IOSR Journal of Engineering (IOSRJEN) **www.iosrjen.org**
ISSN (e): 2250-3021, ISSN (p): 2278-8719
Vol. 12, Issue 4, April. 2022, || Series -I || PP 08-18

A Lifetime Prediction Model for Power Modules by AI Technology

Fang-Hsuan Cheng, Shih-Feng Hsu
(Computer Science & Information Engineering, Chung Hua University, Taiwan)
Received 02 April 2022; Accepted 16 April 2022

Abstract: The power conversion system (PCS) plays a role in improving the efficiency of green energy generation, power quality and grid protection in energy generation, energy storage and energy conservation. The traditional design from process to mass production needs to constantly change the Design of Experiments (DOE) and then go through thermal cycle testing to verify the reliability for the best design. The process is repetitive and takes time. Thermal cycle test (TCT) is one of the most important verification items in the reliability test of high-reliability power modules, and widely used in the electronic packaging industry.

In order to meet the needs of the market for faster time-to-market power modules, the researchers adjusted all the designed and simulated parameters, and then simulated repeated thermal stress to establish the experimental data set. Then, the model is learned through artificial intelligence neural network training, so as to predict the number of thermal cycles which can be converted into the life of the power module.

In this paper, an AI neural network model of lifetime prediction for power modules is proposed. 81 simulated data sets obtained by finite element method which are divided into training set and test set are collected to train the model. By increasing the training set according to the training percentage, the learning ability of the training model can be improved. After the optimization of the experiment, the hidden layer of 2 and the nodes of 50 points, using the training set to verify the training model has an accuracy of more than 97~99%, and using the test set to verify the training model has an accuracy of 96%, If the simulation data set is large enough, the higher learning ability of the training model can be achieved and the prediction gap between the training and test set can be shortened.
Key Word: Power Module; Reliability; Thermal Cycle Test; Artificial Intelligence; Neural Network

I. Introduction

Power conversion systems (PCS) play a role in improving green energy generation efficiency, power quality and grid protection in energy generation, energy storage and energy conservation. In order to meet the requirements of energy saving, high frequency and high speed, manufacturers are looking for high-performance and high-reliability power modules solutions. The current power modules mostly use wire bonding to complete the interconnection between the power element and the substrate. However, the parasitic inductance effect of the wire is unfavorable to the high frequency operation and electromagnetic compatibility of the motor system. Junction temperature may exceed critical temperature, resulting in module and system failure. Improving the efficiency of the power -to-energy conversion system can not only save power and energy by frequency conversion but also reduce the size of modules.

With the increasing demand for high-power module components, the design of the packaging process must also be followed up. The power density of a single power module increases with the demand. Such a huge design demand is continuously improved and repeated in the design, so using artificial intelligence (AI) to help reduce the time of repeated design can not only ensure the correctness of power module component design, but also accelerate the entire power module component design process. When the power module performs power conversion, the power output of high voltage and high current is accompanied by the generation of heat, and the heat dissipation efficiency becomes the most important design issue. The analysis data is constructed mainly through simulation analysis of numerical methods, and the simulation analysis model is optimized by combining the actual measurement results and failure modes of the vehicle, thereby constructing a product life prediction model. The design and analysis procedure of power modules is shown in Figure 1, which focuses on the numerical simulation analysis of the module. The main procedures include (1) product structure confirmation, (2) literature collection and compilation, (3) simulation model construction, (4) parametric DOE (Design of Experiment) analysis, (5) data database establishment.

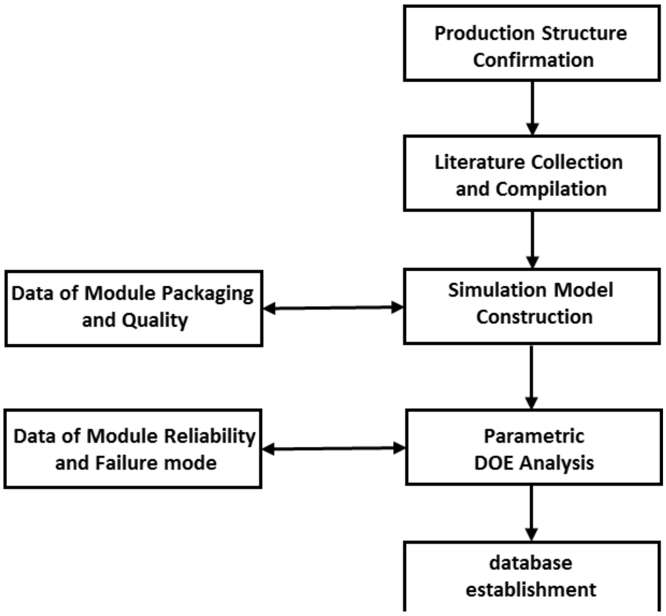

Figure 1 Design and analysis procedure of power modules

Product Structure Confirmation

Structure confirmation of power module mainly includes silicon chip , Fast Recovery Diode (FRD), solder, Al_2O_3 or AlN ceramic substrate (Direct Bonded Copper, DBC), copper substrate (Baseplate) , module housing (Housing), sealant (silicon or epoxy), and this module structure is used as the basis for research and development

Literature Collection and Compilation

When the current power module architecture performs Temperature Cycling Test (TCT) and Intermittent Operational Life (IOL) test or Power Cycling Test (PCT), the failure mode mainly occurs on the solder material layer of the wafer and ceramic substrate (DBC Substrate), and the interface between the wafer aluminum pad and the aluminum wire bonding. The main reason is due to the difference in the thermal expansion coefficient (CTE Mismatch) of the heterogeneous materials in the structure [1], as shown in Figure 2. At present, there is no suitable simulation model for the reliability failure mode of power modules in the world.

