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Lead-Free Solder Reliability Modeling Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract

Lead-free solder is a new material that has been utilized in manufacturing electronic components and packages; therefore, the material behavior had not been analyzed completely. This paper summarizes our effort to model the change in lead-free solder hardness behavior with respect to aging time and temperature as a measure of the components' reliability. ANFIS is a modeling technique that had been used in analyzing the current trend and predicting future progression. The ANFIS model was developed based on the BPN-ANN structure with two inputs and one output using Matlab®. The developed model was compared to different regression models that are being used frequently in the literature. The well-trained ANFIS model gave very accurate results for predicting the hardness (output) with a small Root Mean Square Error (RMSE) compared to the Minitab® regression models. ANFIS is one of the best techniques in modeling non-linear data, and it can give better and more accurate data representation and future prediction.

Keywords: Fuzzy Logic, Neural Network, Behavior Modeling, Lead-Free Solder, Aging, Reliability, Electronic packages, Matlab, Minitab;

1. Introduction

Fuzzy Logic and Artificial Neural Networks (ANN) are very common techniques used for soft computing. While Fuzzy Logic depends mainly on the knowledge from the expert, the neural network is based on the system data that has been collected. Nowadays, there are new techniques that combine neural machine learning with fuzzy systems; these are called "Neuro-Fuzzy" approaches, developed first at Matsushita laboratories for consumer appliances where the ANN learning technique was used to design the fuzzy model itself. In other words, the neural and the fuzzy components are not two separate design components anymore, but rather two different aspects of the same component.

ANFIS stands for Adaptive Network-based Fuzzy Inference System, whichis one example of a neuro-fuzzy approach that uses a hybrid-learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set [1].

In this paper, the reliability of lead-free solder will be modeled using ANFIS. The proposed model will be designed and implemented using Matlab as a software platform. The paper is organized as follows: section 2 is the literature review which includes the Adaptive Neuro-Fuzzy Interface System and a description of the system of interest, section 3 deals with data used for modeling purposes, section 4 provides alternative modeling approaches for comparison, section 5 shows the modeling results, and section 6 concludes the paper and describes the authors' future plan.

2. Literature Review

2.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

In the last decade, Artificial intelligence (AI) techniques became an important approach, which plays a significant role in multiple fields. AI techniques consist of several intelligent methods, such as genetic fuzzy systems, neuro-fuzzy systems, genetic programming, and neural networks, etc. A Neuro-fuzzy system (ANFIS) is an approach that consists of an Artificial Neural Network (ANN) and a Fuzzy Logic Inference System (FIS). The neuro-fuzzy system implements the principle of fuzzy logic-based learning capabilities and neural network techniques, which is a hybrid technique used in soft computing, that utilizes a hybrid-learning algorithm to identify parameters of Sugeno-Type Fuzzy Inference Systems [2].

Fuzzy rules are developed based on a sample dataset training, while ANFIS applies a combination of the least-squares and the back propagation gradient descent methods for training FIS membership function parameters to emulate a given training data set. Neuro-fuzzy systems (ANIFS) are widely used in healthcare applications such as predicting and modeling cardiac disease, brain disorder, and breast cancer [3]. In addition, the neuro-fuzzy system had been used intensively in the production environment, quality control, emergency responses and traffic management, and

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material analysis [4-15]. The FIS, ANN, and the ANFIS structure will be explained in the following subsections [2].

2.1.1. Fuzzy Inference System (FIS)

Fuzzy logic was first introduced by Lotfi Zadeh's proposal of fuzzy set theory in 1965. Since then, fuzzy logic and several applications for fuzzy set theory were developed. Fuzzy logic is a form that has more than two values; it was derived from fuzzy set theory to deal with approximate logic rather than real facts. In contrast with "crisp logic" where binary sets have binary logic, fuzzy logic variables may have a logical value that ranges between "0 and 1" and is not limited to two values (0, 1) like in the binary logic. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions, usually called membership functions [16].

Since Fuzzy logic was a proposal of the fuzzy set theory, it is important to explain what fuzzy set is and how it is different from the classical set. A fuzzy set is a set with a fuzzy boundary, which means that there is a gradual transition in defining whether the element belongs to one set or another; this transition is different due to the difference of the membership function. The membership functions are functions that map each system element of the domain (the input) to a membership value between zero and one. This will allow the fuzzy sets to be flexible in expressing the fuzzy relation in linguistic terms. Figure1illustrates the concept of fuzzy sets and fuzzy relations. In this relation, the membership functions are defined for the linguistic variable X (age) as three membership functions for a different level of age, and those levels are subjective. Choosing these membership functions could be different from one person to another, but this choice will depend on the heuristic knowledge and the common sense, which is usually not random [16-17]. There are differences between binary and fuzzy logic; in binary logic, values can be either zero or one for the values. However, in fuzzy logic, you can find any value between zero and one, so there are more variations and more flexibility for modeling and design.

