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Failure prediction of humidity sensor DHT11 using various environmental testing techniques

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- ✓ Accelerated life testing.

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Abstract
Electronics System has become the integral part of our daily life. From toy to radar, system is dependent on electronics. The health conditions of humidity sensor need to be monitored regularly. Temperature can be taken as a quality parameter for electronics system which works under variable conditions tends to failure of the systems. Using various environmental testing techniques, the performance of DHT11 has been analysed. The failure of humidity sensor has been detected using accelerated life testing and an expert system is modelled using various artificial intelligence techniques i.e. Artificial Neural Network, Fuzzy Inference System and Adaptive Neuro-Fuzzy Inference system. A comparison has been made in between the response of actual and prediction techniques, which enable us to choose the best technique on the basis of minimum error and maximum accuracy. It has been observed that ANFIS is proved as the best technique with minimum error for developing intelligent model. The mean lifetime of DHT11 using environmental testing has been calculated as 26.65 hours. The accuracy of ANFIS is 97.52% in comparison with other artificial intelligence techniques.

1. Introduction
Humidity sensor is a prominent category of sensor and find its application in lie detector system, soil humidity sensor, cold store, quality control in food etc. Because of its ability to detect humidity level in the environment, it is widely used[1]. It can also detect the temperature within specific range. However, like any other electronic component, it also has certain specific range where sensor can withstand environmental or other related operating conditions [2,3]. Temperature has been selected as one of the most important criterion to check the reliability because in practical world sensor may work in different terrain, under harsh physical conditions where temperature may degrade the quality or life of the system [4-5]. Hence the quality is a critical aspect for the life and sudden failure under crucial needs. So, it has been taken temperature (TLR) as an aspect to deal with the reliability [6,7,8]. For intelligent modelling to do estimation, non-conventional approach using soft computing techniques such as Artificial Neural Network (ANN), Adaptive Neuro-fuzzy Inference System (ANFIS) have been used. Artificial Intelligence dependent model has great ability to benefit researchers by developing smart system which can save time, cost as well as man power to achieve similar result [9].

In this paper, Artificial Neural Network, Fuzzy Inference System and Adaptive –Neuro Fuzzy Inference System have been used. ANN has advantage that it can deal with imprecision also it can handle Non-Linearity in data. Fuzzy on the other hand include Linguistic Variable and Membership function which makes more user understandable as answer not only as YES or NO but other terms also (Slightly, moderately etc.), also it can handle the vagueness of the data which is initially not interpreted by ANN. Whereas, ANFIS on the other hand combines the benefit of both the above-mentioned techniques and gives us more precise and accurate result. Here, Learning Mechanism or training mechanism of ANN is used for Membership function and hence provide best result amongst 3 techniques. For input, data set having 18 samples have been used. Out of which 14 are used for training and 4 are used for testing. For FIS and ANFIS, Gaussian Membership function in being used and the topology of ANN is 2:10:1, where 10 neurons are used for hidden layer and out of 1000 best result came at 6th epochs). Derating prediction makes a system more reliable and successful for long term use [10].

2. Artifical intelligence techniques

The various artificial intelligence techniques i.e. artificial neural networks (ANN), fuzzy inference system (FIS) and adaptive neuro fuzzy inference system (ANFIS) have been used while creating an expert model which predicts the residual life of the humidity.

2.1 Artificial Neural Network

ANN stands for Artificial Neural Network is a network which is analogous to humanbrain. It has been constructed by processing unit called 'Neurons' which are working in parallel to frame intelligent network. All the connections are loaded with some weight which are being updated during training process. The actual output as target and system tries to achieve that target by minimizing the error in every iteration it makes is provided [11]. The training process keeps running until the ANN output gets equal or approximately equal to target. This is known as Back Propagation Neural Network (BPNN). It is being more efficient than other methods like single layer or multilayer Perceptron in the way, it handles the complexity when the number of hidden neurons are increased. Method used for weight updating is Gradient–Descent method [12]. Figure 1 shows the Artificial Neural Network with input, output and hidden layer.

