# Physics-Informed Machine Learning for Solder Design and Reliability Prediction in Electronics

**Peter Liu, Ph.D.**
**Auburn University**
**334-844-1428, liu@auburn.edu**

# Outline

- Introduction
- Methodology
- Case study
- Conclusions & Future work
- Acknowledgements *(optional)*
- Q & A

# Introduction

- Solder joints on the electronic packaging are critical to the reliability of electronic products.

- Sn-Ag (Tin-silver) or Sn-Ag-Cu (SAC, tin-silver-copper) solders are promising alternatives to Sn-Pb solders due to their low melting points and excellent solderability.

# Introduction

- Different additives, such as Bi, Zn, Ti, Sb, Ni, and Al, can improve the performance of SAC solders [1-7].

- *Research Question 1: What additives and how many of them can be added into SAC solders to improve the joints' reliability?*

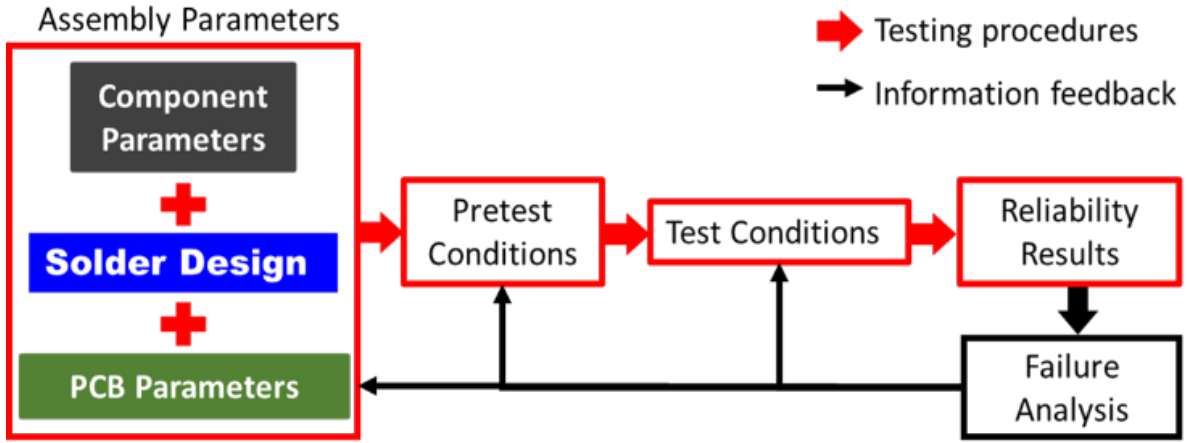
# Introduction

- The reliability of the solder joints depends on solder materials, electronic component packaging, PCBs, assembly process, and application conditions [8-13].

- *Research Question 2: What is a general framework to incorporate the relevant factors into an accurate predictive model for reliability?*

# Methodology

- The manufacturing of electronic products is simplified as the following figure.




- To understand the reliability of solder materials, failure analysis is applied using optical microscopy and SEM.

**Table 1** PCB/Pad design parameters

| | |
|---|---|
| PCB surface finish | OSP, ENIG, etc. |
| PCB materials | FR4, FR5, FR6, etc. |
| PCB thickness | |
| Number of layers | |
| Coefficient of thermal expansion | X-axis, Y-axis |
| Cu thickness | |

**Table 2** Solder parameters

| | |
|---|---|
| Solder alloy | Chemical composition |
| Solder paste powder | type 3, type 4, etc. |
| Solder flux | |
| Solder paste percent solids | |
| Coefficient of thermal expansion | X-axis, Y-axis |

**Table 3** Component parameters

| | |
|---|---|
| Type of component | BGA, SMR, etc. |
| Component dimensions | |
| I/O pitch | |
| Number of I/Os | |
| Component thermal expansion | |
| Component surface finish | ENIG, etc. |
| Area array component pad surface finish | |
| Area array solder sphere alloy | |
| Area array solder sphere diameter | |