In Figure 1, the fuzzy relation consists of five membership functions. The X-axis represents the life span of the human being (0-100 years). The Y-axis represents the membership grade (0-1). The membership grade is different from probability, which also takes the same values (0-1), and this is what makes the fuzzy logic different from the probability theory [18]. At the value of x=20 years, the membership grade from the y-axis is $0.5(\text{young}) + 0.2(\text{very young}) + 0.5(\text{Middle} - \text{Aged})$.

Fuzzy inference is the concept of using fuzzy logic to map the output of each fuzzy input. The mapping then provides a reference to make decisions about what the output will be. The process of fuzzy inference requires the use of Membership Functions, Logical Operations (mostly or/and), and If-Then rules [16].

There are different types of fuzzy inference systems; this research will utilize the "Takagi-type", the "Sugeno-type", the "Takagi-Sugeno-type", and the "TSK-type" (for Takagi-Sugeno-Kang) FIS. It can also be called a "1st order Sugeno Model". In this type of FIS, three terms (S, M, and L as abbreviations for small, medium, and large) for the various variables will be used. In a TSK-style FIS, the rules would look like the following:

Rule #1: IF x is S1 AND x2 is S2 THEN f = c10 + c11x + c12x2.

Rule #2: IF x is S1 AND x2 is M2 THEN f = c20 + c21x + c22x2.

Rule #3: IF x is S1 AND x2 is L2 THEN f = c30 + c31x + c32x2.

Rule #4: IF x is M1 AND x2 is S2 THEN f = c40 + c41x + c42x2.

Rule #5: IF x is M1 AND x2 is M2 THEN f = c50 + c51x + c52x2.

Rule #6: IF x is M1 AND x2 is L2 THEN f = c60 + c61x + c62x2.

Rule #7: IF x is L1 AND x2 is S2 THEN f = c70 + c71x + c72x2.

Rule #8: IF x is L1 AND x2 is M2 THEN f = c80 + c81x + c82x2.

Rule #9: IF x is L1 AND x2 is L2 THEN f = c90 + c91x + c92x2.

Fuzzy inference systems have been successfully applied in different fields of industry, such as automatic control, data classification, decision analysis, expert systems, and computer vision. Fuzzy inference systems have different names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers, and simple (and ambiguously) fuzzy systems [16].