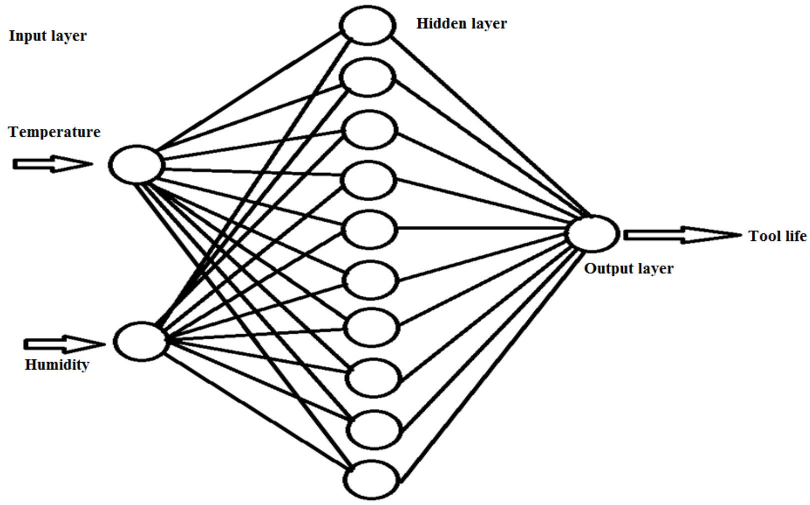

Figure 1: ANN structure

It is liberal to decide number of hidden neurons, but input and output neurons depends upon inputs parameter, required output in modelling is achieved. Back Propagation Neural Networks (BPNN) is one of the supervised learning methods. The flow chart for ANN is shown in figure 2.

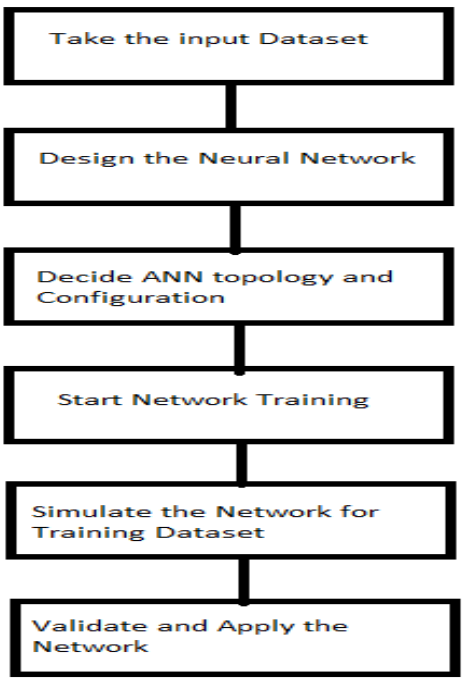

Figure 2: Flow Chart of ANN

To find the Mean Square Error as Comparison parameter,

$$\text{Mean Square Error} = \frac{1}{N}\sum_{k=0}^{n}(\text{Target} - \text{ANN Output})$$

2.2 Fuzzy Inference System

Fuzzy Inference System or Fuzzy Logic is used to handle ambiguity and uncertainty in data. As the complexity increases, exact statement about the behaviour of the system cannot make as in the traditional method, so Binary Logic which says 0 or 1, i.e. YES or NO is used, but the real-world problems are beyond as it can't be TRUE or FALSE only. Taking water problem than the possible answer could be HOT, COLD, SLIGHTLY COLD, SLIGHTLY HOT, EXTREMELY COLD, EXTREMELY HOT etc. [13].

For this purpose, linguistic variables in fuzzy are preferred which are user understandable. Entire input set is known as Crisp Set which after fuzzification convert into fuzzy sets. Here the concept of Membership function is used, it defines the membership of input value in the fuzzy sets, it's range is from 0 to 1. If input value has complete membership, it is 1 otherwise it can be any value in this range. If fuzzy set A is there, then considering the universal set, X can be defined as,

$$A=\{(x,\mu A(x))|x€X\},$$

Where μA is known as A's Membership Function. In FIS, certain rules for fuzzification are defined, to defines crisp relation into Fuzzy relation in I , THEN, ELSE format e.g,

IF (f is x1, x2.....xn) THEN (g is y1, y2….yn) ELSE (g is z1, z2….zn)

This fuzzified data goes to decision-making unit which decides about the membership function and hence attached the related linguistic variable for that particular value [14]. The fuzzy output from this block directly feeds to defuzzifier interface unit, which is reverse of Fuzzifier. And hence after this block, proper output in Crisp set form as defuzzifier convert fuzzy set back to Crisp set is achieved. Fuzzification as well as defuzzification unit are assisted by knowledge base which has design base as well as Rule base for making rules and modifying data [15]. The block diagram of FIS is given below in figure 3.