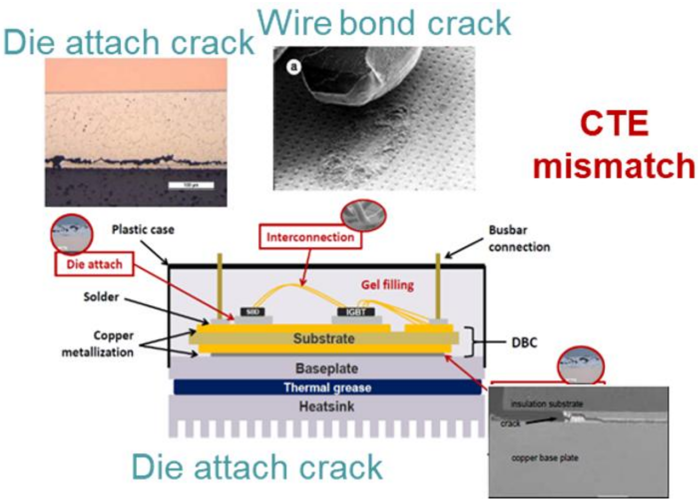

Figure 2 Failure due to differences in thermal expansion coefficients

Simulation Model Construction

The content of the simulation stage is mainly to construct the module simulation model and the reliability life prediction analysis of the module, see Figure 3. All of the geometric shape, material parameters, boundary conditions and load settings and other information need to refer to the actual module structure and process conditions.

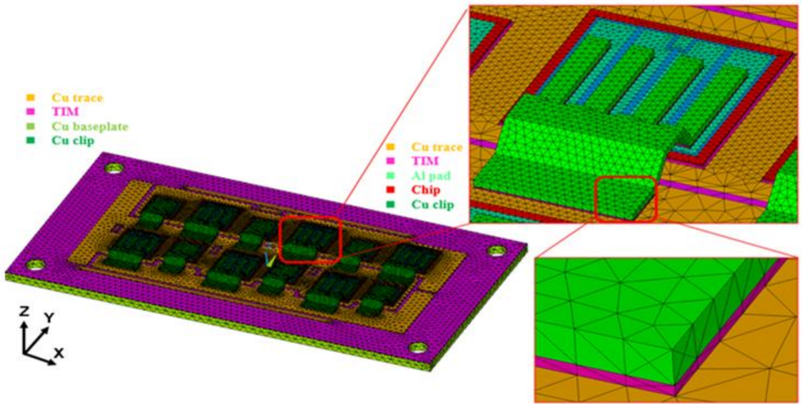

Figure 3 3D model construction and mesh analysi

Analysis of Parametric DOE design

The Design of Experiment (DOE) at this stage mainly carries out the parameterized design of the module structure size, material parameters, load conditions and other factors. Changes of the structure size include wafer, solder layer, DBC substrate, copper substrate, etc.; changes of the material parameter include solder layer, DBC substrate, copper substrate, sealing material, etc. and changes of the load condition include the module assembly process and reliability test, etc., as shown in Figure 4. Through the complete parametric DOE design, the key influencing factors affecting the life of the module are confirmed, which can be used as a reference for future module design evaluation.

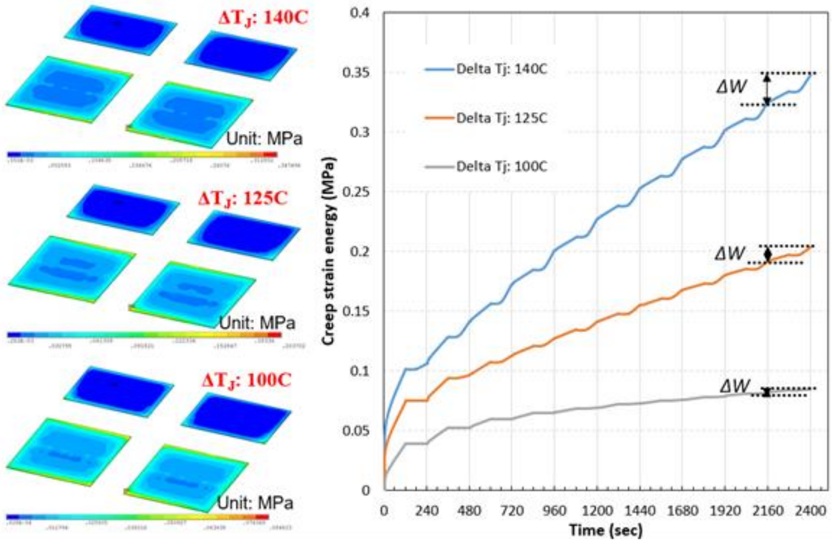

Figure 4 Reliability simulation for different temperatures of the welding layer

Data Database Establishment

The main contents of the work in this stage are the systematic integration of parametric DOE design and analysis of the data obtained in each stage. Through the construction of the module reliability test results and failure mode database, the module TCT/IOL reliability test data and module failure modes are compiled to construct the module design database. A complete database of the process from group design to failure is used as a data set for artificial intelligence training, see Figure 5.

