Improved Testing of Soldered Interconnects Quality on Silicon Solar Cell

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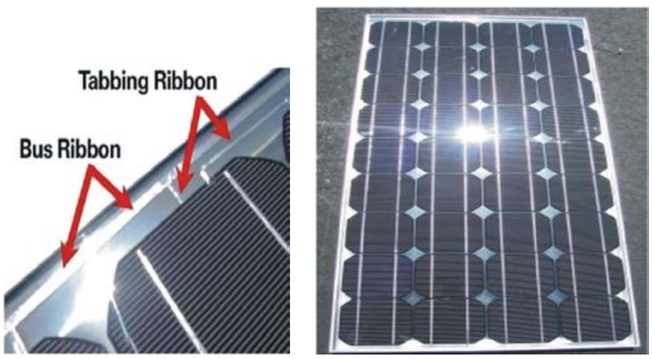
***Abstract-* Accurate estimation of the peel force of the hot-air soldering ribbon interconnects has been recognized as an important issue for the combined tabber/ stringer (CTS) soldering process. Although there are empirical formulas available for quality of adhesive interconnects estimation, but their performances are not all satisfactory due to the complicated nature of the soldering process and the data availability. For this purpose, artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models were developed to estimate force of solder ribbon interconnects on silicon solar cells is implemented. The solderability and quality of the solar cell interconnection zone is an important criterion which has to be ensured. Pulling of ribbons from pre-damaged cells leads to large silicon disruptions. Therefore, instead of testing the solder interconnection, the ribbon peel force test of the solar cells is estimated. The paper focuses on a development of an innovative ANFIS estimator, evaluation of the test method and results for the interconnection quality. The result also indicated that the ANFIS estimator could evaluate the output response in high prediction accuracy even using limited training data.**

Keywords- Solar cells; Soldering; Artificial Neural networks; Fuzzy Logic; Interconnection

I. INTRODUCTION

Solar modules are becoming thinner, while at the same time the surface area increases. Thin solar cells are difficult to interconnect with standard soldering techniques. High temperature during soldering, between 250-400°C, introduces a combination of thermal and mechanical loads on the cells. This can cause warping and possible breakage of cells and decreases yield. The soldering process (cell interconnect) is considered the most critical process in module manufacturing. There are two soldering process steps used to assemble the solar cells; the first step is solar cell interconnection, called stringing or tabbing, and the second step, solar cells assembly, is called bussing (see Fig. 1). Bussing ribbon delivers current to the module's junction box for final electrical output.



(a)Soldering solar cell (b) complete interconnected solar cells

Fig. 1 Two types interconnection onto the solar cells

Cell interconnect is accomplished using an automated combined tabber/stringer (CTS) utilizing one of several soldering methods [1]. The important issues in the manufacturing of solar modules are how to solder ribbons onto a thinner wafer becomes a challenge. After the soldering process or the encapsulation of solar cells, cracks may occur, so how to prevent damages caused by bow or residual stress in the soldering process is currently a major challenge. Ribbons within polysilicon and thin film solar cells can be tested using a ribbon peel test protocol where the force required to peel, or break the bond is measured and the observed failure mode can be used to characterize the quality of the soldering process. Therefore, the quality of either process's output can be measured by the peel force of the ribbon that has been soldered to the cell metallization. In order to assess the soldering process quality of adhesive interconnects and identify possible weaknesses in the manufacturing, a combination of physical tests and numerical computations is commonly carried out. For performing accurate numerical computations, constitutive mathematical models describing the response of the output to the individual inputs are required. Obtaining a mathematical model for this soldering process can be rather complex and time consuming as it often requires some assumptions such as defining an operating point and doing linearization about that point and ignoring some soldering process parameters, etc. This fact has recently led the researchers to exploit the neural and fuzzy techniques in modelling soldering process utilizing solely the input-output data sets. Although fuzzy logic allows one to model a system using human knowledge and experience with IF-THEN rules, it is not always adequate on its own. This is also true for Artificial Neural Networks (ANNs), which only deal with numbers rather than linguistic expressions. This deficiency can be overcome by combining the superior features of the two methods. This paper uses an Adaptive-Network based Fuzzy Inference System (ANFIS) architecture, which was used to model the soldering process, so that a fuzzy inference system is built for achieving a desired input/output mapping i.e. described by its observed responses to the introduced inputs. The learning method used allows the tuning of parameters both of the membership functions and the consequents in a Sugeno-type inference system.