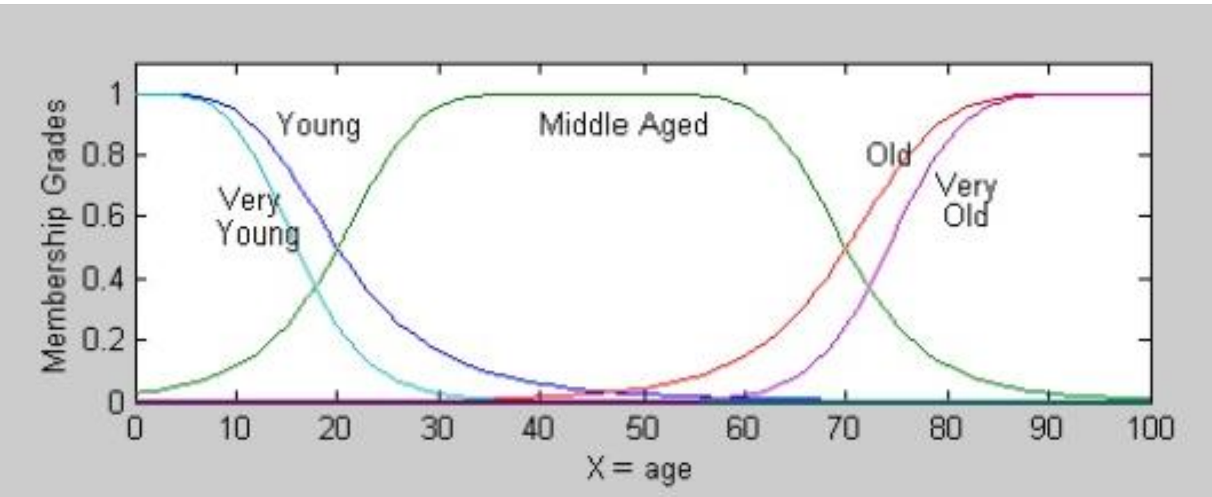

Figure 1. Fuzzy relation for age variable

2.1.2. Artificial Neural Network

The human mind/brain is an amazing complicated network of neurons that can process incomplete and imprecise sensor information very effectively through different neurons. The Artificial Neural Network mimics at a simple level the way that the biological neurons learn or get trained to learn, and this is how it was given a similar name. These models are also known as connectionist models that try to use the principle of learning in the human brain. The ANN consists of several independent processors (neurons) that communicate with each other. The neurons communicate with each other via weighted connections. Current research has been in the development of architectures of the ANN, learning algorithms, and application of these models to information processing tasks [18].

There are different types of neural networks; most of them have common terminologies, like the input layers, hidden layers, and output layers. Neural networks aim to predict the future based on weights assigned to the network layer. Training the network will be done by changing the weights to minimize the error between the predicted and true values. Once these neural networks are trained, the weights will be fixed, and the neural network will be ready to be used for prediction. In this paper, the Back Propagation Neural Network will be used to mode the hardness data as a function of the aging time and temperatures.

2.1.3. Back Propagation Neural Network (BPN)

Back Propagation Neural Network (BPN) is a multilayer network that has a mathematical foundation. The design of a BPN-NN consists of three separate layers as shown in Figure 2 [19]. The input layer is the set of source nodes (sensor units), while the second layer is single or multiple numbers of the hidden layer. The output layer gives the response of the network based on the activation patterns applied to the input layer. The input will be propagating from the left to the right. Sometimes BPN is also called feed-forward networks, as there is no feedback to adjust the system. Each arrow between the input layers and hidden layers, as well as between the hidden layers and output layers, is associated with weight; the value of the weights is the main concern and objective behind training the BPN network. The hidden nodes will use a linear basis function to sum the weighted inputs, and then this sum will go through the sigmoid activation function.

To teach a training set of input-output samples, the BPN provides a computationally efficient method for changing the weights in a feed-forward network, having differentiable activation function units, thereby reducing the computing time [18]. The BPN can be used for prediction after it is trained. The training method for such networks is applying some data samples, assuming first random initial weights, and then the output will be calculated and compared to the real output to calculate the error. Multiple algorithms to minimize this error exist, but the most common is the gradient descent method, which calculates the error function and finds the value of the parameters (weights) that will minimize it using the partial derivative method. Each time the weights are changed, the error is calculated, and then weights should be updated accordingly. These iterations will be conducted until the error is minimized. The Final weights will be saved, and the network is ready for perdition use. One important step besides the training is validation, which is done by using one part of the data that have not been used in training, and the validation error will be calculated. To avoid overtraining, which is also known as memorizing the data, the validation error at each iteration will be checked, and once it starts to increase, training will stop to avoid overtraining.

2.1.4. ANFIS Structure

The structure of the ANFIS model, which is used in this paper, is shown in Figure 3 [20-22]. The structure of the ANFIS has two inputs and one output. Each of the two inputs has three fuzzy terms associated with its value (L, M, and H). This will result in a TSK fuzzy of nine rules as follows [2]:

Rule #1: IF x is S1 AND y is S2 THEN f = c10 + c11x + c12y.

Rule #2: IF x is S1 AND y is M2 THEN f = c20 + c21x + c22y.

Rule #3: IF x is S1 AND y is L2 THEN f = c30 + c31x + c32y.

Rule #4: IF x is M1 AND y is S2 THEN f = c40 + c41x + c42y.

Rule #5: IF x is M1 AND y is M2 THEN f = c50 + c51x + c52y.

Rule #6: IF x is M1 AND y is L2 THEN f = c60 + c61x + c62y.

Rule #7: IF x is L1 AND y is S2 THEN f = c70 + c71x + c72y.

Rule #8: IF x is L1 AND y is M2 THEN f = c80 + c81x + c82y.

Rule #9: IF x is L1 AND y is L2 THEN f = c90 + c91x + c92y.

