Artificial Neural Network Technique for Predicting the Lifetime and Performance of Lead - Acid Battery

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Abstract: Numerous methods and techniques are available to forecast the life and the behavior of storage batteries. However, each has got its own merits and demerits. The main focus of this paper is to predict the life and the behavior of the lead acid battery as a function of less discharge time, less working hour and saving energy. To collect minimum experimental data, various testing procedures are carried out under actual test Conditions furthermore the End life and the Behavior are predicted.For Our Prediction, a Stochastic Network has been developed with Back Propagation Artificial Neural Network technique using MATLAB R (2008)a software version. The training dataset obtained from experiments have been used to predict unknown Results along with the practical results shows that this method has good performances and the generalization capability .Therefore, key aspect is to guide decisions regarding maintenance and battery replacement using self learning technique.

Keywords: Artificial neural network, Back propagation technique, Battery performance, Lead acid battery, life cycle analysis, Neural Network Applications.

I.INTRODUCTION

Qualification testing for a cell or battery is designed to determine whether a cell or battery is fit for the purpose for which it is intended before it is approved for use as product. It also includes testing finished battery packs before the product is approved for release to the customer. The tests are usually carried out to verify that the cells meet the manufacturer's specification; also it could be used to test the cell or battery to arbitrary limits set by the applications engineer to determine how long the cell or battery will survive under adverse conditions or unusual loads, till the end of life.

Battery Testing can be done in more than one way. The most accurate method is measurement of specific gravity and battery voltage. To measure specific gravity a temperature compensating hydrometer and to measure voltage digital D.C. Voltmeter is used. A quality load tester is needed in case of the sealed lead acid battery .For any of these methods, first fully charge the battery and then remove the surface charge. To remove the surface charge the battery must be discharged for several minutes .This complete set of charge - discharge cycles which a battery can perform before its nominal capacity falls below 80% of its initial rated capacity is called battery life cycle.

Based on End of Discharge for specified conditions, lifetime of the battery is studied and based on discharge behavior the performance of the storage batteries is understand .To predict the lifetime of a battery is relatively simple, if there is either very good empirical link or models, such as curve fitting technique. However these empirical models are inflexible due to variation in battery operating conditions [1]. Interpolation and extrapolation from test results and field data can be used to predict life time by means of parameter fitting. But the need for lifetime prediction methods to interpolate between test results and extrapolate outside the tested range cannot be substituted by a large test program. This approach may be successful where there is a wealth of data and the applications are reasonably uniform. However if there are only few data, this approach is not possible [2]-[4]. For Performance study, common modeling approach is to develop an electrical circuit that is designed to be functionally equivalent to the battery. The accuracy of these models depends upon the number of characterization tests performed to identify the values of the circuit elements. In some cases, compensation factors are required to eliminate the influence of temperature [5]-[9]. These limitations make equivalent electrical circuit models impractical for system level battery behavioral simulation.

Therefore, in this paper, we have developed a technique which uses short term information to predict long term information with the experimental data. For this, artificial neural network with specifically feed-forward back propagation algorithm is used. ANN overcomes the limitations of the conventional approaches by extracting the desired information directly from the experimental data.

II.ARTIFICIAL NEURAL NETWORK: AN OVERVIEW

The fundamental processing elements are neurons. A schematic structure of the ANN is shown in Fig .1. Network is a parallel distributed information processing technique. In this Configuration, networks are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world, and hence it is called hidden layers.

