Reflow Thermal Recipe Segment Optimization Model Based on Artificial Neural Network Approach

Zhenxuan Zhang, Yuanyuan Li, Sang Won Yoon, and Daehan Won(✉)

Binghamton University, 4400 Vestal Pkwy E, Binghamton, NY 13902, USA
{zzhang98,yli352,yoons,dhwon}@binghamton.edu

Abstract. The temperature settings for the reflow oven chamber (i.e., recipe) are critical to the quality of the Printed Circuit Board (PCB) in the surface mount technology because solder joints are formed on the boards with the placed components during the reflow process. Inappropriate profiles cause various defects such as cracks, bridging, delamination, etc. Solder pastes manufacturers have generally provided the ideal thermal profile (i.e., target profile), and PCB manufacturers have attempted to meet the given profile by fine-tuning the oven's recipe. The conventional method tunes the recipe to gather thermal data with a thermal measurement device and adjust the profile relying on the trial-and-error method. This method took a lot of time and effort, and it cannot guarantee consistent product quality because it's so dependent on the engineers. We proposed (1) a stage-based (ramp, soak, and reflow) input data segmentation method for data preprocessing, (2) a model for predicting the zone temperature in the soldering reflow process (SRP) using a state-of-the-art machine learning, (3) an algorithm for generating the optimal recipe to reduce the gap between the actual processing profile and the target profile. Our method uses artificial intelligence, specifically a backpropagation neural network, to enable non-contact prediction using thermal data from a single experiment (BPNN). In the fully equipped in-house laboratory, the validity of the approach was tested. As a result, within 10 min of starting the experiment, the generated optimal recipe shows 99% fitness to the targeted profile.

Keywords: Segment reflow thermal recipe optimization · Thermal profile · Surface mounting · Machine learning · Backpropagation neural network

1 Introduction

The soldering reflow process (SRP) is the last process on the surface mount technology (SMT) assembly line after solder paste printing and components are picked and placed. The SRP is of utmost importance as part of the SMT assembly line process [1]. The SRP involves several heating processes, including ramping, soaking, and reflowing. When the SRP is heated, the printed solder paste is melted into a liquid and connects the copper pads on the Printed Circuit Board (PCB) and the joints on the components. Solder joints are formed when melted solder paste cools down and becomes solid through the

K.-Y. Kim et al. (Eds.): FAIM 2022, LNME, pp. 45–53, 2023.
https://doi.org/10.1007/978-3-031-17629-6_6

cooling process of the SRP. Solder joints are evaluated by measuring their strength, location, shape, and other characteristics. The quality of the solder joints is determined by the temperature of the solder joints (thermal profile), which is directly affected by the setting of each zone of the reflow oven chamber. The manufacturer usually recommends a thermal profile for each solder paste based on physical properties, leading to an ideal solder joint. Figure 1 shows the target thermal profile for Indium 8.9HF Pb-free solder paste used in this research, consisting of 96.5% Sn, 3.0% Ag, and 0.5% Cu. The entire SRP includes four stages: ramping, soaking, reflow, and cooling. The target thermal profile has some key features, including the climbing slope liquidus temperature, which is 220 °C. The peak temperature is 240 °C, as shown in Fig. 1.

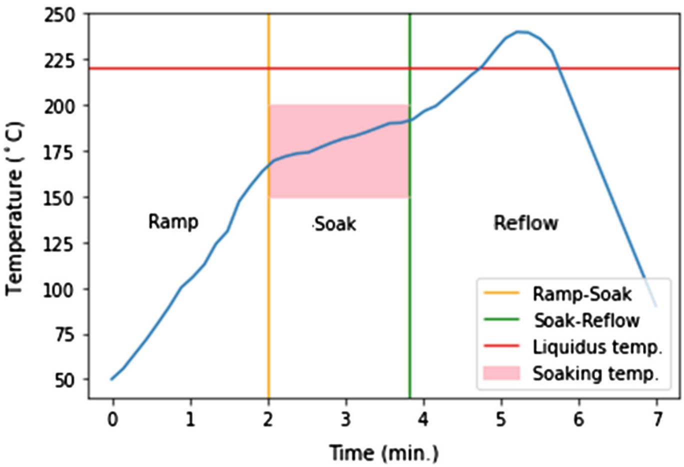


Fig. 1. Target profile of Indium 8.9HF Pb-free solder paste

This study aims to find the best reflow recipe settings for the target thermal profile. Comparing the experimental profile to the target profile is the simplest, most direct, and most effective method of evaluating the quality of a PCB. The k-type thermocouples attached to the solder joints provide the observed profile. A non-contact prediction model proposed in previous research [2] is used to predict solder joint temperature to improve testing efficiency and reduce redundancy of experiments. The result can also be regarded as an evaluation method of the oven status in real-time for quality control by comparing the expected thermal profile and the target profile.