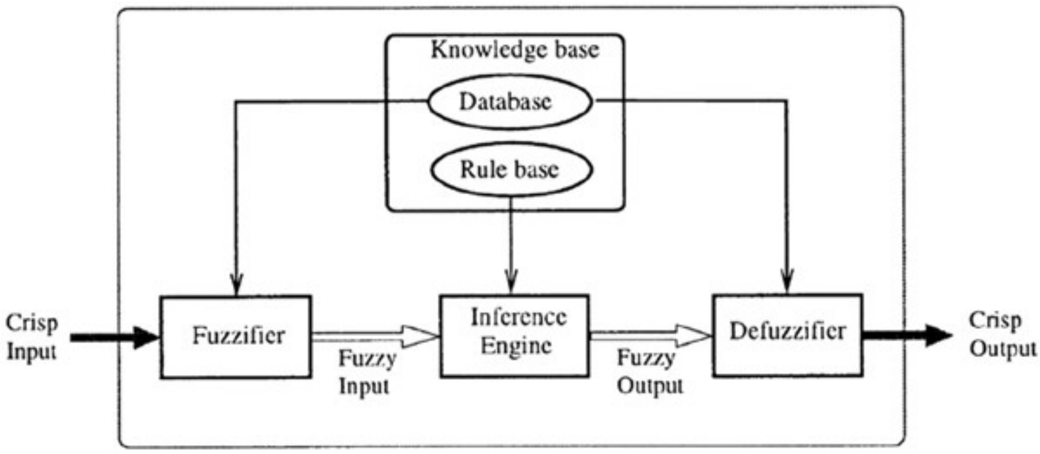

Figure 3: Block Diagram of Fuzzy Inference System

2.3 Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS stands for Adaptive –Neuro fuzzy inference System is basically a hybrid system combines the advantage of both ANN and FIS and overcome their drawbacks [16]. With ANN which cannot handle ambiguity or vagueness and FIS which is not adaptive in nature, ANFIS design a system which use learning mechanism of ANN to design rules for fuzzy and hence provides us the best result amongst all these three techniques [17]. Here, two input (fuzzy layer) m, n and one output (output layer), product layer, normalized layer and the defuzzy layer. The main structure is shown in the figure 4,

Consider one input is X1 and other is Y1 then output,

Rule 1: t $y1= \alpha 1m+\beta 1m+\gamma 1$.

Rule 2: if input is X2 and other one is Y2 then, $y2=\alpha 2m+\beta 2n+\gamma 2$

Where $\alpha 1$, $\alpha 2$, $\beta 1$, $\beta 2$, $\gamma 1$ and $\gamma 2$ depicts Linear parameter and X1, X2, Y1 and Y2 shows non-linear parameter. The membership function is using is gaussian membership function,

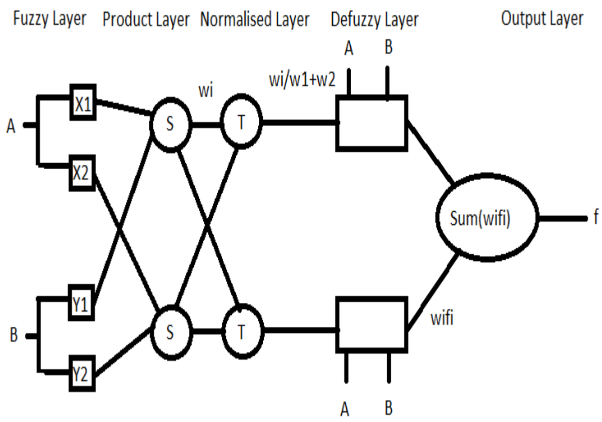

Figure 4:ANFIS Structure

Here A and B are revealed input to node Xi and Yi. These are the linguistic word attached to these nodes. A and B gets its respective membership function. This is the function at fuzzy layer. The second layer is product layer which multiply the input coming from layer 1 and sends out as output. On the output side, weight gets attached to output. The third layer is normalized layer which receive this weighted output as input and normalized it as the weight of the node sending this output to the sum of all the weights,

