THERMAL PERFORMANCE PREDICTION OF PLASTICS BALL GRID ARRAY (PBGA) USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Artificial Neural Network (ANN) based on feed-forward backpropagation model is used to predict junction temperature in PBGA package. The limited results obtained from FEM (using IDEAS software) are used to train the neural network. The effect of source power, substrate and mold compound thermal conductivity, die size, substrate thickness and air velocity on junction temperature and thermal resistance has been investigated using ANN. The predicted junction temperature using ANN agrees closely with the prediction from FEM. ANN method takes a small fraction of the time and effort compared to that required by FEM for prediction.

1. INTRODUCTION

Till recently, electronic packaging has received far less attention than its contribution to overall device performance, reliability and cost should warrant. However, the situation is changing quickly and packaging limitations are beginning to impose restrictions on device and system design. This is most evident in the need to develop and fabricate packages with very large number of leads. Over the past few years, Plastics Ball Grid Array (PBGA) has been making headlines as the next evolution in packaging technology. PBGA delivers high interconnect density and easy handling at reasonable costs. With increase in packaging density and speed, thermal management becomes a critical issue regarding the performance and reliability of the package. However, thermal performance totally depends on the properties of various materials, geometric parameters and the boundary conditions. The dependency of the performance and reliability of the package on the above parameters is quite complex and non-linear[1]. It can also be mentioned here that 55% of the failures in the electronic packaging is due to the temperature effect. Finite Element Method (FEM) has been used for predicting the thermal performance of the packages for more than a decade. It has been observed that FEM takes considerable time and effort in modelling and prediction especially when the behaviour is non-linear and properties are temperature dependent. Therefore, there is a need to supplement the FEM so that we can do the parametric studies in a much less time and with little effort. Thus, ANN is an excellent candidate for this purpose. The artificial neural network is capable of building up the quite complex and non-linear model through training by making use of available data

obtained by simulation using finite element method (FEM). Once trained, the network can then be fed with any unknown input and expected to predict the output with a high degree of accuracy.

The objective of the present paper is to predict performance of PBGA package with various parameters, using the artificial neural network. The study carries out the simulation of 106 PBGA in 2-D. A few parametric studies on the effect of power source, substrate and mold compound thermal conductivity, die size, substrate thickness and air velocity have been investigated. Commercially available software MATLAB version 5.3 is used to generate artificial neural network.

2. MODELLING AND PREDICTION BY USING FEM[2]

In order to train the ANN so that it can be used for parametric studies, we do need a database. This database is provided through the simulation carried out by using FEM. FEM based application software called I-DEAS Master Series is used to simulate the thermal performance. The simulation of PBGA using FEM involves three main steps: pre-processing, solution procedure and post-processing. The model on which the analysis is carried out is 106 PBGA (Plastic Ball Grid Array). It consists of chip, wire bond, die attach (Ag-filled epoxy), die pad, mold compound, BT epoxy resin, solder mask, copper pad, solder balls and PCB as shown in Figure 1.

The PBGA package substrate is composed of two or more metal layers formed on an organic substrate which has glass reinforcement. The number solder balls (106) are accommodated under the bottom surface of the package and arranged in this fashion (11 x 10 = 110 - 4). It means from every corner, one ball has been dropped from the package. The modelling of the package is a rather difficult task in view of the small size of various components consisting of nine different materials. Because of the complexity of the geometry, mapped mesh generation is difficult. The number of elements are 2775 and the