II. Related Research

In the previous section, we mentioned that the thermal influence generated by the power module will affect the reliability of the die soldering to DBC and DBC soldering to the baseplate. A life prediction model of power module welding under thermal cycle test (TCT) is proposed by H. Liao [2]. Finite element method (FEM) is used to simulate the predictive life of power module in TCT experiment using ANSYS simulation software. K. N. Chiang [3] used artificial intelligence technology to simulate and analyze predictive lifetime of the solder layer in wafer level packaging. These two studies are briefly described below.

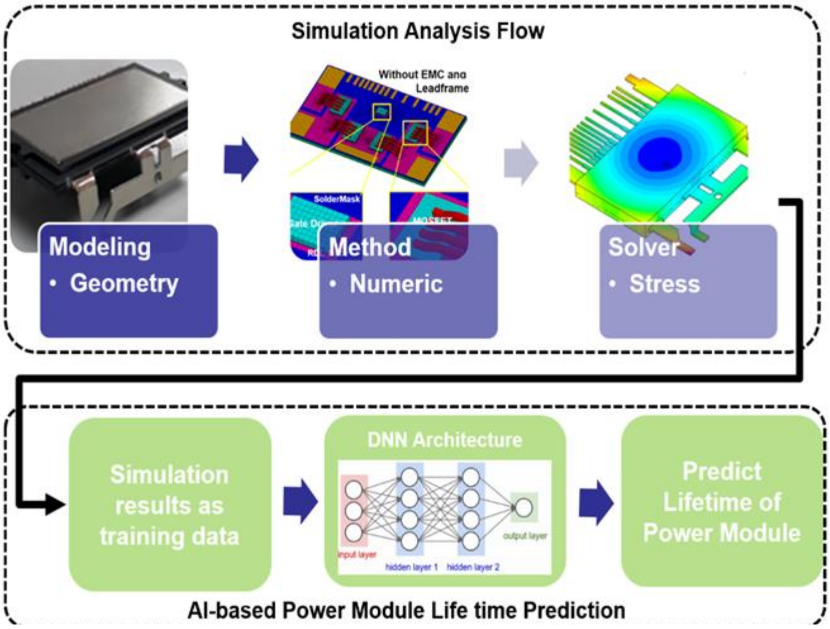

Figure 5 AI power module life prediction platform

Life Prediction Model of Power Module Welding under TCT

The process of life prediction model for the welding layer of the power module can be divided into three steps:

(1) Use FEM to build a model and use ANSYS to simulate the strain force and strain energy generated by the power module in the TCT experiment, and then calculate the predictive life of the power module.

(2) The strain value $\Delta\varepsilon$ of the solder is obtained from the simulation results of the strain equation imported from the finite element method. H. Liao [2] used the Arrhenius strain equation [4], see Eq.(1), as the steady-state strain model to represent the solder alloy. The strain value of the solder is obtained from the simulation results.

$$\dot{\varepsilon}_{cr} = c_1[sinh(c_2)]^{C3}\, e^{(-{c_4}/{T})} \quad (1)$$

Where C_1~C_4 are constants. Table 1 is the strain parameter of Sn, Ag and Cu (SAC) [5]. SAC305 is a lead-free alloy [6], which contains 96.5% tin, 3% silver and 0.5% copper. This alloy is recommended for lead-free soldering by the Japan Electronics and Information Technology Industries Association (JEITA).

Table 1 SAC lead-free solder strain parameters

Solder Alloy	C_1(1/sec)	C_2 (1/MPa)	C_3	C_4 (K)
SAC	277984	0.02447	6.41	6500

(3) Dzrveaux [7] proposed a semi-empirical lifetime prediction formula to predict N_{life}. Life prediction model of weld can be constructed by combining thermal cycling experiments and simulations. N_{life} defines the number of thermal cycles from the product in the thermal cycle test to the end of the product failure. Darveaux use the strain density increment to compute the initial crack life and crack growth rate of thermal cycle test experiments, see Eq.(2) and (3).

$$N_0 = 3.287e^{-6}\,(\Delta\varepsilon)^{-5.195} \quad (2)$$

$$\frac{da}{dN} = 2.83e^{-2}\,(\Delta\varepsilon)^{0.9438} \quad (3)$$

Where N_0 is initial crack life, $\frac{da}{dN}$ is crack growth rate and $\Delta\varepsilon$ is change in strain. Finally, the predictive lifetime can be computed by Eq.(4).

$$N_{life} = N_0 + \frac{L_{failure}}{{da}/{dN}} \quad (4)$$

Where $L_{failure}$ is failure constant defined for different product.