Using this new ANFIS model, ribbon bonds within polysilicon and thin film solar cells can be tested and the force required peeling, or break the bond can be measured and the observed failure mode can be used to characterize the quality of the ribbons. The effective test of peel force allows bond strength modelling to successfully predict the failure mode which can be used as an accurate prediction model of real life loading conditions. A significant advantage is that this ANFIS model for new ribbon peel test can be performed with a standard bond testing system equipped with a solar cell test module. The ANFIS model has been used in evaluation the output response in many applications. The rules of the model are developed based on training data pairs and suggestion from the expert. The ANFIS has been proven to be well-suited for modelling nonlinear industrial processes such as end milling [2], wire-EDM [3], welding [4] and water jet cleaning [5]. In view of the nonlinear conditions of a soldering process, the ANFIS is employed for estimation the peel force of solder ribbon interconnects on silicon solar cells. So far, there is no study has been carried out on application of ANFIS estimator for testing the peel force of solder ribbon interconnects. The main purpose of this study is to investigate the application of ANFIS model for testing the peel force of solder ribbon interconnects with limited experimental data, which are difficult to interpret and lack optimisation. This research examines performance across a broad range of soldering condition variables. Results are reported comparing relative performance and indicating soldering condition variables for optimising solder performance.

II. BACKGROUND OF THE RESEARCH

A. *Soldering Methods*

Electrical interconnection of solar cells is a critical step in manufacturing silicon based photovoltaic solar panels as it impacts yield, throughput and final module efficiency. Stringing cells together allow the cells to form a larger power generation system. Strings of cells are laid side by side and connected together to make a photovoltaic solar panel. Stringer equipment is used to connect the solar cells. Stringer solders interconnectors (ribbons) to a number of photovoltaic cells to make photovoltaic cell strings in series. Solar cell breakage can occur during the solder process due to thermal stress. Solar cell thermal stress is minimized by carefully preheating the cells before the soldering process which followed by a controlled cooling phase afterwards. The technology used for the soldering process is often one of the main differentiators between stringer equipment manufacturers. Various soldering technologies are used including infrared lamp, induction heating, laser and hot air. The solder cycle starts with heating the cell as it moves along through a number of temperature zones toward the soldering probe. Once the cell reaches the soldering probe, the probe is lowered into position just above the cell. To keep the ribbon taut and in the proper position, the ribbon is held down with pins as the soldering process occurs. When the solder process is complete, the soldering probe is withdrawn and the pins are released. The soldering step is the most important processing step for producing a high quality, visually appealing solar panel that is also electrically sound. The interconnection of Si solar cells can be made utilizing the solder coating supplied on tabbing ribbon. The ribbon is used to carry current between cells, but it also forms a mechanical connection.

Most cell foundries have some form of a cell interconnect test, but there appears to be no industry standard as can be found in the more mature electronic sectors such as SMT and thick film hybrid. This is likely due to the explosive growth of c-Si in recent years. With the absence of an industry standard method for soldering interconnect testing, and the goal to have a repeatable and relevant method of test, reported methods were tested and, when possible, improved.

B. *Adaptive Neuro-Fuzzy Inference System(ANFIS)*

Jang first introduced the Adaptive neuro-fuzzy inference system (ANFIS) method by embedding the Fuzzy Inference System (FIS) into the framework of adaptive networks [6]. ANFIS is a modeling technique based on fuzzy sets, which assumes that input and output data are ill-defined with uncertainty that cannot be exactly assess with probability theory based on a two-valued logic. A fuzzy set is a set of elements with an imprecise (vague) boundary. A fuzzy set does not have a crisp boundary. That is, the transition from "belonging to the set" to "not belonging to the set" is gradual and is characterized by membership functions (MF). A fuzzy set A(x) is then represented by a pair of two things - the first one is the constituent elements x and their associated membership values $\mu_A(x)$ (that is their degree of belongingness):

$$A(x) = \{(x,\ \mu_A(x)),\ x \in X\} \tag{1}$$

where X is the universal set consisting of all possible elements. The membership function μ_A ranges from 0 to 1. If the value of the membership function is restricted to either 0 or 1, the fuzzy set is then reduced to classical crisp set with a known boundary. The fuzziness does not come from the randomness of the constituent members of the sets, but from the uncertain and imprecise nature of the abstract thoughts and concepts. In ANFIS the relationship between input and output are expressed in the form of *If- Then* rules. ANFIS used for the present work is based on Sugeno fuzzy model [7] which formalizes a systematic approach to generating fuzzy rules from an input-output dataset.