**Table 4** Assembly parameters

| |
|---|
| Stencil thickness |
| Paste to sphere volume ratio |
| Reflow profile |
| Voids % area volume after reflow |
| Solder joint height after assembly |
| Post assembly microstructure |

**Table 5** Pretest conditions

| |
|---|
| Aging profile |
| Storage profile |
| Post-age microstructure |

**Table 6** Thermal cycling tests

| |
|---|
| Max temperature |
| Min temperature |
| Dwell at max temperature |
| Dwell at min temperature |
| Ramp up rate |
| Ramp down rate |

**Table 7** Reliability parame

| |
|---|
| Life data |
| Life graph with confidence bounds |
| Characteristic life |
| Weibull Shape parameter |
| Weibull location parameter |
| Life at 10% probability of failure |
| Life at 1% probability of failure |
| Sample size |

# Methodology

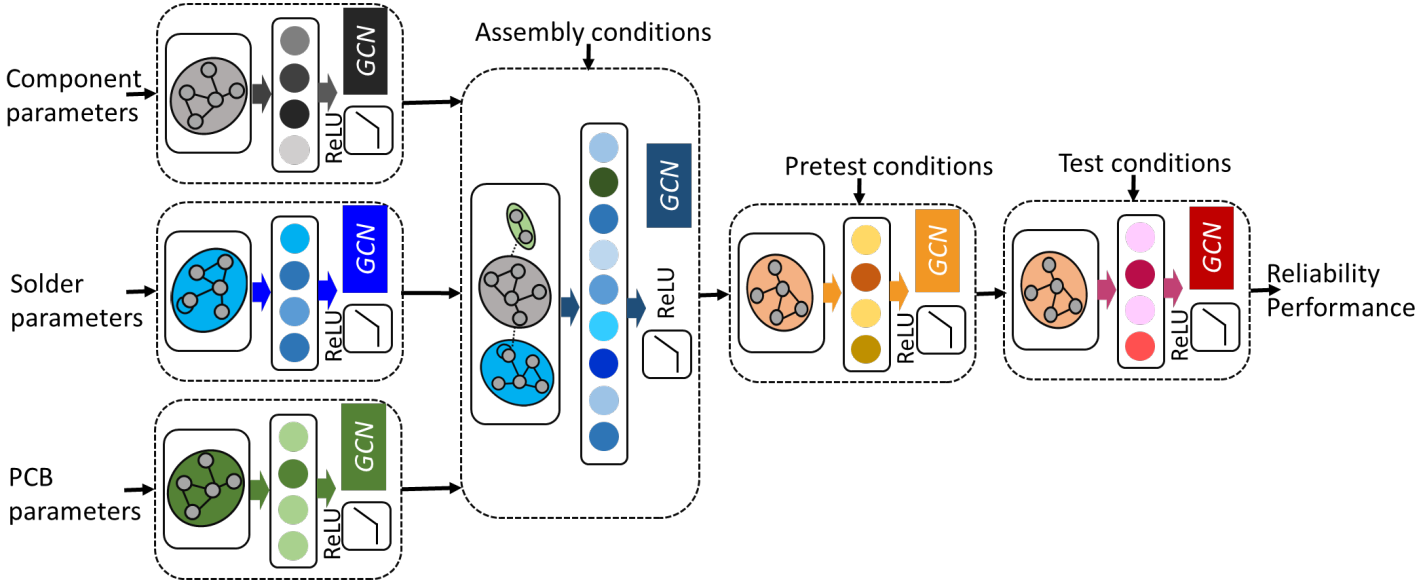
- Machine learning (ML) has the power to obtain the *correlations* among the different factors and model their *complex non-linear* relationships from data.
- ML has been used for solder design and reliability assessment for solder materials in a data-driven [14-20].
- However, there is still a lack of general ML framework for solder design and reliability in a solder-agnostic manner.