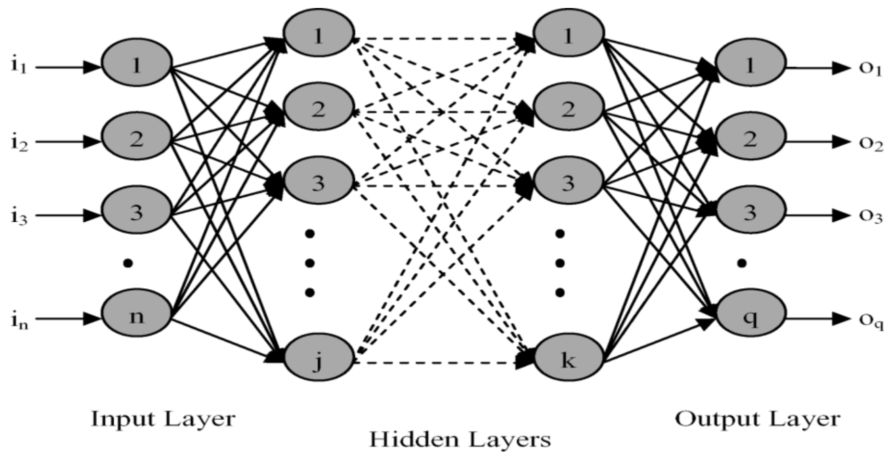

Figure 2. BPN-ANN structure

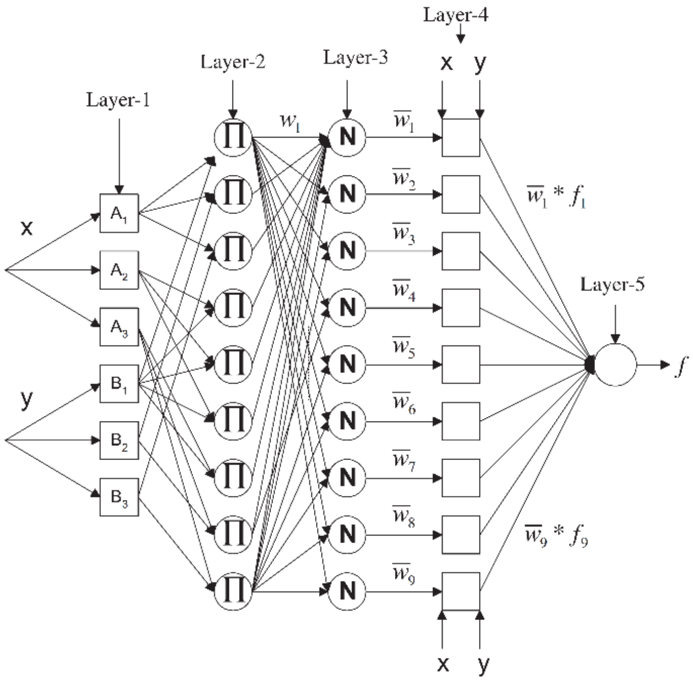

Figure 3. ANFIS two-input one output structure

The membership function that is used to represent each term of the inputs L1, M1 is a generalized Bell function, which has the following mathematical form

$$\mu_{genbell}(x;\ \alpha,\beta,\gamma) = \frac{1}{1+\left|\frac{x-y}{\alpha}\right|^{2\beta}} \quad (2)$$

For this model, eighteen (18) parameter will be needed for each fuzzy term (α, β, γ) because each of the inputs has 3 terms, so the total number of the membership functions will be (6 × 3=18). Since nine rules will be used, Twenty-seven (9 × 3 =27) parameters for the constant values in the outputs (c_{10}, c_{11}…) will be needed.

In the ANFIS training, an initial approximation of the membership functions based on data will be used rather than generating them randomly. This practice usually gives better convergence, and less training will be needed. However, to find the values for the C's, the least square error method will be used to solve the system of the linear equations to minimize this error. The systems consist of a derivative of the error concerning each value of the C's with a matrix of coefficients of 34 × 34, which was solved utilizing Matlab. After finding the C's values, they were fixed, and another epoch through the data was made to fine-tune the (α, β, γ) values using the gradient descent method, followed by another epoch to find the new values of the C's.

2.2. System Description

The reliability of the lead-free solder is the system that will be modeled in this paper. Since 2002, most of the developed countries started to ban Lead use in the electronic packaging industry because of the toxic effect on the health of humans, animals, and the environment. Soldering is the process in which two or more metals are joined together by melting and flowing a filler metal into the joint, the filler metal having a relatively low melting point compared to the other two alloys [23].

The filler material used in such a process is called solder. One major application of soldering is assembling electronic components in printed circuit boards (PCB) [23]. It was not until recently that the ban on the lead began. However, before this, most of the solder materials were based on the SnPb, which is an alloy that contains both Tin and Lead with different percentages. Many types of research in the past have been conducted to measure the reliability of the Lead solders, and it was somehow stable in terms of reliability. However, following the ban of the lead, there was a need to replace the soldering material with different alloys that do not contain lead: lead-free solders [24-29].