A typical fuzzy rule in a Sugeno fuzzy model has the format:

$$\textit{If}\ \ x \in A \text{ and } y \in B\ \ \textit{then}\ \ z = f(x, y), \tag{2}$$

where A and B are fuzzy sets in the antecedent. An adaptive network is a network structure consisting of a number of nodes connected through directional links. The outputs of these adaptive nodes depend on modifiable parameters pertaining to these nodes. The basic idea behind the design of neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data. ANFIS constructs an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and simulated input-output data pairs. It serves as a basis for building the set of fuzzy if-then rules with appropriate membership functions to generate the input output pairs. The parameters associated with the membership functions are open to change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the ANFIS is modeling the input-output data for a given parameter set. Once the gradient vector is obtained, backpropagation or hybrid learning algorithm can be applied in order to adjust the parameters. ANFIS can be used in modeling, estimating and controlling studies in manufacturing processes similar to other artificial intelligence methods such as ANNs and Fuzzy Logic (FL). In this paper, the designed ANFIS is utilized as an estimator. In estimator design process, different ANFIS structure are constructed and trained to find the architecture that gives the best performance as an estimator. ANFIS estimator design consists of two parts:

constructing and training. In constructing part, structure parameters are determined. These are type and number of input Membership Functions (MFs), and type of output MF. Any of several MFs such as Triangular, Trapezoidal and Gaussian can be used as an input MF. Frequently used MFs in literature are the Triangular. For this reason, they are chosen as input MF type in this study. As a second step to design an estimator, the training data sets should be generated to train the estimator networks. These data sets consist of estimator inputs and desired output values. They are produced from the process input output data. Since, ANFIS is a data processing method, it is important that the input-output data must be within the sufficient operational range including the maximum and minimum values for both input and output variables of the soldering process. The limited data set should include data for each soldering process variable.

C. Experiment Setting

This experiment uses the hot air soldering machine commonly used by solar cell module manufacturers to conduct soldering parameter experiments. Since there are many soldering condition variables (i.e. input variables) that affect the soldering process quality (peel force as the soldering process output)of solar cells, the ANFIS model is used for the soldering experiment to analyse the importance of each process variables. The effect of soldering condition variables and output of soldering quality is described below.

Soldering condition variables are the following:

1. Hot air temperature: temperature is a very important factor affecting soldering quality of solar cells. Since the coefficient of thermal expansion varies for all cell components, the higher the soldering temperature, the higher the corresponding stresses. Lower soldering temperature is preferred.
2. Soldering time: soldering time is related to the soldering temperature. Usually, the lower the soldering temperature is, the longer the soldering time is.
3. Pre-heating temperature of solder: if the solar cell is pre-heated before soldering, it reduces the deformation caused by instantaneous temperature increases and increases the process yield.
4. Air flow: the air temperature is constant, so air flow will affect the uniformity of temperature and the heat borne by the solar cell in a short period of time.
5. Probe numbers: the number of solder spots on the solder has a direct impact on the size of cell series resistance. If there are insufficient solder spots on a solder, it will increase the resistance of the solder.
6. Probe pressure: though hot air soldering is a non-contact soldering method, it still needs probes to fasten ribbons so the soldering process will not shift the ribbons. Since the trend nowadays is thinner wafers, good pressure control can reduce the damage ratio.

After soldering, place the solar cell that has a ribbon soldered onto it in the tensile testing machine to test for peel force. This experiment measures the peel force between solar cell and ribbon at a 90 degree angle. The solar cell for testing is fixed on the tensile testing machine while the ribbon is fixed by the pull gauge chuck and shifted by the movement of the testing platform (pull gauge fixed) to measure the peel force. Each collocation parameter is soldered to two solar cells, and the average peel force is used as the experimental data. The control factors are as listed in Table1.