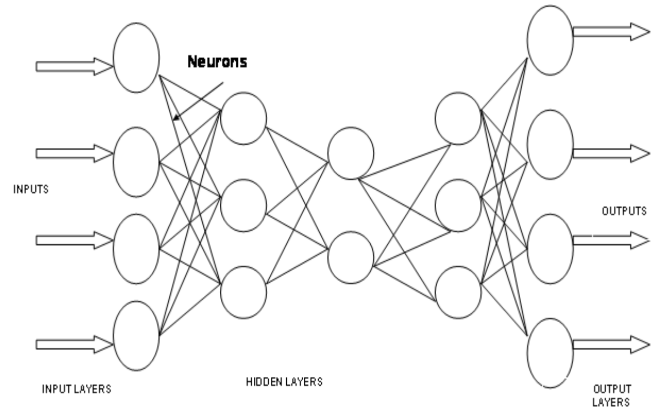

Figure 1. Schematic diagram of General Artificial Neural Network structure

Each layer is connected with Neurons in between them. The sizes of middle (hidden) layers are determined by trial and error methods [10-13]. A typical ANN operation starts with the training stage, which modifies the connection weights in some orderly fashion using a suitable learning method. To train this network, back propagation algorithm based on experimental result is used. Accurate results can be obtained with the choice of smallest number of neuron for a given problem. The single or multiple inputs are applied from the sensor or previously recorded data to the input layer with each of the inputs are multiplied by a weight and the product summed. The summation of the weighted input is passed through sigmoid function which is activation function. The algorithm updates the network weights in such a way that the sum – squared error in network's result is minimized. The architecture, activation function and learning algorithm are the important characteristics of the ANN model [14].

III. EXPERIMENTAL ANALYSIS

A set of different experiments on lead - acid battery is carried out and has led to a variety of data with favorable indications and conclusions about life and cyclic performance using ANN is done. The charge and discharge series were run using an LCN programmable tester, manufactured by Bitrode Corporation which is designed to test as per the standards such as BCI, SAE, DIN, JIS, IEC, and BS.

The following experiments are carried out for our study

1) Prediction of battery life with float service with daily discharge of VRLAB for stationary application.
2) Prediction of battery life with endurance cycle (life cycle test) for stationary application.
3) Prediction of discharge behavior of battery at high discharge rates and cold cranking behavior on VRLA battery at low temperature for automobile application.

A. Prediction Of Battery Life Using Float Service With Daily Discharge

Float service life is defined as the length of time a battery will perform on continuous float charge, until the battery capacity decreases to some specified percent of its rated capacity [15].Factors which effect or control float service life are grid design, alloy, discharge rate, specific gravity of electrolyte and dry out loss of the electrolyte. The float service life of a battery is important to predict the threshold period by which one can be made alert about the battery performance in various service applications. The incorporation of battery management system has got ability to estimate the time remaining capacity for the battery to reach end of life. Float service with daily discharge characteristic were studied by conducting experiment on Valve Regulated Lead - Acid battery as per IEC 60896-21 specification .According to this specification, the cycle life achievable is defined as the number of discharge accumulated within the set discharge time before a final voltage of 1.80Voltage Per Cell is reached. The test shall be carried out with 12V/300Ah Valve Regulated Lead - Acid battery and it is properly connected to bitrode life cycle tester with connecting strips and the whole unit thereby undergo a series charge – discharge cycles using programmable tester . The battery is continuously charged – discharged using programmable tester in such a way of 2h of discharge with the current of $2*I_{10}$ in A immediately followed by a charge of 22h with the current limit to the float voltage specified by the manufacture at a temperature of 20 º or 25 ºC .The unit voltage, time, current, temperature ,watt-hour and ampere- hour and number of cycles achieved with discharge – charge cycle shall be recorded .As per the record , the experimental data showed that at 63rd cycle there is a drop in discharge voltage to 9.55 V and the battery failed . In the designed artificial neural network ,we have taken the first 10 cycles of experimental data and the data's such as Time , current ,Temperature and its corresponding cycles are given in the input layer and voltage, ampere-hour in the output layer in order to train the network . In the next stage, Prediction of data is performed from 11 th cycle by giving only input datas, until the battery reaches its end of voltage to 10.48V.

TABLE 1
END DISCHARGE VOLTAGE OF EXPERIMENT AND PREDICTED DATA SET

No. Of Cycles	End voltage of Experimental data (as per IEC 60896-21)	End voltage of Predicted data (as per ANN)
1	11.83	11.84
5	11.84	11.854
10	11.84	11.863
15	11.81	11.843
20	11.79	11.79
25	11.77	11.79
30	11.78	11.78
35	11.77	11.77
40	11.75	11.75
45	11.78	11.79
50	11.75	11.75
55	11.7	11.71
60	11.59	11.61
61	11.49	11.59
62	9.55	9.4
63	9.4	9.43
64	9.43	9.43