Most of the alloys that are used in today's electronic industry are a mixture of tin, copper, and silver with different percentages. One major alloy that is being used currently in the manufacturing system is SAC305; this solder alloy is a mixture of 96.5 % Tin (Sn), 3% Silver (Ag), and 0.5% Copper (Cu). However, since this alloy SAC305 is relatively new in the industry, a lot of reliability research is being conducted to compare with other mixtures [24-29]. Our purpose in this report is to model the reliability of this alloy by applying an aging experiment and then checking the hardness as one measure of reliability.

2.2.1. Experiment Description

The experiment was conducted to measure the hardness of SAC305 solder spheres under an aging experiment of different storage temperatures and times. In reality, the solder material will become weaker over time, making the material more prone to failures such as cracks. Therefore, in this experiment, the solder balls had been aged at different times. However, only a short time can be afforded to see these cracks; therefore, another approach had been used. This approach is a controlled accelerated aging test, which had been used intensively in the literature, and it involves heating the solder at different temperatures in a controlled oven for some time (dwell). Aging temperature and dwell time will be utilized through acceleration factors calculation to represent the real-life storage conditions. After the solder spheres had been aged for different periods, a hardness test will be conducted using the Knoop hardness tester shown in Figure 4.

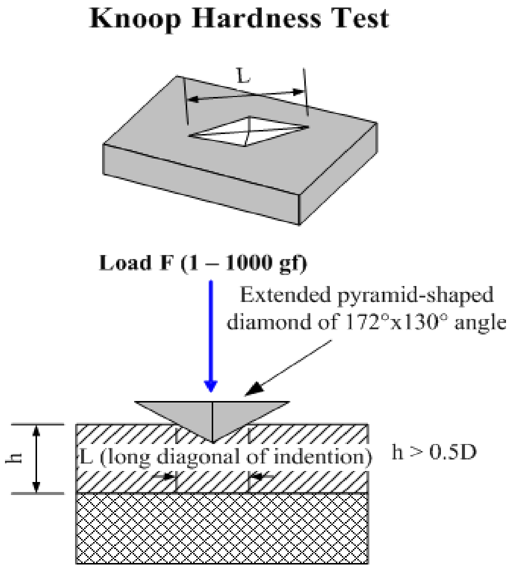

Figure 4. Knoop Hardness Test

2.2.2. Hardness Test:

After the solder material was aged for different times, they had been subjected to a hardness test using a Knoop hardness machine. This machine works as follows:

- A pyramidal diamond point is pressed into the polished surface of the test material with a known force
- The resulting indentation is measured using a microscope
- The Knoop hardness is calculated using the following formula:

$$HK = \frac{Load(kgf)}{Impression\ Area\ (mm^2)} = \frac{P}{C_p L^2} \quad (1)$$

Where

L = Length of the indentation along its long axis

C_p = Correction factor related to the shape of the indenter = 0.070279

P = Load

The hardness test results shown in Figure 5 were collected by measuring the hardness values of different aged solder samples. The figure represents one phase of the experiment where some of the data were collected; hardness decreased as aging temperature increased while hardness decreased with increasing the aging (dwell) period at a fixed temperature. This indicates that as solder ages, it will get less hard (softer), but authors planned to model this relationship and see how long it will take this solder to become relatively not hard enough to withstand regular operation settings. For this purpose, the authors have used the two inputs temperature and time and the output (hardness) to model this relationship using the Adaptive Neuro-Fuzzy Inference System (ANFIS), and they have compared it to the linear regression model, which is being used frequently. The comparison of both models will be shown in the results section.

3. Data for ANFIS Modeling

Table 1summarizes the data obtained for SAC305 solder material that were aged at different aging temperatures and the time spent (dwell time) in the controlled oven. The first thirty-four (34) data points were utilized to train the ANFIS using Matlab while another 8 points of the data were used for verification to avoid overtraining.