TABLE I EXPERIMENTAL SOLDERING CONDITION VARIABLES AND DATA

Run No	Hot air temperature(°C)	Soldering time(Sec)	Pre-heating temperature of solder(°C)	Air flow (lit/min)	Probe numbers (No.)	Probe pressure (gf/mm²)	Peel force (gf)
1	400	2.5	250	10	10	300	205
2	380	2	250	10	13	300	200
3	400	2.5	250	10	13	260	205
4	350	2	250	20	13	280	200
5	400	2	250	20	13	300	205
6	400	2	250	20	13	280	195
7	400	2.5	250	20	13	260	195
8	400	2.5	250	20	13	260	195
9	350	2.3	280	10	13	300	205
10	400	2.5	280	15	7	300	205
11	350	2	280	20	7	260	210
12	400	2	280	20	7	300	205
13	400	2	350	10	7	280	210
14	400	2.3	350	10	13	300	210
15	400	2.5	350	10	13	300	210
16	400	2.5	350	20	7	300	210
17	350	2	350	20	10	260	215
18	350	2.5	350	20	10	300	210
19	380	2.5	350	20	13	260	210
20	400	2	350	20	13	300	215
21	400	2	250	10	7	300	200
22	350	2	250	10	10	300	205
23	380	2	250	10	13	260	205
24	350	2	250	20	13	260	200
25	350	2.5	280	15	13	260	200
26	350	2.5	350	10	10	260	210
27	350	2.5	350	10	13	300	210
28	350	2.5	350	15	7	300	210
29	380	2.5	350	20	10	300	210
30	350	2.5	350	20	13	260	215

III. ANTIS ESTIMATOR METHODOLOGY

The ANFIS estimator learns the rules and membership functions from experiment data. ANFIS estimator is an adaptive network. An adaptive network is network of nodes and directional links. Associated with the network is a learning rule-for example back propagation. It's called adaptive because some, or all, of the nodes have parameters which affect the output of the node. These networks are learning a relationship between inputs and outputs. Adaptive networks cover a number of different approaches but for our purposes we will investigate in some detail the method proposed by Jang known as ANFIS. The ANFIS estimator architecture is shown below. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt. Assume that the FIS has two inputs, x and y, and one output, F. In addition, the rule base of the FIS contains two fuzzy if-then rules, similar to the rule types described by Takagi and Sugeno:

$$\begin{aligned} &If\ \ x\ is\ A_1\ and\ \ y\ is\ B_1 \quad THEN\ \ f_1 = p_1x + q_1y + r_1 \\ &If\ \ x\ is\ A_2\ and\ \ y\ is\ B_2 \quad THEN\ \ f_2 = p_2x + q_2y + r_2 \end{aligned} \tag{3}$$

When f(x, y) is a first-order polynomial as shown above, then the model is called a first-order Sugeno fuzzy model. ANFIS architecture is shown in Fig. 2 where each node within the same layer performs functions of the same type.

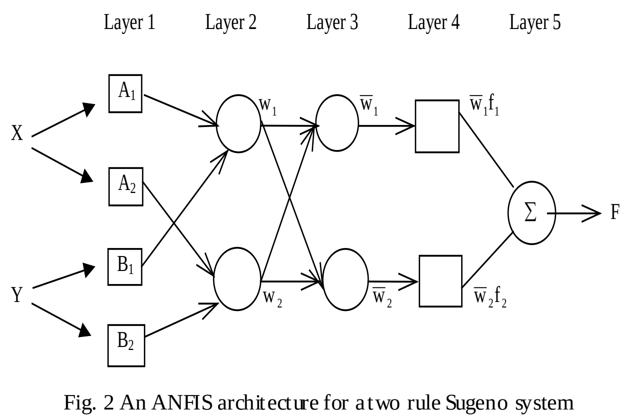


Fig. 2 An ANFIS architecture for a two rule Sugeno system

For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to backpropagation.

Layer 1:

In this layer where the fuzzification process takes place, every node is adaptive. Outputs of this layer form the membership values of the premise part.The output of each node is:

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2 \tag{4}$$
$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4$$

So, the $O_{1,i}(x)$ is essentially the membership grade for x and y. The membership functions could be anything but for illustration purposes we will use the triangular shaped function given by:

$$\mu_{A_i,B_i}(x)=\max[\min\left(\frac{x-a_i}{b_i-a_i},\frac{c_i-x}{c_i-b_i}\right),0] \tag{5}$$

where a_i, b_i, c_i are parameters triangular membership function to be learnt. These are the premise parameters.

Layer 2:

Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades-for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \tag{6}$$

Each node output represents a firing strength of a rule.