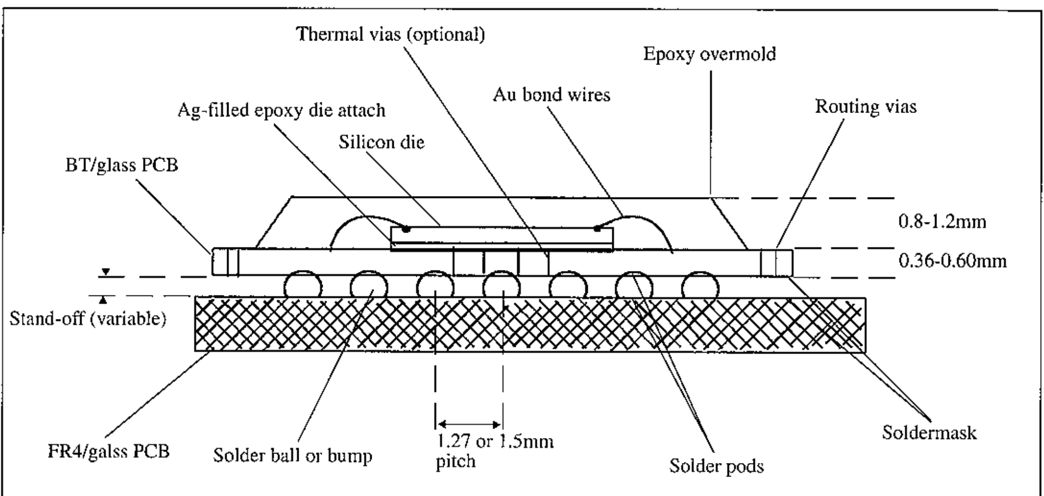

Figure 1: Schematic diagram of the model.

number of nodes are 3018 generated for the package. The solution of the problem takes about 350 seconds of CPU time for 2-D analysis but in the case of 3-D analysis, it takes four to five times higher than 2-D analysis. The results from this FEM heat transfer analysis are temperature and heat flux inside the package. The main purpose of the thermal analysis is to see that the junction temperature does not exceed the allowable maximum limit and also to determine the thermal resistance of the package required for the design of the package. The effect of several parameters on the junction temperature and thermal resistance have been carried out on the 106 PGBA using a 2-D model. The important variables considered for the investigation are as shown in Table 1.

The chip is taken as a constant heat source of given power uniformly distributed. Convection from the outer surface is taken into account with the surface heat transfer coefficient values of 8.5W/m^{2}K in still air conditions. This also takes into account the radiation effect. When the package is subjected to airflow, the junction temperature reduces. However, when the velocity is small, free convection effect exists. Reference value for each parameter is given in Table 2.

Based on the reference values of each of the parameters above, the experiment result for the package's junction temperature is 67.4°C; whereas FEM simulation result gives 68°C[2]. Thus FEM can simulate accurately. Hence, we use FEM as the basis to provide the initial data for training ANN.

3. ARTIFICIAL NEURAL NETWORK[3]

Artificial neural network is based on the working process of human brain in decision making. It is categorised under artificial intelligence method and has been applied in many different fields[3]. Typical neural network consists of sets of input, sets of output and weighting function. By knowing the input values, the output can be predicted. In other words, the network is defined to correlate between the inputs and the outputs by training the network

Table 1: Range of parameters investigated.

Parameters	**Ranges**
Source power, P (W)	0.75 - 2.25
Substrate thermal conductivity, K_S (W/mK)	0.8 - 1.6
Molding compound thermal conductivity, K_{MC} (W/mK)	0.4 - 1.2
Die size, D_s (mm)	6.0 - 9.0
Substrate thickness, t_S (mm)	0.2 - 0.6
Air velocity, V (m/s)	Up to 1

Table 2: Reference value for each parameter.

Parameters	**Value**
Source power, P (W)	0.75
Substrate thermal conductivity, K_S (W/mK)	1.18
Molding compound thermal conductivity, K_{MC} (W/mK)	0.7
Die size, D_s (mm)	8.1
Substrate thickness, t_S (mm)	0.43
Air velocity, V (m/s)	0.04

with available data. Once the network is trained, it can then be fed with any unknown input and is expected to predict the output with a high degree of accuracy.