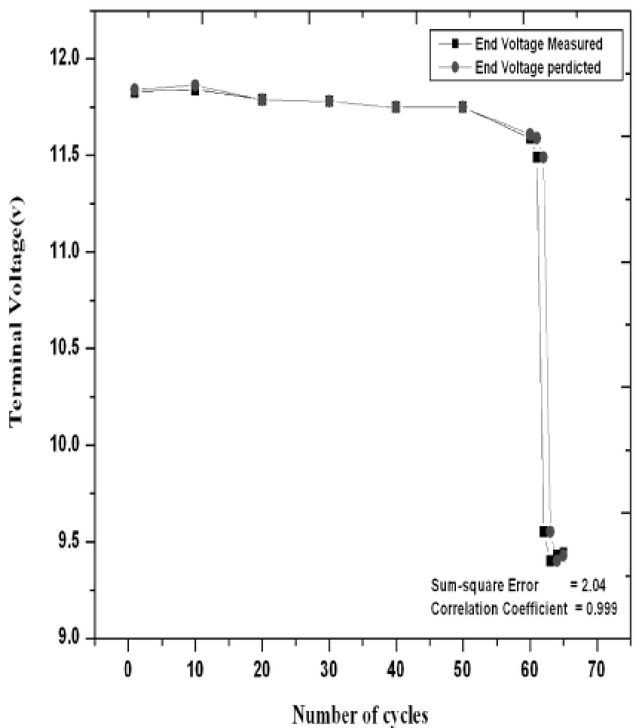

Figure 2. Comparison of measured and predicted data of Battery voltage Vs no.of.cycles.

From the fig.2 and Table I, It is observed that at 63rd cycle the end voltage reached to 9.4V. The network performance measures are also calculated, its correlation coefficient R^2 between measured and predicted is 0.999. This technique can be extended to other temperature also. Thus with less time and less manpower it is possible to predict the float service life of the battery with minimal experiment using ANN technique.

B. Prediction Of Battery Life Using Endurance Cycle Test

It is the ability of a cell (or) monobloc battery to withstand operation under specified conditions for a specified period of time which may be characterized by a test comprising discharge -charge cycles. The charge and discharge cycles wear out the structure of positive and negative active mass and this causes capacity loss. To achieve high cycle life, the degree of over age is paramount importance for VRLAB [16]. Endurance cycle characteristic were studied by conducting experiment on Valve Regulated Lead –Acid battery as per JIS 8702-1 specification. As per specifications, during cycling, if the battery voltage falls below 9.9V stop cycling or if check capacity is less than 60% of C_{20}, terminate the experiment. The experiment has been carried out with 12V/17Ah Valve Regulated Lead –Acid battery which is properly connected to Bitrode life cycle tester and thereby undergoes a series charge – discharge cycles using programmable tester in such a way of 3h of discharge with the current of $3.4*I_{20}$ in A immediately followed by a charge at a constant voltage or constant current for 9h specified by the manufacture at a temperature of 20º or 25 ºC .The unit voltage, time, current, temperature, watt-hour and ampere-hour and number of cycles achieved with discharge – charge cycle shall be recorded .The experimental data collected up to 110 th cycles till now .