Layer 3:

In this layer where the normalization process is performed, the nodes are fixed as they are in Layer 2.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \tag{7}$$

Layer 4:

Since the nodes in this layer operate as a function block whose variables are the input values, they are adaptive. Consequently the output of this layer forms TSK outputs and this layer is referred to as the consequent part. The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{8}$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5:

This is the summation layer. which consists of a single fixed node. It sums up all the incoming signals and produces the output.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

This then is how, typically, the input vector is fed through the network layer by layer. ANFIS has a hybrid learning rule algorithm which integrates the gradient descent method and the least square methods to train parameters. In the forward pass of the algorithm, functional signals go forward until Layer 4 and the consequent parameters are identified by the least squares method to minimize the measured error. In the backward pass, the premise parameters are updated by the gradient descent method. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules.

A. Training of ANFIS Estimators

ANFIS estimator structure design and training are realized using MATLAB software. There are many types of parameters need to be set in ANFIS estimator structure design. The parameters give a minor and major influence to the estimation output performance:

1. the type of membership function (MFs) (triangular, Gaussian, bell shape, trapezoidal etc),
2. the type of consequent part (linear or constant),
3. the number of MFs (>1),
4. the number of training epoch,
5. the number of training data,
6. the inputs selection method (the more details presented in the next section),
7. the optimization method (backpropagation, or hybrid of the least-squares and the back propagation gradient descent).

In this sub-section, three variables, for example, were selected for inputs of the ANFIS estimator to estimating an output response. The estimator was developed using different shape of input membership function (MFs) type which was triangular with number of the MFs was three. In purpose of training the estimator, a hybrid of the least-squares method and the backpropagation gradient descent method was used to emulate a given experiment data as training data set. The linear and constant output MFs type was employed to produce the peel force value. Fig. 3 shows the flowchart for estimating ribbon peel force using ANFIS estimator. The estimator setting is shown in Table 2.

TABLE II PARATERMETERS SETTING FOR ANTIS ESTIMATOR

ANFIS Estimator Setting	Details
Input soldering condition variables	hot air temperature、pre-heating temperature of solder and air flow.
Output Response	Peel force
Type of Input MFs	Triangular
No. of MFs	Three
Type of Output MFs	Linear and constant
Optimization Method	Hybrid of the least-squares and the backprogation gradient descent method
Epochs	100

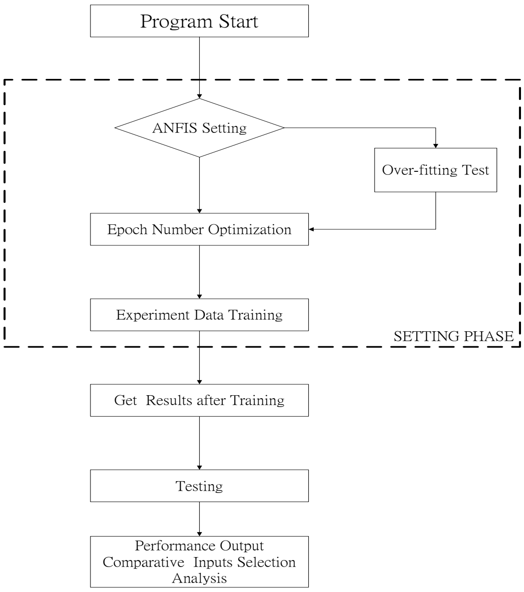


Fig. 3 Flowchart of ribbon peel force estimation of ANFIS estimator

As mentioned earlier, three triangular fuzzy membership functions were selected to describe the input and output variables. This is translated in 3×3^2 =27 rules (regarding the three inputs with three fuzzy sets each) as shown in Fig. 4. In the structure of Fig. 4, each neuron in the first layer is three inputs (hot air temperature, pre-heating temperature of solder and air flow) and the second layer is an adaptive with a parametric activation function. Its output (peel force estimation) is the grade of membership to which the given input satisfies the triangular type membership function (as selected). The membership function is stated through a parametric expression, based whose change affects the shape of the membership function. The third layer output is the firing strength of the *i*-th rule which all of its nodes are fixed. the process which happens in the third layer is that they calculate the ratio of the *i*-th rule's firing strength relative to the sum of all rule's firing strength resulting in a normalized firing strength. In the Layer 4, each of the 27 nodes contains the adaptive node (Eq. (8)). The single node in Layer 5 synthesizes information transmitted by Layer 3 and returns the overall output using the Eq. (9).