The main factor of the thermal profile is the environment inside the reflow oven, including but not limited to the temperature settings, blow rates, and conveyor speed. The forced convection reflow ovens are widely used in the SMT assembly lines. This kind of reflow oven can handle high throughput, and the heat applied to the PCBs is evenly distributed. The convection reflow oven used in this study contains seven heating zones, followed by one cooling zone. Heat is transferred from the heated air to the board, component, and solder paste inside the oven chamber during the heating process. The temperature performance of forced convection reflow ovens during SRP has been extensively studied. Based on the previous research, one of the studies shows that heat transfer coefficients differ between periods [3]. The heat transfer coefficient should be obtained and applied to the prediction model for evaluation purposes. This study calculates the heat transfer coefficients for each zone separately. The prediction and optimization model is used in stages with a thermal profile segmented by the periods in the reflow process.

The remainder of this article is organized as follows: Sect. 2 introduces some literature related to reflow setting optimization; Sect. 3 discusses the proposed methods in this research; Sect. 4 contains the experiment material, parameter settings, and results; and Sect. 5 considers conclusions and future work.

2 Literature Review

The comparative research published relating to the SRP is described in this section. The temperature has been widely studied because it is the most critical factor in the SRP. The two primary research directions are either simulation-based or experiment-based studies. According to the experiment-based studies, many significant conclusions were obtained. The comparable research projects show that the temperature difference between the surface and middle plane when the PCBs reach peak temperature has a difference under 10 °C, which can be considered negligible [7]. With this result, the simulation and optimization can be acceptable within the 10 °C range.

For the machine learning optimization approaches in the reflow setting optimization studies, the comparative studies, multiple techniques were used, i.e., ANN, NLP, and GA [4–6, 8, 9]. From the comparative studies, the heating factor Q_n is presented as a comprehensive formulation of the two parameters, the peak temperature T_p and the time above liquidus (TAL) [4, 5]. With the heating factor, the backpropagation neural network (BPNN), one of the ANN approaches, was introduced to describe the non-linear relationship between the reflow settings and the thermal reflow profiles. With each period's upper and lower bound constraints, the problem can be formulated as NLP and solved to get optimal solutions. The GA is widely used to find the global optimal solution among the optimized reflow settings.

By inputting factors such as soak time, reflow time, and peak temperature in the SMT domain, ANNs were also applied to predict the shear force tolerance of the reflowed solder joint. High accuracy was obtained when comparing the prediction results with the experimental results [6]. ANN has many advantages; for example, it is very good at handling non-linear data with high generalization capability. A neural network model fits this research well due to the nonlinearity of the data and the need to apply the proposed model to unknown data. The comparative studies show that the thermal profile can be well-predicted from the reflow settings, which means the optimized reflow parameters can be well-optimized from the ideal target thermal profile. This study proposes a multi-stage BPNN model to predict the zone air temperature from the target thermal profile.

3 Methodology

The linear regression model cannot accurately capture the relationship and data characteristics because the thermal data is continuous and non-linear. To investigate the relationship between the recipe, zone air temperature, and board temperature, a multi-stage BPNN model is used to optimize the reflow recipe.

3.1 Data Collection

The first stage of this study is to prepare the data. In this study, only one experiment is required to collect the data. The data is collected from the initial recipe, obtained from segmenting the target thermal profile by the corresponding zones' stages. The peak temperature for each corresponding zone has been set as the initial recipe to get the data.

The data obtained from the experiment include the solder joint thermal profile and the zone air temperature above the measured solder joint. The solder joint thermal profile and the zone air temperature obtained were split into segments according to the stages of the corresponding heating zones in the reflow oven. The data was divided into seven zones, and the zones in the same period, i.e., ramping, soaking, and reflowing, were combined. In the end, the data were split into five segments with five stages, namely (1) room temperature to ramping corresponding to zone 1; (2) ramping corresponding to zone 2; (3) ramping to soaking corresponding to zone 3; (4) soaking corresponding to zone 4 and 5; and (5) reflowing corresponding to zone 6 and 7. Sequentially, the data segments corresponding to each of the five stages have been applied to the model. The solder joint thermal profile is the model's input, and the simulated zone air temperature is the model's output. The center point of each zone's predicted zone air temperature has been set as the reflow recipe of the heating zones. The process is shown in Fig. 2.