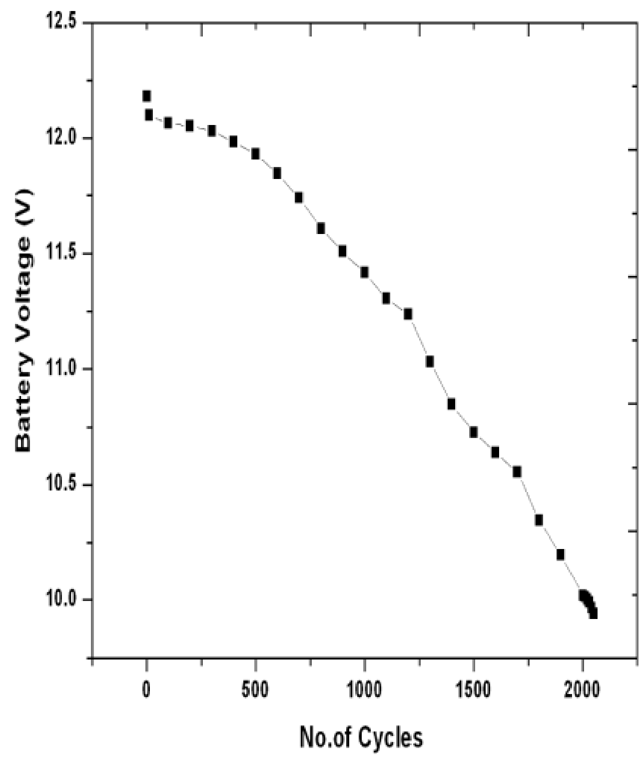

Figure 3. Life Cycle Analysis of 12V/17Ah Lead-Acid battery up to end of life

These 110 th cycles data are implemented in the training part of ANN with its time, current, temperature and number of cycles in the input layer and voltage, ampere hour in the output layer for learning purpose. Remaining cycle data are predicted in the testing part, until the EOD voltage falls to 9.9 V. Fig 3. Shows, predicted cycle life data from the neural network output indicates that at 2030 cycle EOD voltage is 9.9 V. Experimental verification is going on. Lifetimes of 500 to 1200 cycles are typical. The actual ageing process results in a gradual reduction in capacity over time. When a cell reaches its specified lifetime it does not stop working suddenly. The ageing process continues at the same rate as before so that a cell whose capacity had fallen to 80% after 1000 cycles will probably continue working to perhaps 2000 cycles when its effective capacity will have fallen to 60% of its original capacity. There is therefore no need to fear a sudden death when a cell reaches the end of its specified life. As the cycle life testing is a long process lasting for several months. Thus by using ANN technique ,it consumes less time which will help for new battery construction development and to speed up this process in order to examine more variations of the construction.

C. Prediction of Discharge Behavior at High Rates and Cold Cranking Behavior at Low Temperature for Automobile Application

If the discharge takes place over a long period of several hours as with some high rate applications such as electric vehicles, the effective capacity of the battery can be as much as double the specified capacity at the C rate. Different levels of battery quality are being delivered by a variety of battery suppliers .This study presents the test of health of batteries in their applications and this method can also be utilized as a quality assurance tool .The final conclusion of this work will demonstrate how battery operators can have better control over the quality of batteries, and the performance of the batteries of different models. It also provides reasonable indication of the need for replacement of a battery, thus maximizing maintenance efficiency. Hence, capacity test has been carried out with different rates, fully charged 12V/45 Ah Valve Regulated Lead –Acid battery is discharged according to 20 Hr and 10 Hr until the battery voltage dropped under the cutoff voltage of 10.5V. The unit voltage, time, current, temperature watt-hour and ampere-hour achieved shall be recorded. The measured data such as time, current, temperature of C/20, C/10 is fed into the input layer and corresponding voltage, ampere-hour in the output layer of the training sets of ANN and Corresponding datas of C/5, C/1 are predicted .With experimental data at C/20, C/10 and predicted data at C/5, C/1, it is again fed into the training part of neural network in order to predict high rate discharge behavior. Using this, we can predict the high rate discharge behavior of the battery without performing the experiments. While predicting HRD behavior of battery large no. of training samples have to be considered to get accurate results..

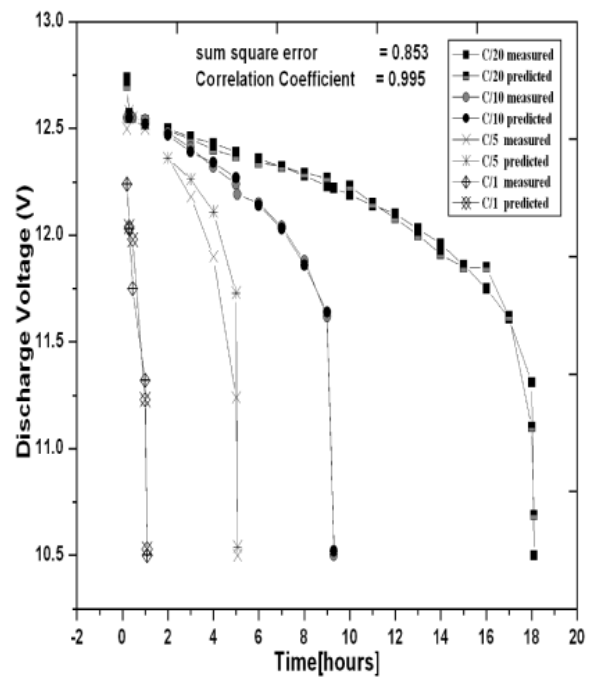

Figure 4. Comparison between experimental and predicted discharge curves at discharge rates of C/20, C/10, C/5, and C/1.