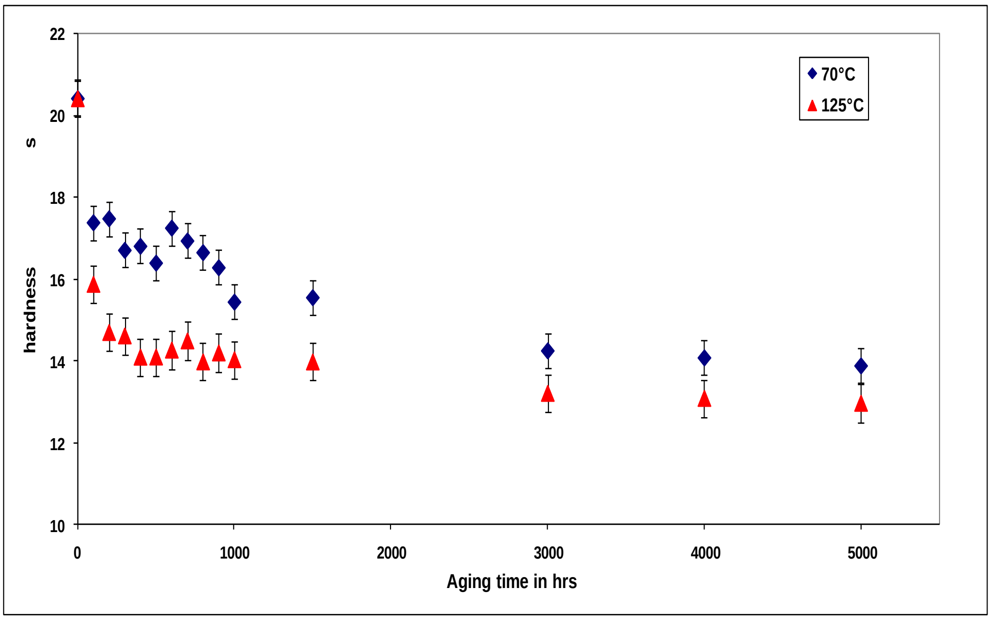

Figure 5. Hardness change with aging time

Table 1. ANFIS Development Data

Temp. (C)	Time (hrs.)	Knoop Hardness	Temp. (C)	Time (hrs.)	Knoop Hardness	Temp. (C)	Time (hrs.)	Knoop Hardness
70	0	20.1	100	0	20.1	125	0	20.1
70	24	19.23	100	24	19.02	125	24	18.21
70	48	18.44	100	48	18.23	125	48	17.54
70	72	18.09	100	72	17.85	125	72	16.23
70	100	17.39	100	100	15.05	125	100	15.88
70	200	17.49	100	200	14.97	125	200	14.7
70	300	16.71	100	300	15.59	125	300	14.62
70	400	16.81	100	400	15.28	125	400	14.1
70	500	16.4	100	500	14.76	125	500	14.1
70	700	16.94	100	700	15.61	125	700	14.5
70	1000	15.45	100	1000	14.5	125	1000	14.04
70	1500	15.56	100	1500	14.34	125	1500	13.98
70	3000	14.26	100	3000	13.11	125	3000	13.21
70	5000	14.22	100	5000	13.09	125	5000	13.09

4. Alternative Approach (Regression)

The regression approach was used to compare and validate the ANFIS model developed. In this case, Minitab was used to fit the input data into multiple models:

4.1. Original Data:

4.1.1. Linear regression model: the output of the Minitab regression model is shown below:

- Regression Equation

Knoop Hardness = 19.15 - 0.0207 Temp. (C)- 0.001013 Aging Time (hrs.)

- **Coefficients**

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	19.15	1.16	16.45	0.000	
Temp. (C)	-0.0207	0.0120	-1.73	0.093	1.04
Aging Time (hrs.)	-0.001013	0.000190	-5.33	0.000	1.04

- **Model Summary**

S	R-sq	R-sq(adj)	R-sq(pred)
1.40315	48.36%	45.03%	36.61%

- **Analysis of Variance**

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	2	57.150	28.575	14.51	0.000
Temp. (C)	1	5.903	5.903	3.00	0.093
Aging Time (hrs.)	1	56.035	56.035	28.46	0.000
Error	31	61.033	1.969		
Total	33	118.183			

- **Fits and Diagnostics for Unusual Observations**

Obs	KnoopHardness	Fit	Resid	Std Resid	
14	14.220	12.633	1.587	1.41	*Unusual*
28	13.090	12.011	1.079	0.97	*Unusual*

This model provided the following error parameters:

SE	78.89843
MSE	1.87853
RMSE	1.37060

4.2. Normalized Data: data were normalized by diving every value by the largest available as shown in the equations below and Table 2.

$$Normalized\ Aging\ Temperature = \frac{Temp}{125^oC}$$

$$Normalized\ Aging\ Time = \frac{Time}{5000\ hrs.}$$

$$Normalized\ Knoop\ Hardness = \frac{Knoop\ Hardness}{Knoop\ Hardness\ (at\ time = 0\ \&\ temp = 22^oC)}$$