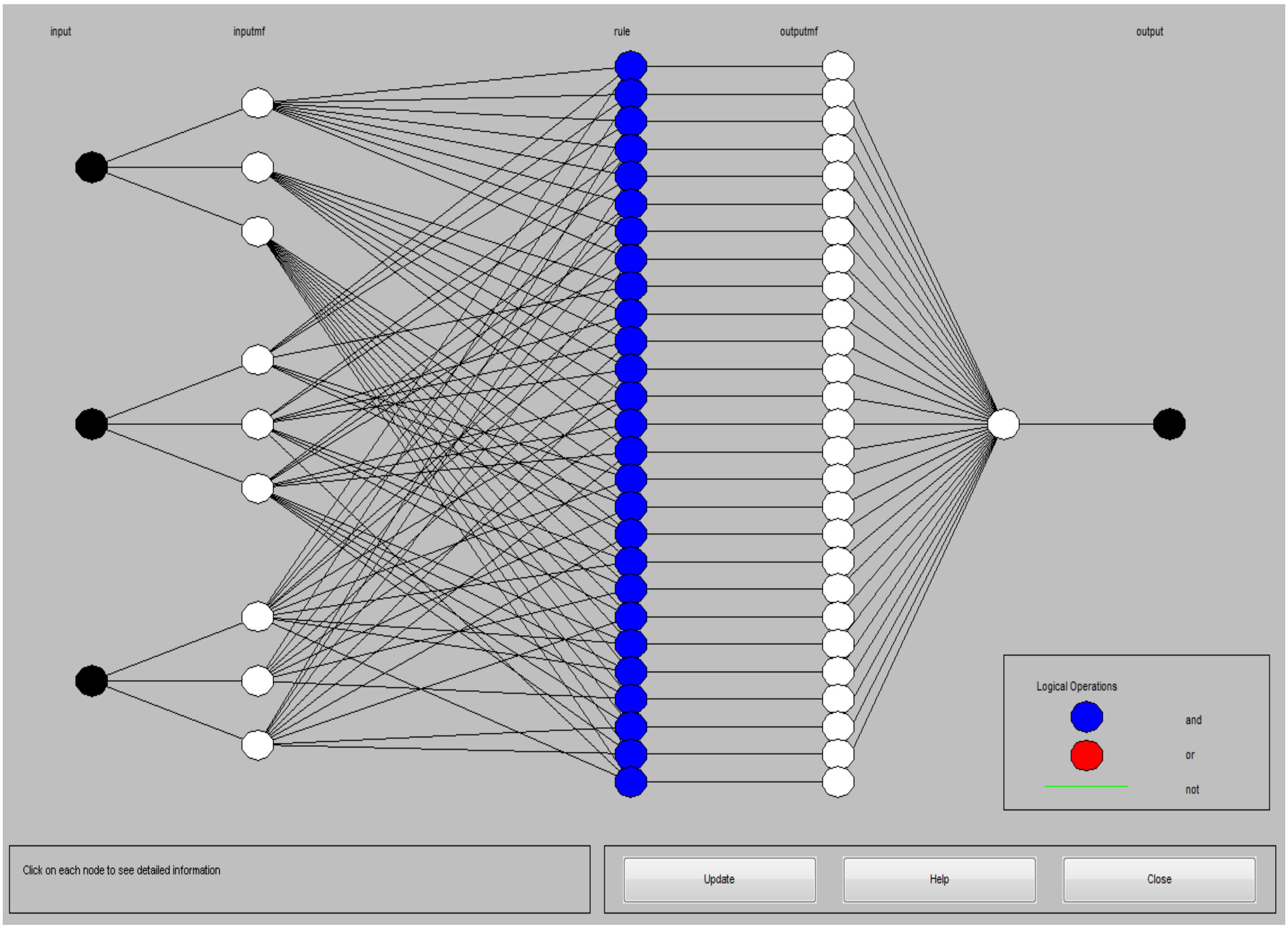


Fig. 4 Adaptive Neuro-Fuzzy structure for peel force estimation

Rule viewer presents a sort of micro view of the fuzzy inference system, where the rule viewer displays a roadmap of the whole fuzzy inference process. It is bases the fuzzy inference diagram with a single window with plotted curve nested in it as shown in Fig. 5. The plotted red lines across the 27 rules top of the figure represent the antecedent and consequent of the fired rule. The rule numbers are displayed on the left of each row. The previous three columns of plots show the membership functions referenced by the antecedent, or the if-part of each rule. The last column of plots represents the aggregate weighted decision for the given inference system.