In fig.4.comparison between experimental and predicted discharge curves at discharge rates of C/20, C/10, C/5, and C/1 are shown. The test is repeated for different capacity lead - acid batteries. In all cases the experimental and prediction level are same thereby confirming suitability of this technique for high rate applications. As testing capacity of a battery is a long procedure continuing for several Hours. But this whole process will greatly decrease the overall work load and cost investment with more understanding of neural network technology will do less discharge testing over time.

Batteries that are utilized for starting engines like SLI (Starting Lighting and Ignition) batteries are not rated in AH but rather in the CCA (cold-cranking amps) due to the fact that they are designed only for use in starting the engine, once the engine has started they should not be used.[17] Having a rating in CCA in colder temperatures is the standardized labeling; the reasoning is that CCA is how many amps a battery will put out for 30 seconds at 0 degrees F before the voltage drops below 1.2 volts per cell. The AH capacity is a measurement of how much it puts out before reaching 100% DOD (depth of discharge). The DOD is how much of the available charge is used compared to 100% (or 1.75 volts per cell, or 7.2 volts for 12 volt batteries). Discharge duration of lead - acid batteries are significantly reduced at sub-zero centigrade temperature [18].As the discharge precedes the concentration of the acid decreases, with a consequent increase in the freezing temperature. In this study we have used ANN technique to predict the cranking behavior of 12V/40Ah VRLA battery at sub-zero temperature. We have noticed the following cranking conditions namely the time - voltage behavior of the battery every 10s discharge time and time to reach final discharge voltage of 7.2V so that only we can easily analyses how much of time is required before reaching 100 % DOD. Experiment is carried out in four different sub zero - temperatures namely -20ºC,-15ºC,-10ºC,-5ºC for the currents of 1C, 3C, and 5C. Data's such as time, current, temperature are fed into the input layer of training set of ANN and voltage at the output layer ,in order to predict datas for the currents of 7C, 9C 11C, 13C, 15C and 17C.

TABLE II

THE EXPERIMENTAL PREDICTED AND VALIDATED VOLTAGE DATAS AT -20 º

Time (s)	Training set			Prediction set					Validation set	
	1C	3C	5C	7C	9C	11C	13C	15C	17C	
									Measured	Predicted
1	11.14	10.57	9.52	8.24	6.95	5.30	5.09	4.30	3.39	3.66
2	11.14	10.54	9.43	8.04	6.56	5.38	4.58	3.95	3.29	3.23
3	11.15	10.52	9.37	7.88	6.24	4.87	4.00	3.49	3.04	2.88
4	11.15	10.49	9.32	7.76	5.98	4.41	3.41	2.93	2.65	2.52
5	11.15	10.47	9.28	7.68	5.78	4.03	2.84	2.32	2.15	2.15
6	11.14	10.45	9.25	7.61	5.63	3.73	2.35	1.70	1.57	1.68
7	11.14	10.43	9.23	7.57	5.53	3.51	1.95	1.12	0.96	1.05
8	11.14	10.41	9.20	7.53	5.46	3.36	1.65	0.62	0.36	1.05
9	11.13	10.38	9.18	7.50	5.41	3.26	1.43	0.23	0.17	.08
10	11.12	10.36	9.16	7.48	5.38	3.20	1.29	0.06	0.08	0

TABLE III
THE EXPERIMENTAL PREDICTED AND VALIDATED VOLTAGE DATAS AT -15 ºC

Time (s)	Training set			Prediction set					Validation set	
	1C	3C	5C	7C	9C	11C	13C	15C	17C	
									Measured	Predicted
1	12.44	11.25	9.84	9.70	8.68	7.43	6.10	4.90	4.90	5
2	12.26	11.22	9.82	9.59	8.53	7.25	5.92	4.75	4.53	4.72
3	12.13	11.18	9.81	9.47	8.37	7.06	5.74	4.61	4.22	4.41
4	12.01	11.12	9.79	9.35	8.20	6.87	5.56	4.47	3.95	4.11
5	11.90	11.06	9.77	9.21	8.03	6.68	5.38	4.34	3.69	3.77
6	11.81	10.97	9.76	9.07	7.84	6.48	5.21	4.21	3.44	3.47
7	11.73	10.88	9.73	8.91	7.65	6.29	5.05	4.10	3.21	3.14
8	11.66	10.77	9.71	8.75	7.46	6.09	4.89	3.98	2.98	2.85
9	11.60	10.66	9.69	8.58	7.26	5.90	4.73	3.88	2.74	2.35
10	11.55	10.54	9.67	8.39	7.05	5.71	4.59	3.78	2.50	2.3