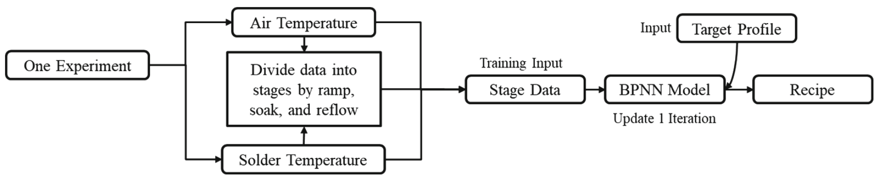


Fig. 2. The flow of the proposed reflow parameter optimization model.

3.2 Model Construction

The second stage of the study is to construct and train a multi-stage BPNN model with five layers in Python. The model takes the joint thermal profile as the input, passing through the three fully connected hidden layers. The predicted zone air temperature is the output of the model. According to the previous subsection, the optimized reflow recipe is obtained accordingly. Each hidden layer has 100 neurons. The activation functions used in the model are rectified linear units (ReLu) for each of the hidden layers, and the linear activation function is used in the output layer. As for the optimizer of the multi-stage

BPNN, the adaptive moment (Adam) estimation is used. The framework of the model is shown in Fig. 3.

The 3 hidden layers are fully connected layers, meaning that each node in the first hidden layer is directly connected to every node in the second hidden layer. Each node in the second hidden layer is directly connected to every node in the third hidden layer. Because the hidden layers are fully connected to each other, the input data would be processed through every node during the iterations, and the weight could be updated after each iteration accordingly. With the stage-segmented data as inputs, a 3-hidden-layer construction can result in a promising outcome compared to other model constructions. Meanwhile, the computing time is over 10 times faster than complicated constructed neural network models.

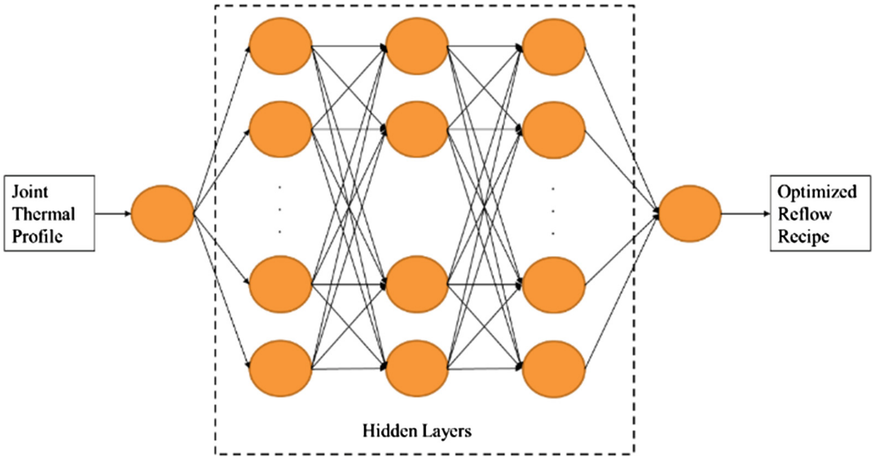


Fig. 3. Multi-stage BPNN framework of the proposed reflow parameter optimization model.

3.3 Reflow Recipe Optimization

The final stage is the optimization model for the reflow recipe from the test data. The test data input is the target thermal profile since the optimized recipe is to optimize the reflow setting to let the solder joint's thermal profile fit the target thermal profile as much as possible. In this research, the multi-stage BPNN optimization model is trained for each of the five stages sequentially as the stages flow in the RSP. After the training process, the well-trained model has been applied to the segmented target thermal profile corresponding to the five stages to obtain the optimized reflow recipe settings.

In this research, the experiments are performed, and the optimization model is applied to the solder joint temperature under the small passive components. According to results from a comparative study, the solder joints' temperature of the passive components is almost the same as the board temperature [9]. The components used in this research are the passive capacitors and resistors with 0.4×0.2 mm, 0.6×0.3 mm, and 1×0.5 mm. The experiment results and the validating results of the optimized reflow recipe will be discussed in Sect. 4.