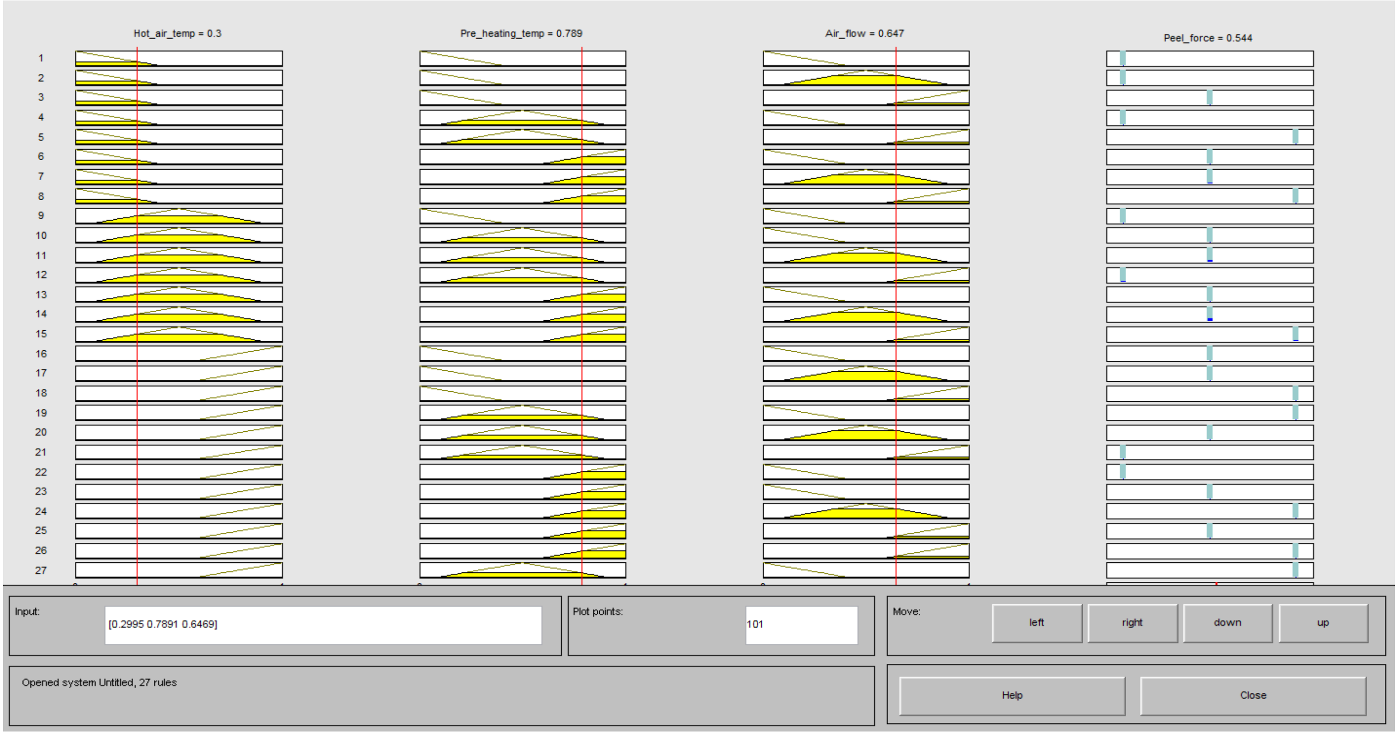


Fig. 5 The rule viewer for the ANFIS estimator

IV. TESTING AND PERFORMANCE EVALUATION

The last block in Fig. 3 illustrates the ANFIS estimator performance for the input soldering condition variables selection. In this Section, we implement the heuristic way to do input variables selection for ANFIS estimator to identify the significant variables in the estimating the ribbon peel force of solar cells. In this heuristic way, all input candidates are treated equally and the best input arguments are selected sequentially. In order to evaluate the selects of our heuristic selection method, the procedure was applied to one, two, three, and four inputs trained ANFIS estimator, corresponding to four types configurations (in the following labeled with I1, I2, I3, I4). This is the first stage of the heuristic way and starting one input selected which includes: hot air temperature (1), soldering time (2), pre-heating temperature of solder (3), air flow (4), probe numbers (5), or probe pressure (6). The number in the brackets indicated input variables code. The training performance of the ANFIS estimator can be checked by the RMSE and the accuracy of percentage (A%). Table 3 shows the results of training and test success of ANFIS estimator for different one input (input code: 1-6) with three triangle MFs.

