	Mar-17	2532	2404	2277	2021	2008	1360	896	429	383	335
24	Apr-17	2295	2111	2042	1629	1193	1004	764	649	408	260
25	May-17	2296	2115	2100	1994	1437	1148	808	681	463	354
26	Jun-17	2438	2206	2040	2012	1639	1304	1110	795	486	357
27	July-17	2497	2374	2068	1877	1594	1086	917	784	583	374
28	Aug-17	2376	2176	2021	2010	1850	1404	1166	876	539	364
29	Sept-17	2199	2108	2047	1824	1493	1276	884	636	418	354
30	Oct-17	2407	2153	2074	2029	1396	1076	905	744	565	254
31	Nov-17	2742	2523	2404	2207	2154	1322	1020	804	513	374
32	Dec-17	2620	2465	2332	2263	2108	1222	837	512	446	357
33	Jan-18	2591	2456	2304	2286	2104	1390	704	593	403	374
34	Feb-18	2523	2378	2261	2102	2073	1404	832	678	437	364
35	Mar-18	2441	2206	2115	2084	2033	1546	1212	825	519	354
36	Apr-18	2446	2372	2110	1367	1219	974	602	589	376	254
37	May-18	2391	2274	1883	1584	1235	1016	778	581	422	354
38	Jun-18	2432	2117	2064	1521	1207	967	793	524	476	357
39	Jul-18	2392	2111	2042	1629	1193	1004	764	649	408	374
40	Aug-18	2296	2115	2100	1994	1437	1148	808	681	463	364
41	Sept-18	2438	2206	2040	1812	1639	1304	1110	792	486	354
42	Oct-18	2497	2374	2068	1877	1594	1086	917	785	583	254
43	Nov-18	2676	2476	2321	2110	2050	1404	1166	876	539	364
44	Dec-18	2599	2308	2247	2124	2093	1706	1484	866	508	351
45	Jan-19	2407	2353	2274	2029	1396	1076	905	754	541	384
46	Feb-19	2542	2321	2206	2107	1554	1322	1020	807	518	377
47	Mar-19	2420	2265	2132	1763	1308	922	837	512	446	395
48	Apr-19	2344	2328	2315	1443	1412	946	844	601	481	344