# Methodology

- Artificial neural network (ANN) draws inspiration from human brains, and it uses artificial neurons and their connections to model complex, non-linear relationships among data.
- ANN has interconnected neurons in various layers:
  - An input layer: predictors (e.g., different factors)
  - An output layer: response (e.g., reliability measures)
  - Hidden layers: modeling complex relationships with non-linear activations and weighted summations of neurons.

# Methodology

- Deep modular ANN framework imitates the sequential relations in electronic product manufacturing, bypassing complex physics but providing data-driven insights



# Methodology

- The proposed deep modular ANN can be represented as

$$\boldsymbol{y} = f_T\left(\boldsymbol{x}_T, f_P\left(\boldsymbol{x}_P, f_A\left(\boldsymbol{x}_A, f_{PCB}(\boldsymbol{x}_{PCB}), f_S(\boldsymbol{x}_S), f_C(\boldsymbol{x}_C)\right)\right)\right)$$

  - where $\boldsymbol{y}$ is the reliability measure, $\boldsymbol{x}_{PCB}$, $\boldsymbol{x}_S$, $\boldsymbol{x}_C$, $\boldsymbol{x}_A$, $\boldsymbol{x}_P$ and $\boldsymbol{x}_T$ are the factors in PCB, solders, components, assemble, pretest conditions, and test.
  - $f_{PCB}$, $f_S$, $f_C$, $f_A$, $f_P$ and $f_T$ are their respective ANN modules to model their non-linear relationships to the reliability measure.

# Case Study

- A pilot case study has been implemented here to use the proposed ML framework to predict the characteristic life of solders on several components in thermal cycling (TC) tests.

- The TC test has a thermal profile with fluctuating temperatures to simulate service conditions and evaluate the solder joint's thermo-mechanical fatigue.

# Case Study

- Eight solder materials (including the Sn-Pb) are used to evaluate their characteristic life in TC tests.

**Table 8** Solder materials used to evaluate their characteristic life.

| *Solder material* | *Solder alloy composition* |
|---|---|
| *SnPb* | 63Sn-37Pb |
| *SAC105* | 98.5Sn-1Ag-0.5Cu |
| *SAC305* | 96.5Sn-3Ag-0.5Cu |
| *Innolot* | 90.95Sn -3.80Ag-0.70Cu-0.15Ni -1.40Sb-3.00Bi |
| *90SCLF318AGS88.5* | 95.5Sn-3.8Ag-0.7Cu-0.02Ni-1.5Sb-3.00Bi |
| *NC 258 91-2,88.5-T3* | Unknown Composition |
| *Material 2* | SAC doped Sb |
| *Ecorel Free 405Y-16* | 95.35Sn-4Ag-0.5Cu-0.05Ni |

# Case Study

- PCB with two different materials are used in the TC test

**Table 10** PCB used to evaluate the characteristic life of solder joints.

| *PCB* | *Data* |
|---|---|
| **PCB material** | FR-406 and Megtron6 |
| **PCB surface finish** | Organic Solderability Preservative (OSP) |
| **PCB dimensions** | 254 x 173 x 5 mm |
| **Stencil thickness (mm)** | 0.127mm (Top), 0.076mm (Bottom) |