Using AI to Predict the Lifetime of Solder Layers in Wafer-level Packaging

K. N. Chiang [3] applied artificial intelligence technology to the solder layer of wafer level packaging, designed a small amount of data based on the thermal stress simulation of the Coffin-Manson life prediction equation [8], and used the trained prediction model to make the solder layer Life prediction. From Wafer Lever Package (WLP) [9, 10, 11] to electronic product modules packaging, thermal cycle testing is used to verify the reliability of the product [12]. The current method based on finite element method (FEM) for simulation and experimental design is expensive and time-consuming, so K. N. Chiang established a Design of Simulation (DoS) reliability database, used AI neural network as a supervised learning regression model to train database and construct a life prediction model.

Research Motivation

With the advancement of science and technology, related electronic products tend to be light, thin, short, small, high reliability and fast in operation. However, the heterogeneous integrated package structure has difference in material thermal expansion coefficient (CTE Mismatch) [13], which often leads to failure of the package structure. It is important to design and manufacture a highly stable and reliable hetero-integrated package structure. It is necessary to continuously compare the experimental and simulated data to establish a correct analysis model and obtain accurate simulated design parameters. However, this is a time-consuming process. It is inspired by the research of K. N. Chiang that the soldering life of wafer-level tin balls can be predicted by artificial intelligence training. The solder tin layer of the power module we studied is relatively large or even screen-printed with tin paste for power modules which are mainly composed of silicon chip, solder, DBC substrate, Cu substrate, PPS and epoxy. According to the literature [13], the structural reliability failure mode mainly occurs in the solder material layer of wafer and the DBC substrate, and the interface between the wafer aluminum pad and the aluminum wire bonding. The main reason is due to the difference in thermal expansion coefficient of the heterogeneous material in the structure. How to overcome these reliability failure problems in the design and development stage is very important. The experimental data is constructed mainly through simulation analysis of numerical methods, and the simulation analysis model is optimized by combining the actual measurement results and failure modes of the vehicle, thereby constructing a product life prediction model. The database required by the artificial intelligence design platform is built by compiling simulation data, which shortens the calculation time of product simulation and improves the accuracy of product design. The purpose of this paper is to develop a lifetime prediction model for power modules by AI Technology.

III. Lifetime Prediction by AI Technology

The above-mentioned FEM simulation results organize the data into parameters that can be used in artificial intelligence neural network as listed in Table 2. The architecture of the neural network is shown in Figure 6. In Table 2, only 9 simulation data sets of totally 81 are shown. Each data set contains four input feature parameters; Top Cu, Ceramic, Bottom Cu, Solder thickness, and 1 output labeled parameter which represents strain energy generated by the thermal experiment per cycle period. It is equivalent to the index of predicting the lifetime, so life prediction model can be trained by applying the data to the neural network. Then, we can apply the trained model to find the index of the optimized predictive life in short time, which will be a great contribution to shortening the time in thermal cycling experiments of power module design. The limitation of its application is that different power module architecture must train its own neural network models.

Table 2 Input and output parameters of finite element simulation

Input parameters					Output parameters
Thickness					life time index
LEG	Top Cu	Ceramic	Bot Cu	Solder	Creep strain energy per cycle
Uint	mm				Mpa
1	0.1	0.38	0.1	0.1	0.9110
2	0.3	0.38	0.1	0.1	0.4166
3	0.5	0.38	0.1	0.1	0.3911
4	0.1	0.38	0.3	0.1	2.9162
5	0.3	0.38	0.3	0.1	1.5638
6	0.5	0.38	0.3	0.1	1.1788
7	0.1	0.38	0.5	0.1	4.3111
8	0.3	0.38	0.5	0.1	2.8918
9	0.5	0.38	0.5	0.1	[illegible]

Figure 6 is a Fully-connected Neural Network (FNN) which is a connection mode of DNN (Deep Neural Network) with multiple neuron perceptron. In fact, many neural network models are only related to various neuron perceptron, and the fully connected neural network is the simplest one. The feature of the fully connected neural network is that the neuron perceptron in the upper layer is connected with all the neuron perceptron in the next layer. Each neuron perceptron can be treated as a function which gives one value as input and the function will output another value. The composition of each neuron perceptron is the input parameters multiplied by the weights plus the error, and finally converted into the output value through the activation function. Each neuron perceptron receives the input values, and after the weight operation, it activates and converts the input to the next layer of each connected neuron perceptron. This is so called Forward Propagation Algorithm (FPA) of FNN. By FPA, the error will be calculated by the Back Propagation Algorithm (BPA). A typical cost function of Mean Squared Error (MSE) is used to evaluate the error. The flowchart of entire training process is shown in Figure 7, and the training steps are listed as follows;

Step 1 Prepare the input training value X and output label y
Step 2 Each weight W is randomly initialized, generally in the (0.1) interval
Step 3 Use forward propagation algorithm (FPA) to obtain the prediction output $\hat{y}$
Step 4 Use the predicted output $\hat{y}$ and the real output y to calculate the loss value
Step 5 Uses the back propagation algorithm (BPA) to calculate the parametric gradient in each neural network for the loss value.
Step 6 Update the weights W using the optimizer and parametric gradients
Step 7 Repeat Steps 3 to 6 until the training model is well established
Step 8 Use the trained model to perform prediction

In this paper, the ReLU function is selected as activation function. If the input value is positive, the output of the ReLU function will be equal to the input value. If the input value is negative, the output of the ReLU function will be 0. Because the backward algorithm requires differentiation, not all intervals of the ReLU function can be differentiated. If a non-differentiable interval is encountered, the sub-gradient method can be used to solve it. ReLU is the most commonly used activation function in recent years because of many advantages of less gradient vanishing problem, quick convergence and simple and fast operation.