4 Experiment and Results

4.1 Experimental Environment

The experiment is conducted on the Heller 1707MKEV reflow oven with a temperature control accuracy is ± 3 (ºC). The testing board is a 15 × 16 cm sized FR-4 glass epoxy board with three components, 0402M, 0603M, and 1005M. The amount of the components is 250 pieces each. The temperature is measured by the Mega MOLE with 20-channel K-type thermocouples.

The experiment was conducted with the initial recipe mentioned in Sect. 3.1. After the data is collected from the investigation, the temperature of the solder joints and the zone air temperature collected above the measured solder joints are used for training the model. In actual production lines, less experiment data is preferred with multiple advantages, including faster obtaining the optimized result, fewer materials wastes, and less labor required. This AI-based approach requires only the sample data from one experiment for training the model. After training, the model was tested with 7 different profiles as "target profiles," and the optimized recipe obtained for each profile was validated with 1 experiment. Cross-validation has also been performed using the experimental data from the different recipes as training input and validated with other test cases.

After training the model, the optimization can be conducted using the target thermal profile as the input data. The optimized reflow recipe has been validated with one more experiment, and the performance is evaluated based on the R^2, , and root means square error (RMSE). R^2 is an indicator to show the fitness of the thermal profile from the optimized recipe compared to the target profile and can be calculated with the following Eq. (1), and the RMSE is a measurement that indicates the difference between the optimized recipe result to the target profile and can be calculated with Eq. (2). $\widehat{y_i}$ represents the predicted value, and $\overline{y_i}$ represents the mean value.

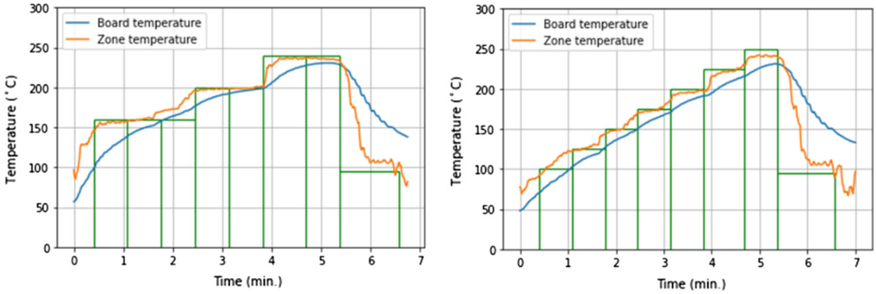
$$R^2 = 1 - \frac{\sum_1^n \left(\widehat{y_i} - y_i\right)^2}{\sum_1^n (y_i - \overline{y_i})^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_1^n \left(\widehat{y_i} - y_i\right)^2} \tag{2}$$

4.2 Results Analysis

The results of the experiments are shown in Figs. 4 and 5. The R^2 fitness score is increased from 0.92 to 0.99. The RMSE has been reduced by 65.2%. The optimization model requires only one iteration to obtain the optimized recipe, and the calculation time for this model is less than 5 s. The optimized recipe can be brought with one experiment and validated with one more experiment.

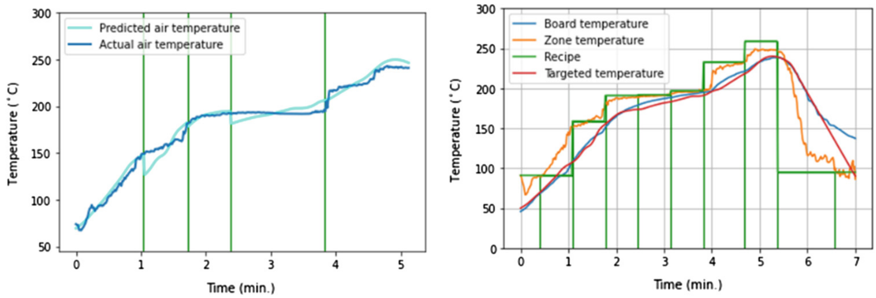
The model has been proved to be generalized for any random initial recipes by training with the data collected on the identical product but with a random recipe setting as an initial recipe. Two different initial recipes were used for validating the performance, and the model obtains an optimized recipe setting with the same performance. Even



(a) (b)

Fig. 4. a) Initial recipe result ($R^2 = 0.92$, RMSE $= 14.09$), (b) random initial recipe

with the limit of in-field experience of SMT assembly line, the optimized recipe can be obtained within 10 min, including the experiment time. Also, in the same reflow oven and the same production (boards and components), with different target thermal profiles provided, the optimization can be performed with the data from one experiment. Another advantage of this multi-stage reflow parameter optimization model is separating the zones by the corresponding stages. This model can be extended to different reflow ovens with a different number of zone and designs.