The multilayered perceptron network trained by the means of backpropagation algorithm is used here[4]. A multilayered neural network is made up of one or more hidden layers placed between the input layer and output layer. Each layer has a number of nodes connected with each other layer. Thus the node in the lower layer is connected with each of the nodes in the other layer. The information flow is only allowed in one direction during the training process, from input layer to the output layer through the hidden layers. Each of the first layer obtains some information signals from the input layer nodes, and then the output of the layer gives some information signals into the second layer nodes and so on. The network used in this application is shown in Figure 2.

The present study also used multiple linear regression (MLR) to fit the curve and predict the parameters for comparison purpose only.

4. RESULTS AND COMPARISON[4]

All tables and figures show the results generated from the finite element method (FEM), artificial neural network (ANN) and multiple linear regression (MLR). The results shown indicate the effect of each single parameter on the junction temperature and thermal resistance with the other parameters fixed.

In order to compare the predicted results for ANN, the alternative way of function fitting is by using multiple linear regression. The curve fitting using multiple linear regression is carried out by Microsoft Office EXCEL. By MLR, the relationship between various parameters are produced as given below:

Junction Temperature, $Tj = 157.65*P^{0.72}*K_S^{0.09}*K_{MC}^{0.30}*D_S^{0.32}*t_S^{0.10}*V^{-0.01}$

Thermal Resistance, $\theta ja = 156.73*P^{-0.03}*K_S^{-0.14}*K_{MC}^{-0.39}*D_S^{-0.46}*t_S^{0.15}*V^{-0.01}$

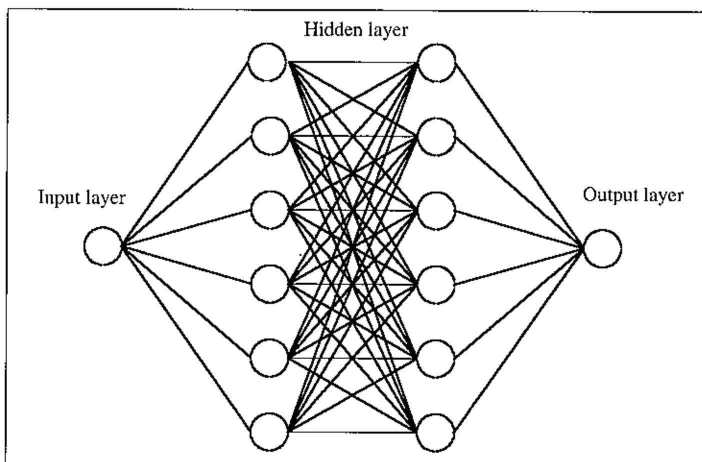

Figure 2: Illustration of multilayered perceptron network.

Table 3: Effect of source power on junction temperature.

P	*Tj*			ANN%	MLR%
	FEM	ANN	MLR		
0.5	53.125	53.1208	50.5963	-0.0079	-4.7598
0.654	62.5	62.7222	61.4100	0.35552	-1.7438
0.75	68	68.031	67.7877	0.04558	-0.3121
0.756	68.75	68.3822	68.1785	-0.5349	-0.8312
1.003	83.438	83.4872	83.6027	0.05896	0.19740
1.202	95.625	95.4213	95.2631	-0.2130	-0.3784
1.395	106.875	106.926	106.066	0.04781	-0.7566
1.595	119.375	119.288	116.829	-0.0724	-2.1321
			Average	-0.0400	-1.3396

Table 4: Effect of source power on thermal resistance.

P	*θja*			ANN%	MLR%
	FEM	ANN	MLR		
0.5	64.842	64.8582	62.9018	0.02498	-2.9921
0.654	63.789	63.74	62.4323	-0.0768	-2.1267
0.75	63.091	62.5944	62.1942	-0.7871	-1.4213
0.756	63.105	62.8155	62.1804	-0.4587	-1.4651
1.003	62.368	62.372	61.6918	0.00641	-1.0840
1.202	61.947	61.9492	61.3811	0.00355	-0.9134
1.395	61.421	61.4239	61.1266	0.00472	-0.4792
1.595	61.263	61.2665	60.8986	0.00571	-0.5948
			Average	-0.1596	-1.3846

Tables 3 and 4 above show the effect of source power on junction temperature and thermal resistance respectively. It can be observed that the junction temperature increases linearly with the source power. This is due to the large amount of heat to be dissipated from the package.