TABLE IV.
THE EXPERIMENTAL PREDICTED AND VALIDATED VOLTAGE DATAS AT -10 ºC

Time(s)	Training set			Prediction set					Validation set	
	1C	3C	5C	7C	9C	11C	13C	15C	17C	
									Measured	Predicted
1	12.56	10.75	10.68	10.01	9.80	8.66	7.17	5.73	5.39	5.35
2	12.40	10.73	10.68	10.00	9.78	8.65	7.16	5.72	5.06	5.07
3	12.28	10.73	10.67	9.99	9.76	8.63	7.14	5.70	4.78	4.92
4	12.17	10.73	10.66	9.98	9.73	8.53	7.12	5.68	4.52	4.69
5	12.07	10.73	10.65	9.96	9.70	8.49	7.08	5.66	4.27	4.38
6	11.98	10.74	10.63	9.95	9.66	8.46	7.04	5.63	4.01	4
7	11.89	10.74	10.61	9.93	9.62	8.41	6.99	5.59	3.75	3.61
8	11.82	10.74	10.59	9.92	9.56	8.36	6.93	5.55	3.47	3.21
9	11.76	10.74	10.56	9.90	9.50	8.30	6.86	5.49	3.18	3.03
10	11.71	10.74	10.53	9.88	9.43	8.23	6.83	5.49	2.88	2.88

TABLE V
THE EXPERIMENTAL PREDICTED AND VALIDATED VOLTAGE DATAS AT -5 ºC

Time (s)	Training set			Prediction set					Validation set	
	1C	3C	5C	7C	9C	11C	13C	15C	17C	
									Measured	Predicted
1	11.19	10.78	10.27	9.65	8.94	8.14	7.30	6.44	5.59	6.05
2	11.22	10.81	10.30	9.68	8.95	8.14	7.28	6.39	5.51	5.51
3	11.24	10.83	10.32	9.69	8.96	8.13	7.24	6.32	5.41	5.41
4	11.26	10.85	10.34	9.71	8.96	8.11	7.19	6.23	5.28	5.28
5	11.28	10.87	10.35	9.71	8.94	8.07	7.11	6.12	5.13	5.13
6	11.29	10.88	10.36	9.70	8.92	8.01	7.02	5.98	4.95	4.95
7	11.30	10.89	10.35	9.68	8.87	7.93	6.90	5.81	4.74	4.74
8	11.30	10.89	10.34	9.65	8.81	7.83	6.75	5.61	4.50	4.5
9	11.31	10.88	10.32	9.61	8.73	7.70	6.56	5.38	4.23	4.33
10	11.30	10.87	10.29	9.55	8.63	7.55	6.35	5.11	3.93	3.98

Table II, III, IV, V. gives data for the experimental, predicted and validated voltage for the above mentioned temperatures. It is clear that the prediction made by using ANN technique is better. The technique employed does not require the use of expensive instruments. One of the key factors limiting the use of neural networks is the source of errors arises from the input data which differs significantly from the data used to train the n

(1) *Discussion of Reason for decrease in capacity*

From the results of actual tests, it may be said that lead-acid batteries are not offended in any way by the high discharge rate used when a starting motor cranks the engine**.** It is the rapidity with which acid takes the place of that used in the pores of the active materials that affects the capacity of a battery at high rates, and not only limitation in the plates themselves. Consequently the capacity will be greater in a battery, all of whose active materials are in contact with the acid, than in one in which the acid reaches only a portion of the active materials. It is also important that all parts of the plates carry the same amount of current, in order that the active materials may be used evenly. As a result of these considerations, we find that the active materials are supported on grids of lead, that the plates are made thin, and that they have large surface areas. For heavy discharge currents, such as starting motor currents, it is essential that there be large surface areas. During rapid discharge the electro chemical reactions take place mostly on the surface of the plate. This is due to the limited time available for the diffusion of the electrolyte into the pores of the active material. The average concentration of the electrolyte at the pores can be deduced from the discharge capacity is known from the following equation in [19].

$$\mathbf{C = C_i - [(3600\,Q)/\,n\,F] * [I / V_{el}]} \qquad (1)$$

Where,

C - Concentration in Mol cm -3.
Q - Electric Capacity (Ah).
N - No. of .electrons.
I - Total current (A).
V_{el} - Electrolyte Volume (cm $^{3)}$.
C_i - Initial concentration.(mol cm -3).