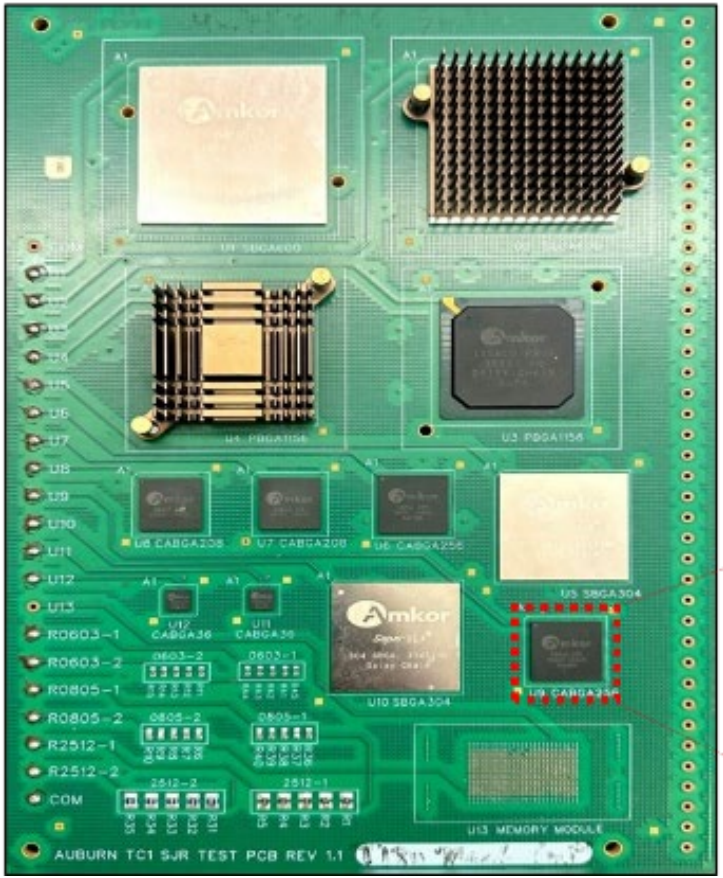
# Case Study

- There are four types of components used in the TC tests with different sizes, I/Os, and solder ball alignment.

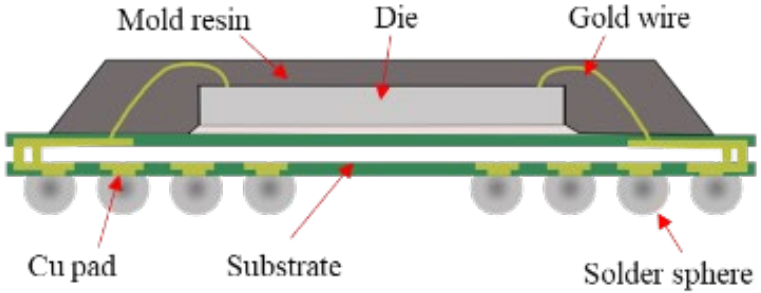
**Table 9** Components used to evaluate the characteristic life of solder joints.

| *Component* | *Body size (mm)* | *I/O* | *Pitch distance (mm)* | *Solder ball alignment* |
|---|---|---|---|---|
| ***CABGA 208*** | 15 | 208 | 0.8 | Perimeter |
| ***CABGA 256*** | 17 | 256 | 1.0 | Full array |
| ***CVBGA 432*** | 13 | 432 | 0.4 | Perimeter |
| ***PBGA 1156*** | 35 | 1156 | 1.0 | Full array |

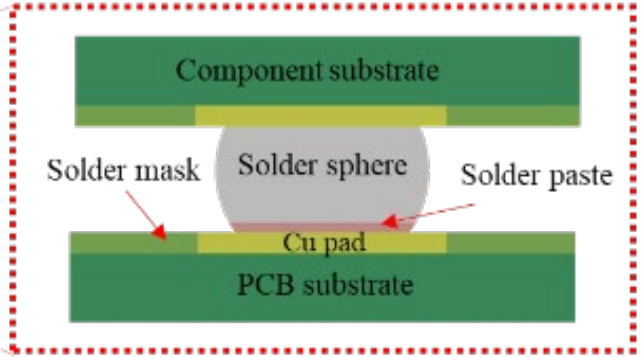
## Printed circuit board (PCB) (Top view)