The tables also show the comparison between the values that were fed in FEM and the results that were generated by the ANN and MLR. Both methods give reasonably good results but the results generated by ANN fit very well with the FEM results. It can be seen that, the average percentage of difference for MLR is greater than ANN by 33 times for junction temperature and 9 times for thermal resistance. Therefore, ANN is capable of providing higher accuracy results than that of MLR.

Figures 3 and 4 show the effect of substrate thermal conductivity on junction temperature and thermal resistance respectively. From Figure 3 it can be seen that the junction temperature drops linearly as the substrate thermal conductivity increases. Heat will dissipate more as the thermal resistance drops (Figure 4) due to the increase of the substrate thermal conductivity.

The average percentage of difference for MLR is greater then ANN by 27 times for junction temperature and 14 times for thermal resistance, therefore ANN is capable of providing higher accuracy results than that of MLR.

Figures 5 and 6 show the effect of mold compound thermal conductivity on junction temperature and thermal resistance respectively. It can be seen from Figure 6 that the junction temperature drops linearly as the mold compound thermal conductivity increases.

As a comparison, the effect of mold compound thermal conductivity on the junction temperature is more significant than that of the effect of substrate thermal conductivity. This is due to the influence of higher volume of mold compound compared to the substrate.

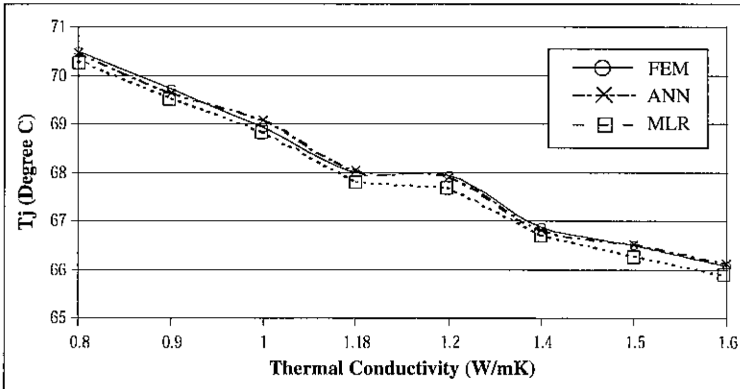

Figure 3: Effect of substrate thermal conductivity on junction temperature.

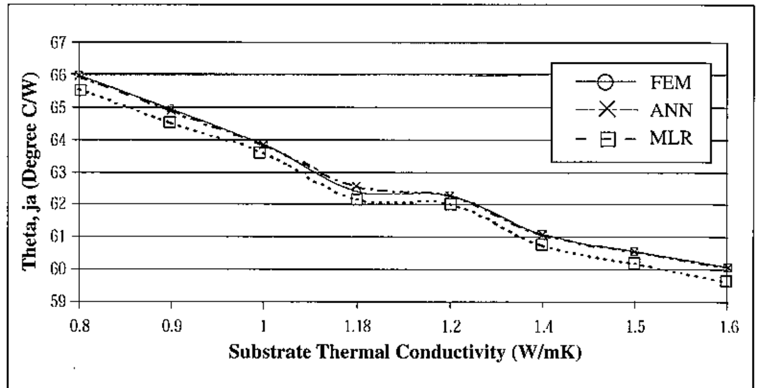

Figure 4: Effect of substrate thermal conductivity on thermal resistance.