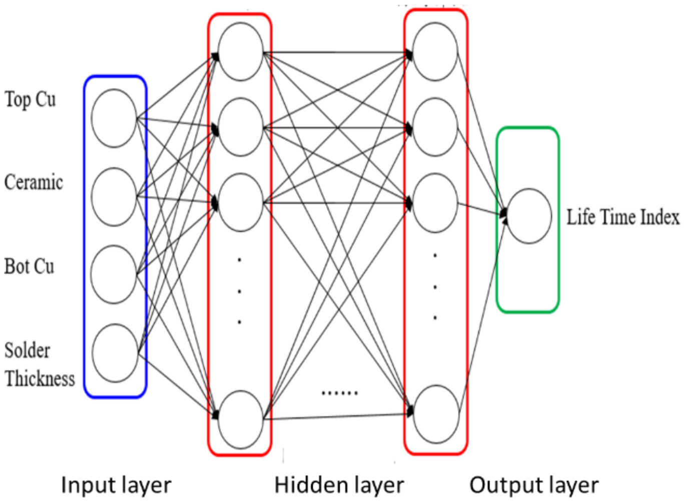

Figure 6 Four feature inputs and one labeled output

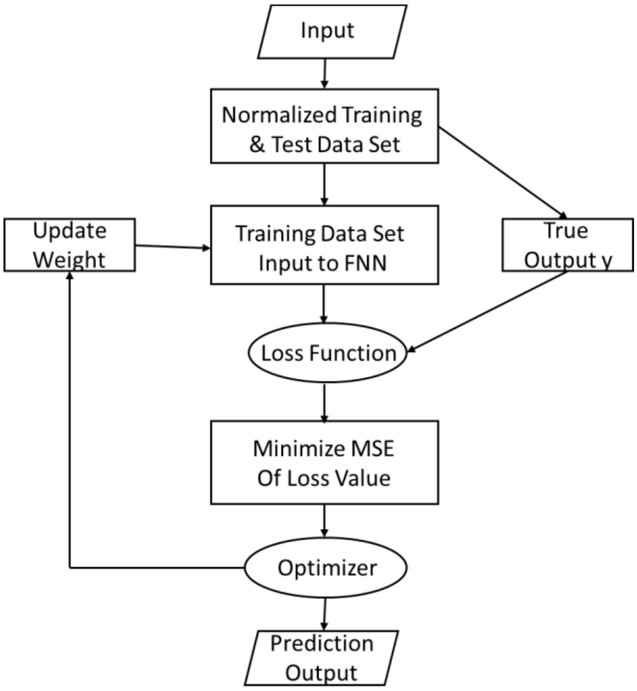

Figure 7 Flowchart of AI Training

.When the neuron outputs the prediction, it will compare the prediction value with the real value, and then do the differentiation to update the weight. Adam (Adaptive Moment Estimation) automatically adjusts the learning rate according to the square of the past gradient. Adam has a bias correction ability which makes the iterative learning rate have a fixed interval, so that the update of the weight is stable. The operation efficiency of Adam is high, and the update of the weights is not affected by gradient magnitude.

The input data set will be divided into training data set and test data set. It is necessary to adjust the range of all the features of the input data set, so that the data range selected as the test set does not exceed the training range of the training data set. Many algorithms are very sensitive to the extent of the dataset. Therefore, in order to make the model training more accurate and powerful, the usual practice is to adjust the feature values to make the data set more suitable for the algorithm. Generally speaking, we tend to apply scaling to features when performing learning. The Min Max normalization is used to scale data into [0,1] by Eq.(5).

$$X_{Normalized} = \frac{X_n - X_{min}}{X_{max} - X_{min}} \qquad (5)$$

IV. Experimental Results and Discussion

The program is written in Python with Keras framework of Tesorflow and run in a PC platform of Intel i7 6700 CPU (3.4GHz), memory size of 8G and NVIDIA graphics card GTX950. The input data set for the neural network in the experiment is the power module simulation thermal cycle test data as listed in Table 2. The time required for each data simulation is about 2 hours, and the computer hardware used for the simulation requires faster Win10 Graphics workstation of Intel Xeon E5-1620v4 (3.50 GHz), memory size of 128G and NVIDIA GTX1080 8GB high-performance graphics card. Thermal stress simulation software is ANSYS Mechanical v17.2. In the experiment, the limited 81 set of simulation data are used to train life prediction model. After the learning is completed, a training model will be created, which is the life prediction model used for this type of power module. If different types of power modules also want to predict lifetime, it is necessary to retrain a training model that conforms to different types of power modules. In the experiment, we adjusted the number of layers and nodes, and observed under what combination the neural network would have the smallest and most stable MSE convergence curve.