$$Wi' = \frac{\mathrm{wi}}{\mathrm{w1+w2}}, \text{ O3 (output of this layer)}$$

Forth Layer is defuzzifier layer, which receives O3 and convert it into de-fuzzified output. Finally, output layer sums up the de-fuzzified output coming from previous layer and gives us a function f

$$\mathrm{f} = \sum_{i=1}^{2} wifi$$

The failure of humidity sensor can be predicted using part count method or using accelerated life testing technique '18]. The artificial neural networks predict the response of the sensor in comparison to actual data [19].

3. Environmental testing

Real time data is the most reliable data, for conducting experiment, environmental testing i.e. highly accelerated life testing has been performed to check the point up till which humidity sensor can withstand the accelerated temperature [20]. For respective purpose, DHT11 sensor has been kept in various environment conditions of varying temperature from 0^0C to 68^0C, where the system fails completely which shows it cannot withstand that temperature the dice of the sensor starts melting at this point to make it dysfunction. The digital hot plate, having range 0^oC-450^oCis used for this purpose, which shows temperature as a function of time [21].

Figure 5: Experimental setup

Also, it is observed that at any time, humidity will have same effect as temperature is having [22,23]. One level of humidity can be observed at two or more temperature level corresponding data of extracted life is summarized in table 1.The life is calculated as,

Life = 1/TDH * AF

Where, AF is failure rate which is given by:

$$A_F = e^{\frac{Ea}{K}\left[\frac{1}{Tm} - \frac{1}{Ta}\right]}$$

Where, Tm is maximum temperature, Ta is applied temperature, Ea is activation energy, K is Boltzman's constant and TDH is Total no. of devices * Hours of operation

Table 1: Life estimation using experimental approach

S.No	Temperature (degree)	Humidity	L.E ($*10^4$) (hours)
1	0	47	159.8
2	4	43	104.13
3	8	41	68.67
4	12	38	45.82
5	16	34	30.9
6	20	31	21.09
7	24	30	14.53
8	28	28	10.11
9	32	27	7.1
10	36	25	5.04
11	40	23	3.6
12	44	19	2.6
13	48	16	1.8
14	52	14	1.3
15	56	12	1.02
16	60	9	0.7
17	64	7	0.57
18	68	3	0.37

The experimental data then used for artificial intelligence modelling using MATLAB 2014a version [24,25]. MATLAB SIMULINK has been for reliability and life prediction.

4. Results and discussion

Discussing about Artificial Neural Network first, the topology of the network used here is 2-10-1 i.e. two inputs, one output and ten neurons in hidden layer. Neural Network formed is shown below:

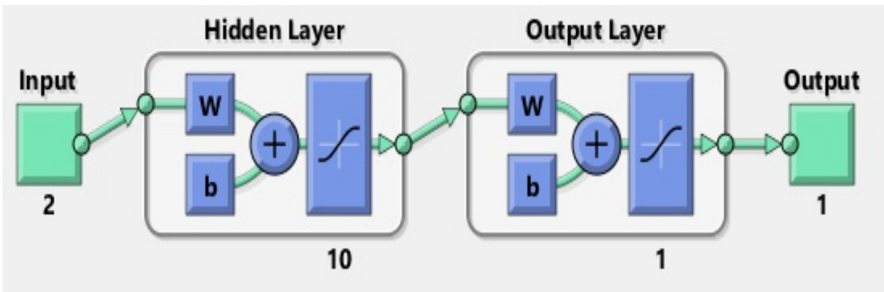

Figure 6: Formed Artificial Neural Network

Total 18 sample for training and same 18 have been used for simulation also. The number of epochs taken are 1000 and best validation performance 0.35 observed at iteration 6.