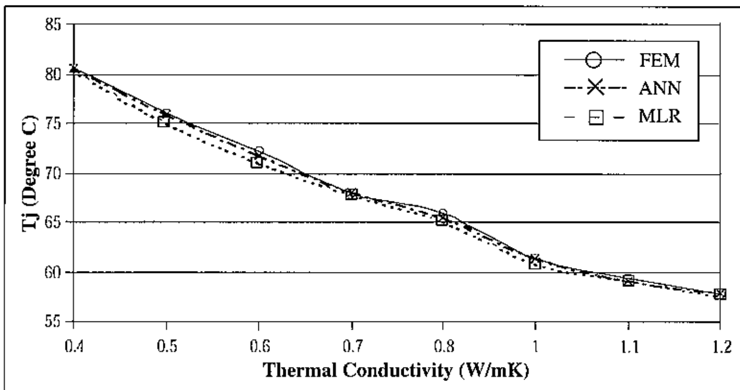

Figure 5: Effect of mold compound thermal conductivity on junction temperature.

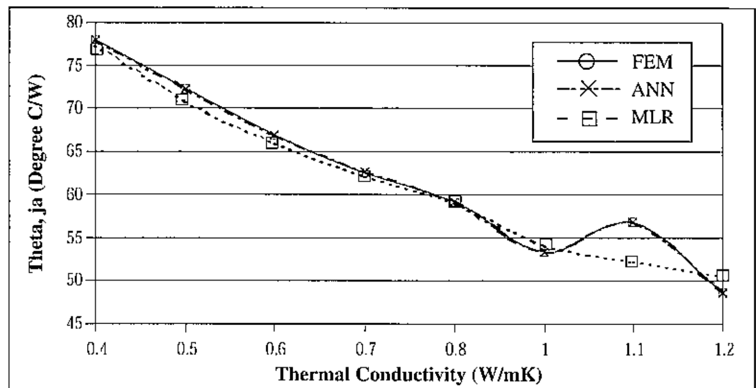

Figure 6: Effect of mold compound thermal conductivity on thermal resistance.

The average percentage of difference for MLR is greater then ANN by 4 times for junction temperature and 31 times for thermal resistance, therefore ANN is capable of providing higher accuracy results than that of MLR.

Figures 7 and 8 show the effect of die size on junction temperature and thermal resistance respectively. From Figure 7, the junction temperature drops almost linearly as the die size increases. An increase of die size by a factor 1.5 reduces the junction temperature by about 13%.

The average percentage of difference for both are almost the same. Therefore in this case, both methods perform equally well.

Figures 9 and 10 show the effect of substrate thickness on junction temperature and thermal resistance respectively. From Figure 9, the junction temperature increase, almost linearly as the substrate thickness increases.

The average percentage of difference for MLR is greater than ANN by 21 times for junction temperature and 69 times for thermal resistance. Therefore ANN is capable of providing higher accuracy results than that of MLR.

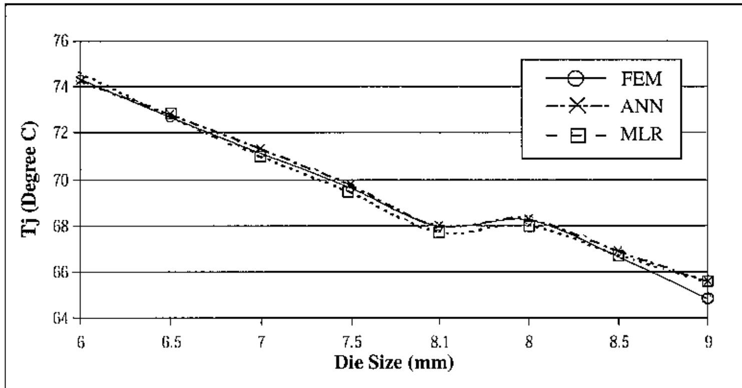

Figure 7: Effect of die size on junction temperature.