The experiments are conducted according to the number of nodes (20, 50, 100), the training percentage (50%, 60%, 70%, 80%, 90%) and the number of Epochs (100, 300, 500, 2000), etc.. The experimental results show that performing 500 Epochs with 2 hidden layers and 50 nodes in each layer gets the best prediction. During the experiments, it is found that each model retrained each time is not exactly the same and each retrained model will have a new prediction accuracy, so at least 10 or even 20 retrained models is necessary. Therefore, we train the model 20 times for each combination, perform 20 different predictions at the same time, and finally calculate the average accuracy of the 20 times predictions. The calculation formula of accuracy is as shown in Eq.(6).

$$\text{Accuracy} = \left(1 - \frac{|predictive\ value - true\ value|}{true\ value}\right) \times\ 100\% \qquad (6)$$

In order to verify whether the training model is effective, we first use the training set to validate whether the training model planned for each experiment is effective. The experimental results are listed in Table 3. All the experimental conditions are to retrain the model 20 times, get 20 prediction accuracy and then take average. From Table 3, it is concluded that no matter what percentage of the training data and regardless of the number of nodes are used to create a training model, the average accuracy is over 97~99% when performing over 500 Epochs. It shows that prediction model can be trained very well even for 81 small data set.

Table 3 Average Prediction Accuracy for Training Set

	Epochs	Training Percentage				
		50%	60%	70%	80%	90%
20 nodes	100	90.13%	91.74%	92.50%	93.27%	93.07%
	300	95.83%	95.70%	95.94%	95.90%	96.46%
	500	97.12%	97.24%	97.58%	97.43%	97.95%
	2000	98.49%	99.03%	98.25%	98.33%	98.42%
50 nodes	100	95.14%	95.04%	94.83%	94.15%	94.68%
	300	97.29%	97.42%	97.60%	97.63%	98.15%
	500	98.05%	98.53%	98.50%	98.01%	98.19%
	2000	98.67%	99.15%	98.65%	98.40%	98.81%
100 nodes	100	96.01%	95.21%	95.05%	94.37%	95.54%
	300	97.49%	97.90%	97.54%	97.25%	97.87%
	500	98.57%	98.04%	97.13%	97.28%	97.46%
	2000	98.20%	98.19%	98.70%	98.07%	99.02%

Now, we use the test set to verify the accuracy of the training model with different training percentages. The experimental results are listed in Table 4. The average prediction accuracy of the test set is also the average accuracy of 20 times predictions obtained by retraining the model 20 times. According to the experimental data in Table 4, we draw three graphs showing the average prediction accuracy according to the changes of node number, training percentage and Epoch number as shown in Figures 8, 9, and 10.

Table 4 Average Prediction Accuracy for Test Set

	Epochs	Training Percentage				
		50%	60%	70%	80%	90%
20 nodes	100	85.01%	85.62%	87.69%	89.20%	89.20%
	300	87.32%	90.35%	91.19%	93.15%	91.30%
	500	87.30%	90.92%	91.72%	93.93%	94.50%
	2000	89.40%	92.90%	92.88%	94.13%	96.13%
50 nodes	100	88.56%	89.16%	89.97%	91.27%	90.99%
	300	89.19%	89.67%	92.10%	94.45%	95.33%
	500	90.66%	92.22%	93.32%	95.09%	96.58%
	2000	90.95%	94.05%	94.32%	95.05%	96.38%
100 nodes	100	88.26%	89.75%	89.84%	91.97%	92.28%
	300	88.80%	90.53%	93.38%	94.15%	94.25%
	500	89.57%	91.43%	94.05%	93.96%	95.90%
	2000	90.52%	91.80%	94.14%	94.43%	95.87%

Figure 8 shows the average accuracy of prediction for different node numbers at 90% training percentage. It can be seen from the figure that the best average prediction accuracy can be achieved under 50 nodes. Since 100 nodes may cause overfitting, the average prediction accuracy of 100 nodes is lower than that of 50 nodes. The same conclusion is obtained for the other training percentages.

Figure 9 shows the average prediction accuracy of the test set for different training percentages under 50 nodes. It can be seen from the figure that the increase in training percentage contributes to the increase in average prediction accuracy. It can also be noted that at 80 % and 90 % training percentage, the highest average accuracy has been reached at 500 Epochs. The average prediction accuracy of 80 % training percentage at 500 and 2000 Epochs is 95.09 % and 95.05 %, and the average prediction accuracy of 90 % training percentage at 500 Epochs and 2000 Epochs is 96.58 % and 96.38%.

Figure 10 shows the average prediction accuracy of the test set for different Epochs under 50 nodes. It can be seen from the figure that the best average prediction accuracy of 95.09 % and 96.58% can be obtained at 500 Epochs under 50 nodes and the training percentages of 80% and 90% respectively, and which is higher than that of 95.05% and 96.38% at 2000 Epochs.