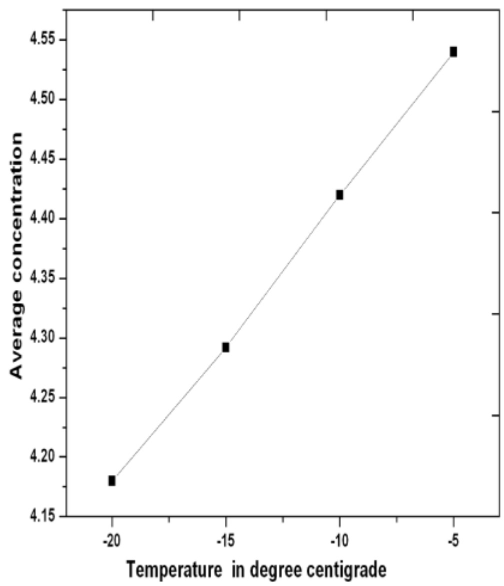

Figure 5. Average concentration at different temperature.

Fig 5.shows the average concentration of sulphuric acid available at the pores of the plate for different sub zero degree centigrade temperature .The diffusion coefficients is also calculated using the equation [19]

D= D $_i$ (0.706 + 58.8 C) (2)

where D $_i$ = 7.2 * 10 -6 cm 2 s -1

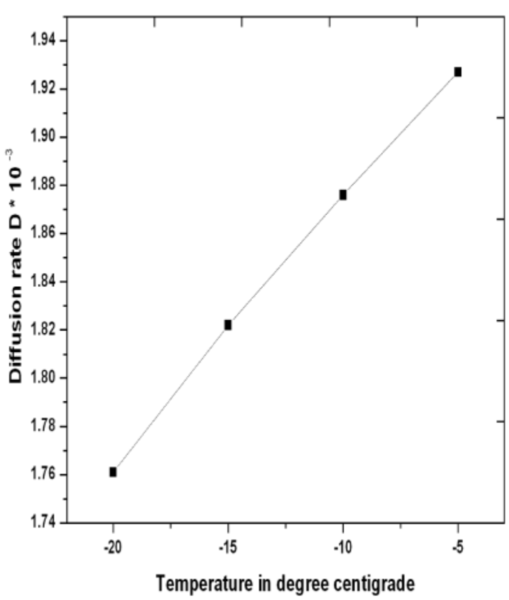

Figure 6. Diffusion rate at low temperatures

Fig.6 shows the diffusion rate is decreased as the temperature is decreased below sub zero degree centigrade which is in agreement with our findings. The cold cranking current (A) decreases as the temperature decreases. Battery capacity is also affected by discharge rates, only when the discharge is continuous, and the reduction in capacity caused by the high rates of continuous discharge does not occur if the discharge is a discontinuous one, such as is actually the case in automobile work. If conditions should demand it, these batteries would give their rated capacity while operating intermittently at a rate which would completely discharge them in three or four minutes.

TABLE VI
CRANKING CURRENTS AT SUB-ZERO TEMPERATURE DEGREE CENTIGRADE

Time to reach End voltage of 7.2v (s)	TEMPERATURE	Cold Cranking Amps
41	-20°C	360A
43	-15°C	440A
61	-10°C	520A
62	-5°C	600A

Table VI Shows that time to reach particular cut off voltage of 7.2 V at different cranking currents and sub zero centigrade temperature. Therefore, when an engine is cold and stiff, the work required from the battery is even more severe, the discharge rate being equivalent in amperes to probably more times the ampere-rating of the battery.

IV. CONCLUSION

Use of Artificial Neural Network technique for predicting the life time and performance of lead acid battery for various fields in batteries such as stationary and automobiles applications are indicated in this communication. The developed stochastic network using back propagation artificial neural network technique is based on off line learning system from observed data to carry out the process .The results shows good prediction with minimal experimental data.

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