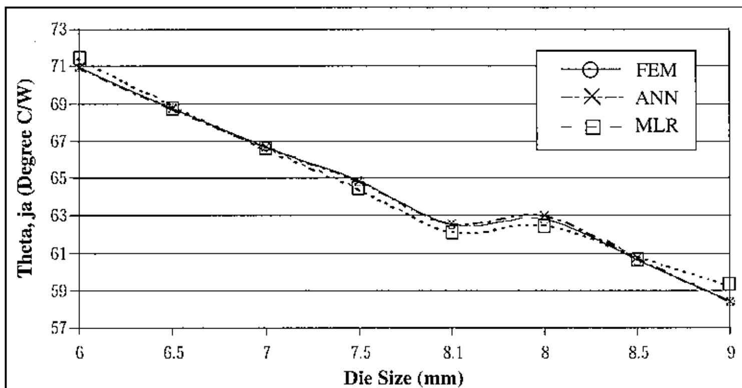

Figure 8: Effect of die size on thermal resistance.

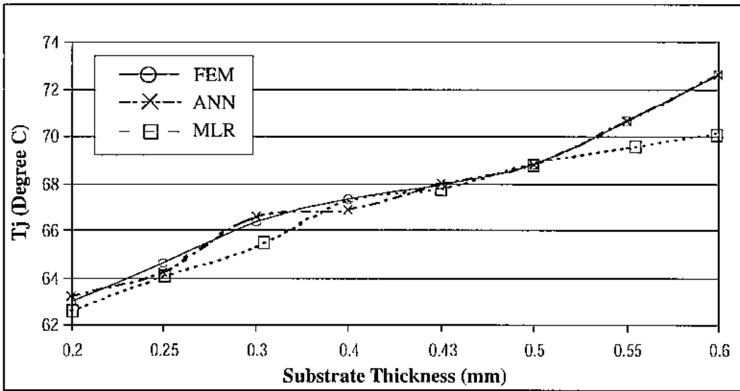

Figure 9: Effect of substrate thickness on junction temperature.

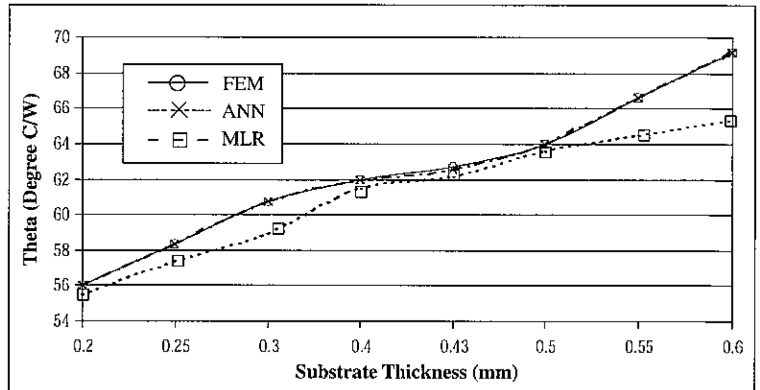

Figure 10: Effect of substrate thickness on thermal resistance.

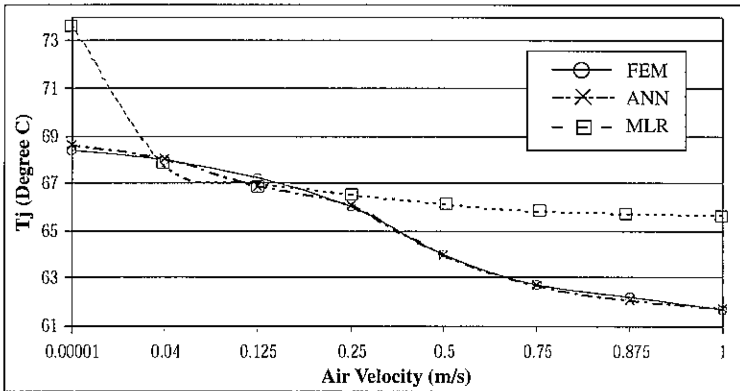

Figure 11: Effect of air velocity on junction temperature.