Based on the above experimental analysis, we have concluded that the neural network architecture for predicting the life of the power module has 1 input layer, 2 hidden layers and 1 output layer, and each hidden layer has 50 nodes. Under such a neural network architecture, the best average prediction accuracy of 96.58% can be achieved by performing 500 Epochs at 90% training percentage.

V. Conclusion

An AI neural network model of lifetime prediction for power modules is proposed in this paper. 81 simulated data sets obtained by finite element method which are divided into training set and test set are collected to train the model. From the experimental results, it is concluded that the neural network architecture for predicting the lifetime of the power module has 1 input layer, 2 hidden layers and 1 output layer, and each hidden layer has 50 nodes. Using the training set to verify the training model has an accuracy of more than 97~99%, and using the test set to verify the training model has 96% accuracy. Under such a neural network architecture, the best average prediction accuracy of 96.58% can be achieved by performing 500 Epochs at 90% training percentage. If the simulation data set is large enough, the higher learning ability of the training model can be achieved and the gap of prediction accuracy between the training and test set can be reduced.

Because the simulation analysis software ANSYS can perform more warpage analysis and stress analysis of the substrate, solder layer and wafer position, the stress is in the wafer or in the ceramic substrate allows the design to control warpage more effectively. In the near future, quantified failure factors of power modules will be considered, and more input features can be applied to train the lifetime prediction model, so that the trained model will be closer to the realistic situation.

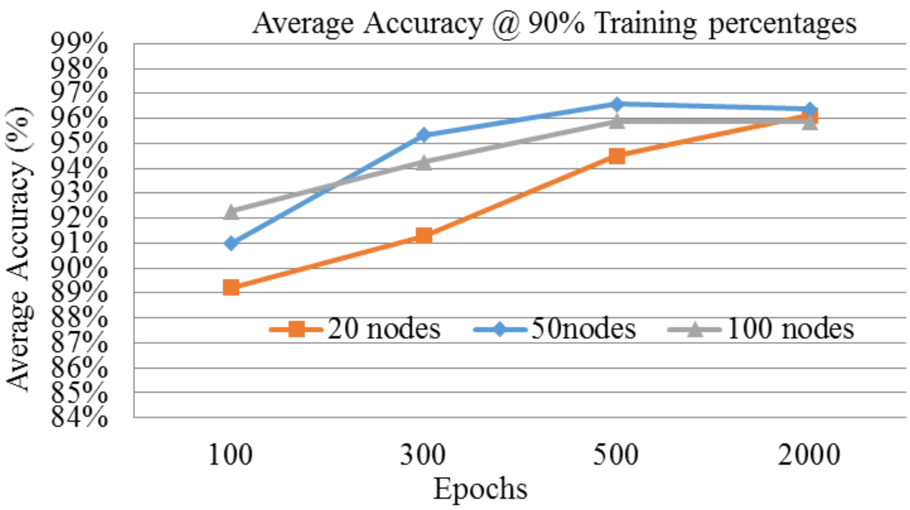

Figure 8 Average accuracy of prediction for different number of nodes at 90% training percentage

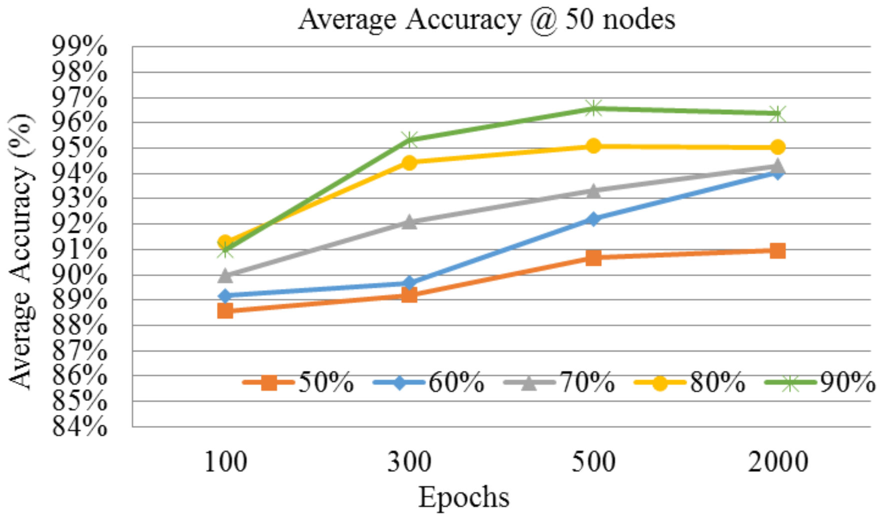

Figure 9 Average accuracy of test set prediction for different training percentages under 50 nodes