Fuzzy Inference System specified with 5 Membership function i.e, {very low, low, medium, high and very high}. Based on this fact, fuzzy rules for defining the relation between input and Membership function are formed. Total 25 rules were formed to get the final life estimation result. The required graphs for fuzzy are shown in the figure 7 below.

Taking into consideration the ANFIS then best result is achieved so far. The Life estimation value acquired over here has shown the minimum error. Also, 5 membership function same as taken for FIS method have been used. The graph for predicted as well as real value is shown Figure 8, It is obtained through Neuro-Fuzzy MATLAB Simulink.

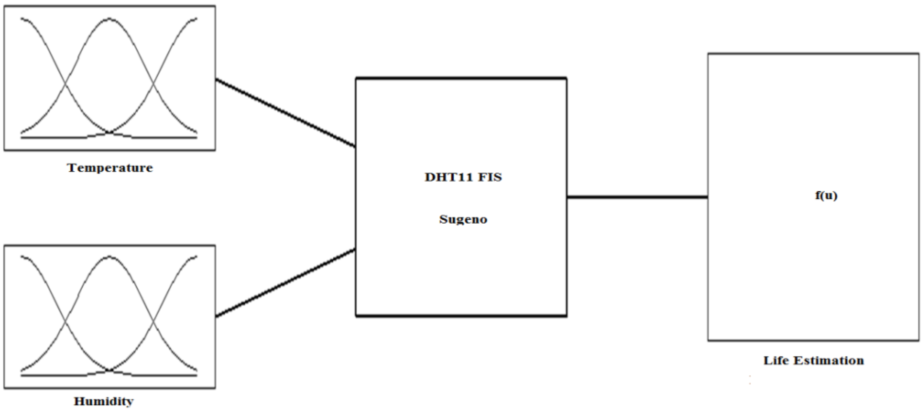

Figure 7: Fuzzy Inference System

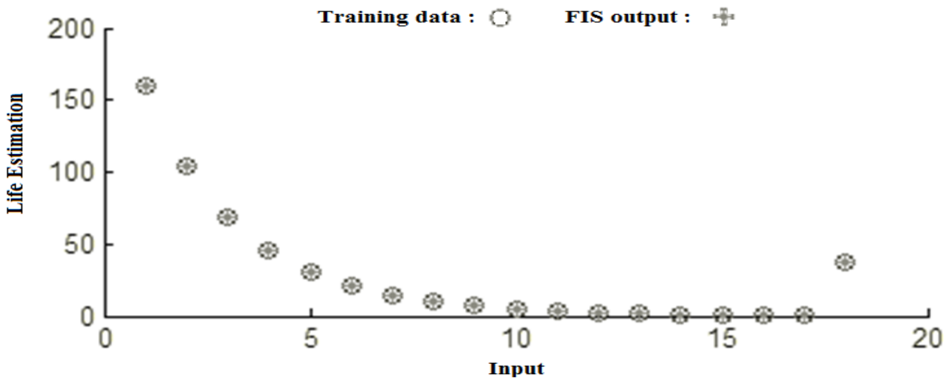

Figure 8: ANFIS response

The comparison of the result obtained through three techniques is shown in the table 2.

Table 2: Comparison of three prediction techniques

Trial Number	Actual Value	ANN	FIS	ANFIS
1	159.81	158.22	151.42	148.13
2	104.13	57.62	96.79	110.99
3	68.67	86.23	66.92	47.76
4	45.82	39.81	44.71	50.71
5	30.92	29.91	29.43	35.68
6	21.09	20.77	21.17	23.01
7	14.53	14.98	12.59	15.67
8	10.11	10.28	10.16	9.33
9	7.11	7.13	5.99	7.78
10	5.04	5.03	4.87	5.23
11	3.62	3.72	3.46	2.37
12	2.65	2.62	2.81	3.2
13	1.83	1.67	2.01	2.12
14	1.32	1.31	1.11	1.29
15	1.02	0.96	0.99	0.98
16	0.71	0.57	0.63	0.54
17	0.57	0.45	0.49	0.53
18	0.37	0.21	0.35	0.27
Mean Life time(hours)	26.62	24.55	25.31	25.86

The error analysis can be explored using following formula

$$Error(\%) = \frac{Experimental\ life - Predicted\ life}{Experimental\ life} \times 100$$

the error analysis of all the techniques have been summarized in table 3.