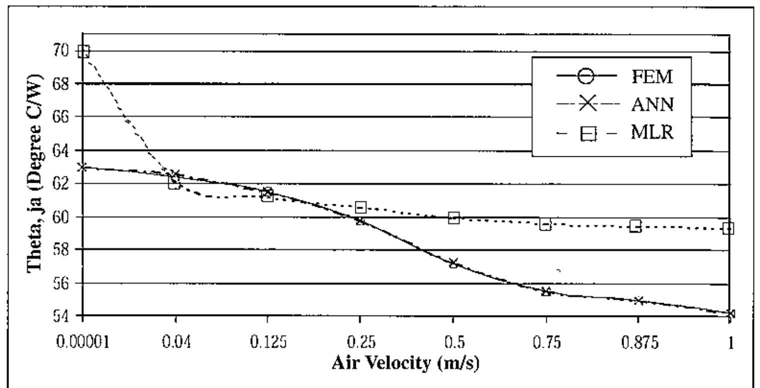

Figure 12: Effect of air velocity on thermal resistance.

Figures 11 and 12 show the effect of air velocity on junction temperature and thermal resistance respectively. It can be seen from Figure 11 that the junction temperature reduces non-linearly with the increase in air velocity. Increasing the velocity beyond 0.75m/s is not effective, as it brings about only a slight drop in junction temperature.

The average percentage of difference for MLR is greater than ANN by 352 times for junction temperature and 130 times for thermal resistance, therefore ANN is capable of providing higher accuracy results than that of MLR.

5. PREDICTION OF JUNCTION TEMPERATURE AND THERMAL RESISTANCE USING ANN[5]

As mentioned earlier, dependency of each parameter on junction temperature and thermal resistance is totally affected by each other and their relationships are highly non-linear and complex. The artificial neural network technique can be a solution to map such complex and highly non-linear input-output relationships.

Each training set is composed of 8 data points obtained from FEM simulation results. The 200-epoch number is pre-set in this training process. The training process is terminated when the pre-set number is reached, or when the difference between the training data and the network prediction is within the pre-set tolerance. The pre-set training tolerance is taken as 5e-5 of the normalised network prediction in this study[5].

Table 5 demonstrates predicted results of junction temperature and thermal resistance with changes in the inner structure of the package, and with changes in power source, substrate and mold compound thermal conductivity, die size, substrate thickness and air velocity.

Table 5: Sets of input and output in artificial neural network model.

Parameters	***Tj***		***θja***	
	ANN	**FEM**	**ANN**	**FEM**
Power source (W), 1.0	80.16	80.12	62.50	62.50
Substrate thermal conductivity (W/mK), 1.3	67.45	67.50	61.58	61.60
Mold compound thermal conductivity (W/mK), 0.9	64.15	64.20	56.01	56.08
Die size (mm), 8.3	67.53	67.50	61.89	61.86
Substrate thickness (mm), 0.27	64.94	65.10	59.80	59.82
Velocity (m/s), 0.6	63.41	63.40	56.53	56.52

The predicted results obtained from the artificial neural network agreed well with the simulation results in this study. It is because of the fact there is no scattered data in the FEM simulation results. This technique can be used in a deterministic manner to predict thermal performance of the package for given variations in any of the design parameters. Once the database of thermal performance of the package for any design parameters is set up using the artificial neural network, desired result can be acquired within few minutes. On the other hand, an average finite element method analysis take several hours for the given model if not days.

6. CONCLUSION

The performance of a PBGA package has been determined using FEM for a limited number of parameters. Using this limited data, an artificial neural network is trained to generate additional data for other parameters. The neural network gives results in a matter of minutes compared to several hours with FEM. The predictions from neural network are in good agreement with FEM results indicating that this approach provides a faster solution to predict the performance of PBGA package and hence the expectation of the industry.

7. REFERENCES

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