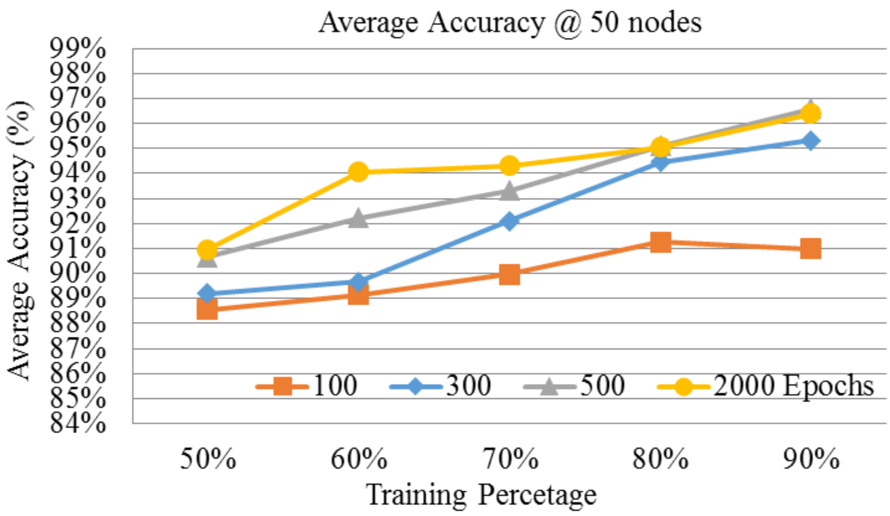

Figure 10 Average prediction accuracy of the test set with different epochs under 50 nodes

References

[1]. C. Durand, M. Klingler, M. Bigerelle, D. Coutellier,,“Solder fatigue failures in a new designed power module under Power Cycling”, Microelectronics Reliability 66 (2016) 122–133.
[2]. H. Chen, S. Guo and H. Liao, “The Solder Life Prediction Model of Power Module under Thermal Cycling Test (TCT)”, 2018 13th International Microsystems, Packaging, Assembly and Circuits Technology Conference (IMPACT), 2018, pp.104-107, doi:10.1109/IMPACT.2018.8625778.
[3]. P.H. Chou, H.Y. Hsiao and K.N. Chiang, “Failure Life Prediction of Wafer Level Packaging using DoS with AI Technology”, 2019 IEEE 69th Electronic Components and Technology Conference (ECTC), 2019, pp.1515-1520, doi:10.1109/ECTC.2019.00233.
[4]. Emeka, H. Amalu, NN Ekere, “Modelling evaluation of Garofalo-Arrhenius creep relation for lead-free solder joints in surface mount electronic component assemblies”, Journal of Manufacturing Systems 39 (2016) 9–23.
[5]. A. Schubert, R. Dudek, E. Auerswald, A. Gollbardt, B. Michel, H. Reichl, “Fatigue life models for SnAgCu and SnPb solder joints evaluated by experiments and simulation”, Electronic Components and Technology Conference, 2003, pp.603-610.
[6]. Y.J. Xu, L.Q. Wang, F.S. Wu, W.S. Xia, H. Liu, “Effect of Interface Structure on Fatigue Life under Thermal Cycle with SAC305 Solder Joints”, IEEE Electronic Packaging Technology International Conference, pp. 959-964, Aug 11-14, 2013.
[7]. R. Darveaux, “Effect of simulation methodology on solder joint crack growth correlation and fatigue life prediction”, Transactions of the ASME. Journal of Electronic Packaging, Vol. 124, Issue 3, pp.147-154, 2002.
[8]. L.F. Coffin, “A study of the effects of cyclic thermal stress on a ductile metal”. Transactions ASME, Vol.76, pp. 931-950, 1954.
[9]. M. Hsieh and S. Tzeng, "Solder joint fatigue life prediction in large size and low cost wafer-level chip scale packages", 2014 15th International Conference on Electronic Packaging Technology, 2014, pp.496-501, doi:10.1109/ICEPT.2014.6922704.
[10]. M. Hsieh, "Modeling correlation for solder joint fatigue life estimation in wafer-level chip scale packages", 2015 10th International Microsystems, Packaging, Assembly and Circuits Technology Conference (IMPACT), 2015, pp.65-68, doi:10.1109/IMPACT. 2015.7365195.
[11]. B. Rogers and C. Scanlan, “Improving WLCSP Reliability Through Solder Joint Geometry Optimization”, International Symposium on Microelectronics, Vol. 2013, No.1, pp.546-550, 2013..
[12]. Y. Hung, C.J. Huang, C.C. Lee, C.C. Wang, K.C. Lu, and K.N. Chiang, “Investigation of Solder Crack Behavior and Fatigue Life of the Power Module on Different Thermal Cycling Period”. Microelectronic Engineering, Vol.107, July 2013, pp.125-129.
[13]. J. Thebaud, E Woirgard, C. Zardini, S. Azzopardi, O. Briat and J. Vinassa, "Strategy for designing accelerated aging tests to evaluate IGBT power modules lifetime in real operation mode", IEEE Transactions on Components and Packaging Technologies, Vol.26, No.2, pp.429-438, June 2003, doi:10.1109/TCAPT.2003.815112.

Fang-Hsuan Cheng. "A Lifetime Prediction Model for Power Modules by AI Technology." *IOSR Journal of Engineering (IOSRJEN)*, 12(04), 2022, pp. 08-18.