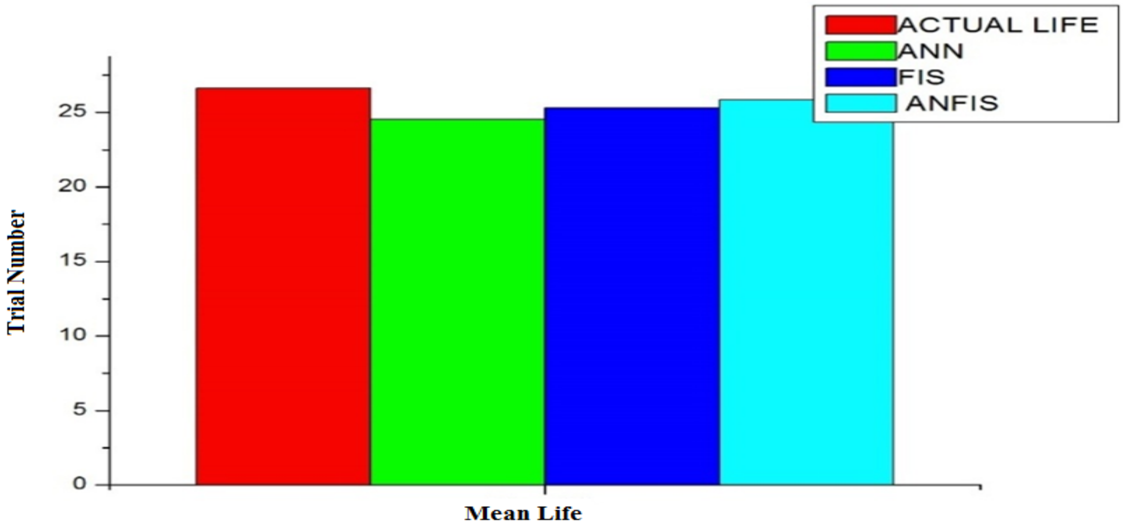

Figure 9: Mean life comparison of all techniques

The lifetime of DHT11 has been calculated and compared using various techniques. Figure 9, shows the mean life plot of all techniques.

Table 3: Error analysis of all the techniques

Trial Number	Error calculation (%)		
	ANN	FIS	ANFIS
1	0.994931	5.249984	7.308679
2	44.66532	7.048881	-6.58792
3	-25.5716	2.54842	30.44998
4	13.11654	2.422523	-10.6722
5	3.266494	4.818887	-15.3946
6	1.517307	-0.37933	-9.10384
7	-3.09704	13.35169	-7.84584
8	-1.6815	-0.49456	7.715134
9	-0.28129	15.75246	-9.42335
10	0.198413	3.373016	-3.76984
11	-2.76243	4.41989	34.53039
12	1.132075	-6.03774	-20.7547
13	8.743169	-9.83607	-15.847
14	0.757576	15.90909	2.272727
15	5.882353	2.941176	3.921569
16	19.71831	11.26761	23.94366
17	21.05263	14.03509	7.017544
18	43.24324	5.405405	27.02703
Average Error (%)	**7.27**	**5.09**	**2.48**
Average Accuracy (%)	**92.73**	**94.91**	**97.52**

After comparison, it can conclude that the best result in shown by ANFIS which 97.52%, whereas ANN result was 92.73% and FIS gives accuracy of 94.91%, which is the minimum amongest all three prediction techniques. ANN and ANFIS explore an advantage that the non-linearity in the data can be handled with adequate accuracy.

Conclusion

Temperature has been concluded as one of the most prominent factors which can cause device failure. The residual life of humidity sensor is estimated using environmental testing i.e. accelerated life testing. Then using various artificial intelligence techniques, expert system is created which monitors the health of sensor. On comparison, it is concluded that ANFIS is the best technique because it has minimum average error i.e. 2.48% whereas ANN error rate is 7.27% and Fuzzy system has error of 5.09%. so, efficient accuracy of 97.52% is achieved using ANFIS modelling and hence it can be selected as a technique to develop Intelligent Model.

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