The de-normalized hardness can be calculated using the equation below:

$$Denormalized\ Dardness = (Normalized\ Hardness * Hardness\ (at\ t = 0\ \&\ RT))$$

4.2.1. Linear regression model: the output of the Minitab regression model is as follow

- **Regression Equation**

Normalized Measurements =0.9854 - 0.1856 Normalized Aging Temp- 0.2305 Normalized Aging Time

- **Coefficients**

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.9854	0.0515	19.14	0.000	
Normalized Aging Temp	-0.1856	0.0631	-2.94	0.005	1.00
Normalized Aging Time	-0.2305	0.0413	-5.59	0.000	1.00

- **Model Summary**

S	R-sq	R-sq(adj)	R-sq(pred)
0.0735721	50.55%	48.01%	42.81%

- **Analysis of Variance**

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	2	0.21576	0.107881	19.93	0.000
Normalized Aging Temp	1	0.04681	0.046814	8.65	0.005
Normalized Aging Time	1	0.16895	0.168947	31.21	0.000
Error	39	0.21110	0.005413		
Total	41	0.42686			

- **Fits and Diagnostics for Unusual Observations**

Obs	Normalize Measurements	Fit	Resid	Std Resid	
14	0.7075	0.6510	0.0565	0.90	*Unusual*
15	1.0000	0.8369	0.1631	2.26	*Large Residual*
28	0.6512	0.6064	0.0448	0.70	*Unusual*
29	1.0000	0.7998	0.2002	2.82	*Large residual*
42	0.6512	0.5693	0.0819	1.30	*Unusual*

This model provided the following error parameters:

SE	85.28701
MSE	2.030643
RMSE	1.425006

4.2.2. <u>Nonlinear regression model</u>: the output of the Minitab regression model is illustrated below

- **Equation**

Normalized Hardness = -2.33776 *(Normalized Aging Temp^ 0.0777865) + 15.7782 * (Normalized Aging Time^ -0.00218908) - 12.8074

- **Parameter Estimates**

Normalized Measurements = A * 'Normalized Aging Temp' ^ B + C * 'Normalized Aging Time' ^ D +E

Parameter	Estimate	SE Estimate
A	-2.3378	54.317
B	0.0778	1.850
C	15.7782	411.575
D	-0.0022	0.057
E	-12.8074	415.155

- **Summary**

Iterations	200
Final SSE	0.0586358
DFE	37
MSE	0.0015848
S	0.0398089

This model provided the following error parameters:

SE	23.66744
MSE	0.56351
RMSE	0.750673

Table 3. Parameter Summary for All Regression Models

	Original Data Linear Regression	**Normalized Data Linear Regression**	**Normalized Data Nonlinear Regression**
SE	78.89843	85.28701	23.66744
MSE	1.87853	2.030643	0.56351
RMSE	1.3706	1.425006	0.750673

As seen in Table 3, the minimum value of the Root Mean Square Error (RMSE) was obtained from all the regression models developed for the hardness measurements. The smallest RMSE value was about 0.75, which is associated with the nonlinear regression model of the normalized data set. This result shows that assuming a linear relationship between the inputs and the outputs is not justified, and a nonlinear relationship exists as shown previously in Figure 5. Therefore, the authors developed an ANFIS model that resulted in a much smaller error, and it will be discussed in the next section.

Table 2. ANFIS Development Normalized Data

Temp. (C)	Time (hrs.)	Knoop Hardness	Temp. (C)	Time (hrs.)	Knoop Hardness	Temp. (C)	Time (hrs.)	Knoop Hardness
0.560	0.000	1.000	0.800	0.000	1.000	1.000	0.000	1.000
0.560	0.005	0.957	0.800	0.005	0.946	1.000	0.005	0.906
0.560	0.010	0.917	0.800	0.010	0.907	1.000	0.010	0.873
0.560	0.015	0.900	0.800	0.015	0.888	1.000	0.015	0.807
0.560	0.020	0.865	0.800	0.020	0.749	1.000	0.020	0.790
0.560	0.040	0.870	0.800	0.040	0.745	1.000	0.040	0.731
0.560	0.060	0.831	0.800	0.060	0.776	1.000	0.060	0.727
0.560	0.080	0.836	0.800	0.080	0.760	1.000	0.080	0.701
0.560	0.100	0.816	0.800	0.100	0.734	1.000	0.100	0.701
0.560	0.140	0.843	0.800	0.140	0.777	1.000	0.140	0.721
0.560	0.200	0.769	0.800	0.200	0.721	1.000	0.200	0.699
0.560	0.300	0.774	0.800	0.300	0.713	1.000	0.300	0.696
0.560	0.600	0.709	0.800	0.600	0.652	1.000	0.600	0.657
0.560	1.000	0.707	0.800	1.000	0.651	1.000	1.000	0.651