(a) (b)

Fig. 5. a) predicted and validated air temp., (b) optimized recipe ($R^2 = 0.99$, RMSE $= 4.91$)

5 Conclusion and Future Works

This research proposes a systematic way to optimize the reflow recipe and parameter settings for the SRP. With the multi-stage BPNN optimization model, the optimized result can be obtained within 10 min. The training process takes the actual solder joint temperature as the input. In this study, the actual thermal profile of the passive components solder joints has been proved to be close to the board temperature, which is easy to be obtained. The optimization process takes the target thermal profile as the solder paste manufacturer's input. From comparing the initial and optimized recipe results, the R^2

and RMSE has been improved by 7.6% and 65.2%, respectively. In addition, multiple advantages can be found with the proposed model. For instance, the optimization process with the multi-stage BPNN model does not require any SMT-related field experience for subjective judgment, which increases the automation and fulfillment of the industry 4.0 requirements. In addition, compared to the approach of taking the complete profile data as the input of the model, the 5-staged data leads to a significantly shorter computation time, with a promising result.

Comparing the thermal profile from the optimized recipe with the thermal profile from the initial recipe, the offset of the actual profile from the target thermal profile is majorly caused by the recipe settings, including the temperature of each zone and the conveyor speed. The conveyor speed has been pre-determined by the length of heating zones and the heating period, the temperature of each zone became the fundamental cause of the offset. Using an AI-based machine-learning algorithm, the thermal transfer relationship between air and board is revealed and applied to find out the “ideal” zone air temperature to obtain the target thermal profile and eventually obtain the optimal reflow recipe settings.

However, there are some limitations of this research. The proposed model mainly satisfies the passive components on the PCBs. For the larger components and packages, the temperature of the solder joints underneath the package could have some gap with the passive component solder joints. Therefore, an adaptive optimization model for the reflow recipe should be proposed that satisfies both the passive components and the large-sized packages (e.g., BGAs) to be close to the target thermal profile. Moreover, since the solder joint temperature underneath the bigger sized packages is hard to be measured, a prediction model can be proposed to perform prediction based on the size and thickness of the large sized components. It will increase the possibility of studying the relationship of thermal profiles between the passive components and big packages and propose a model that can eventually provide the optimal solution to satisfy all the components on the same board.

References

1. Tsai, T.N.: Modeling and optimization of stencil printing operations: a comparison study. Comput. Ind. Eng. **54**(3), 374–389 (2008)
2. Li, Y., He, J., Won, D., Yoon, S.W.: Non-contact reflow oven thermal profile prediction based on artificial neural network. IEEE Trans. Compon. Packag. Manuf. Technol. **11**(12), 2229–2237 (2021)
3. Illés, B.: Distribution of the heat transfer coefficient in convection reflow oven. Appl. Thermal Eng. **30**(13), 1523–1530 (2010)
4. Tsai, T.N.: Thermal parameters optimization of a reflow soldering profile in printed circuit board assembly: a comparative study. Appl. Soft Comput. 2601–2613 (2012)
5. Ma, G., Huang, X., Liu, S.: Heat transfer modeling and oven temperature curve optimization of integrated circuit board reflow soldering. IEEE Access **9**, 141876–141889 (2021)
6. Lin, Y., Deng, W., Shie, J., Yang, Y.: Optimization of reflow soldering process for BGA packages by artificial neural network. Microelectron. Int. **24**(2), 64–70 (2007)
7. Straubinger, D., Bozsóki, I., Bušek, D., Illés, B., Géczy, A.: Modelling of temperature distribution along PCB thickness in different substrates during reflow. Circuit World (2019)

8. Jing, S., Li, M., Li, X., Yin, P.: Optimization of reflow soldering temperature curve based on genetic algorithm. Energy Rep. **7**, 772–782 (2021)
9. Schüßler, F., Kozic, D., Franke, J.: Influences on the reflow soldering process by components with specific thermal properties. Circuit World **35**(3), 35–42 (2009)