## Electronic component

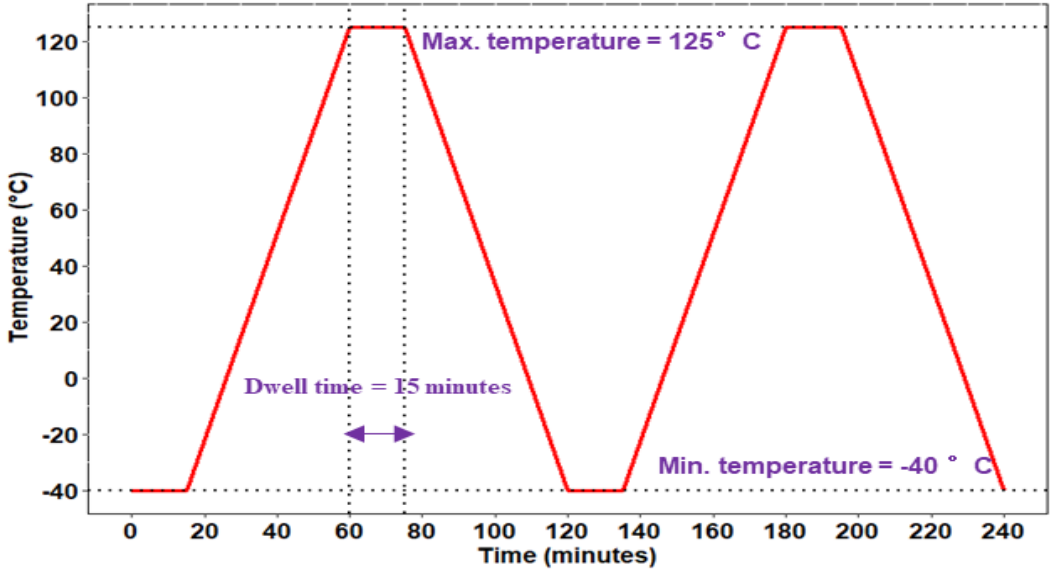



## Schematic of the solder joint (Side view)



# Case Study

- Min temperature (-40 °C)
- Max temperature (+125 °C)
- 15-min periods of dwells
- 45-min of ramp up/down
- A total cycle: 120 minutes



# Case Study

- During the TC test, electronic components are monitored until a single solder joint failure leads to an instantaneous open electrical circuit (failure) for the respective component.

- The reliability of the solder joints is represented by characteristic life, which is derived from fitting a Weibull distribution and defined as the failure cycles at which 63.2% of the components fail.

# Case Study

- A total of 584 data points are collected from the experiments.
- Predict characteristic life from solder materials, PCBs, components, and TC test conditions

**Table 11** Characteristic life prediction accuracy and consistency for the proposal ANN framework, compared with MLR.

| *Model* | *R-squared (testing)* | *RMSE (testing)* | *SD (R-squared)* | *SD (RMSE)* |
|---|---|---|---|---|
| *MLR* | 88.2% | 247.7 | 0.03 | 30.96 |
| *ANN* | **96.0%** | **143.2** | **1.00%** | **18.29** |

# Case Study

- By analyzing ANN structure and its sensitivity, it is found:
- Components, PCBs, and aging time have more significant impacts. Conversely, aging temperature, stencil thickness, and heatsink have less influence.
- Ecorel Free 405Y-16 and Innolot have superior performance in the TC test.
- Aging time exhibited a negative coefficient regardless of the component type.
- Heatsinks adversely affect solder joint life.

# Conclusions

- A general ML framework, deep modular ANN, is proposed for solder materials design and reliability prediction for electronics.
- It discovers physics insights and provides interpretability in a data-driven manner.
- In the preliminary study, it outperformed the multiple linear regression in prediction accuracy and consistency.
- It can be extended to other ALTs to simulate the real application scenarios and predict reliability.

# Future Work

- Enhance the model with more datasets
- Revise the ANN structure by incorporating the insights obtained during the preliminary research
- Create a new approach to incorporating data without deactivating ANN modules
- Represent categorical variables in the ANN model by numerical values obtained from physics knowledge and part specifications

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# *THANK YOU!*


- Peter Liu
- Auburn University
- liu@auburn.edu
- 334-844-1428