5. Results

The hardness of lead-free solder (SAC 305) was modeled as one output measure of the solder material reliability. The hardness was measured for two variables inputs aging temperature and aging time. Using ANFIS to model that data, the results were very reasonable since, after only ten epochs of training, the Root Mean Square Error (RMSE) for the calculated output (hardness) was calculated for the different models based on the formula below:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)}{n}^2}$$

$where\ \hat{y} = harndess\ value\ from\ the\ mode\ (predicted)$

$y = actual\ observed\ value$

$n = 42$

The ANFIS model's RMSE value was less than 5%, which is very promising and indicates the ANFIS is a very good choice for modeling this type of output.

Epoch	Training error	Validation error	Epoch	Training error	Validation error
1	0.9099	1.1673	9	0.1351	0.3691
2	0.6974	0.7116	10	0.1093	0.3579
3	0.5631	0.6017	11	0.0891	0.3515
4	0.4431	0.5367	12	0.073	0.3489
5	0.3444	0.4858	13	0.0604	0.3494
6	0.2686	0.4436	14	0.0506	0.3525
7	0.2115	0.4105	15	0.0435	0.3576
8	0.1683	0.3861			

Per Figures 6 and 7, the RMSE from the Matlab output shows that the error was decreasing as more epochs of training were used. However, to avoid the problem of overtraining, the training was stopped after 20 epochs or iterations. Furthermore, the ANFIS output was compared with the linear and non-linear regression models, and it was found that the ANFIS model outperformed the other models with a smaller error of 0.35 for the validation.

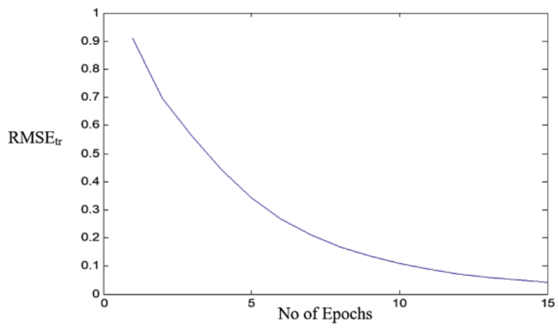

Figure 6. ANFIS Training Error

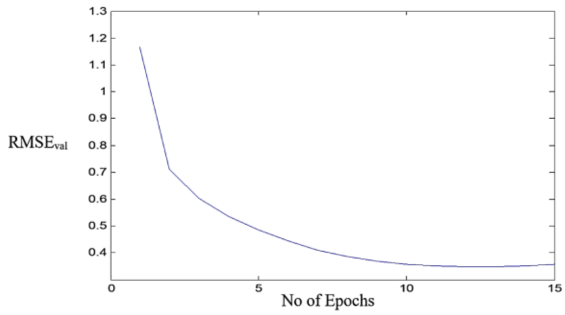

Figure 7. ANFIS Validation Error

6. Conclusion

In this work, the relationship that represents the lead-free solder hardness with respect to the aging temperature and the aging time was modeled using ANFIS. The model gave accurate results in predicting the output (hardness) with a small root mean square error compared to the Minitab linear regression model. Because of this comparison, the ANFIS is a very good technique in modeling non-linear data and it can give a better representation for the data.

ANFIS is a powerful technique in modeling the nonlinear system since in some cases it is difficult to come up with an exact analytical model (ex: differential equations). If the ANFIS is well-trained with small errors, then it can be used for output prediction without measuring the real output, which will save time and cost. It is easy to train the ANFIS again if there is any doubt in the data. Once the ANFIS model is developed, new data could be integrated and the model could be trained again to determine the required parameters, which means there is no need to start from scratch again.

One of the challenges for the ANFIS is to determine the initial values for the parameters, especially for the generalized bell function (membership function) because these values change with the choice of the data. However, developing a code to find these initial values, or by choosing these initial values at random will ease this challenge as the ANFIS model converges, which might require additional epochs.

In the future, the authors are planning to consider other approaches to model the data, comparing these modeling techniques with ANFIS, and utilizing other types of ANFIS configuration.

Conflict of interest

The authors declare that they have no conflict of interest.

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