TABLE III THE PERFORMANCE OF SELECTED ONE INPUT ANFIS PERFORMANCE EVALUATION

No	Performance Measures	Train RMSE	Train A(%)	Test RMSE	Test A(%)	Inputs code
1	Hot air temperature (1)	5.58	97.79	5.59	97.71	1
2	Soldering time(2)	5.56	97.73	5.77	97.65	2
3	Pre-heating temperature of solder (3)	3.24	98.75	2.99	98.88	3
4	Air flow(4)	5.56	97.72	5.76	97.65	4
5	Probe numbers(5)	4.71	98.24	6.96	96.87	5
6	Probe pressure(6)	5.43	97.74	5.54	97.78	6

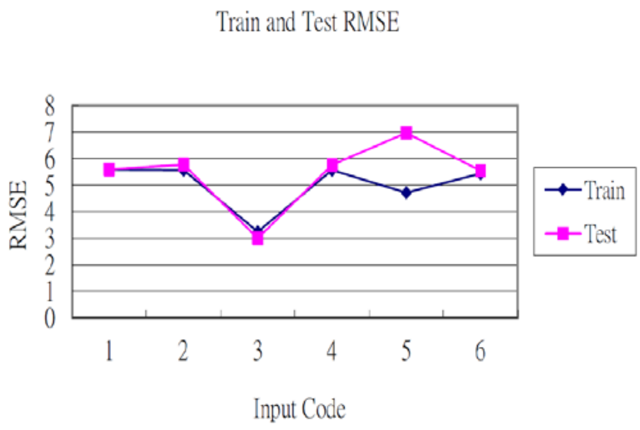


Fig. 6 The performance of selected one input for ANFIS estimator

As an illustrative example, Fig. 6 shows the RMSE of one input (I1) of the six ANFIS estimators during the input node selection process. The pre-heating temperature of solder of the third variable is the most influential input that contains the lowest RMSE and test error close to train RMSE in the list of all input variables.

To calculate two inputs combination (I2), we build C_2^6=15 for ANFIS estimator. The available inputs to select the fifteen set of input combinations that most influence the output. The pre-heating temperature of solder (3) and air flow (4) inputs combination is the most influential input shown in Table 4 and Fig. 7.

TABLE IV THE PERFORMANCE OF SELECTED TWO INPUTS ANFIS ESTIMATOR PERFORMANCE EVALUATION

No	Performance Measures	Train RMSE	Train A(%)	Test RMSE	Test A(%)	Inputs Code
1	Hot air temperature (1), Soldering time (2)	5.35	98	6.75	97.44	1, 2

2	Hot air temperature (1), Pre-heating temperature of solder (3)	3.16	98.78	3.04	98.96	1, 3
3	Hot air temperature (1), Air flow (4)	5.15	98.04	5.42	97.86	1, 4
4	Hot air temperature (1), Probe numbers (5)	4.59	98.37	7.03	97.18	1, 5
5	Hot air temperature (1), Probe pressure (6)	4.7	98.04	6.1	97.39	1, 6
6	Soldering time (2), Pre-heating temperature of solder (3)	2.73	99.07	3.59	98.57	2, 3
7	Soldering time (2), Air flow (4)	5.56	97.82	5.73	97.69	2, 4
8	Soldering time (2), Probe numbers (5)	4.58	98.47	7.24	96.86	2, 5
9	Soldering time (2), Probe pressure (6)	5.22	97.91	5.49	97.88	2, 6
10	Pre-heating temperature of solder (3), Air flow (4)	2.53	99.05	2.65	98.94	3, 4
11	Pre-heating temperature of solder (3), Probe numbers (5)	3	98.8	5.14	98.12	3, 5
12	Pre-heating temperature of solder (3), Probe pressure (6)	2.9	98.91	3.11	98.76	3, 6
13	Air flow (4), Probe numbers (5)	4.52	98.54	6.69	97.04	4, 5
14	Air flow (4), Probe pressure (6)	4.47	98.4	5.72	97.8	4, 6
15	Probe numbers (5), Probe pressure (6)	3.85	98.57	6.21	97.43	5, 6

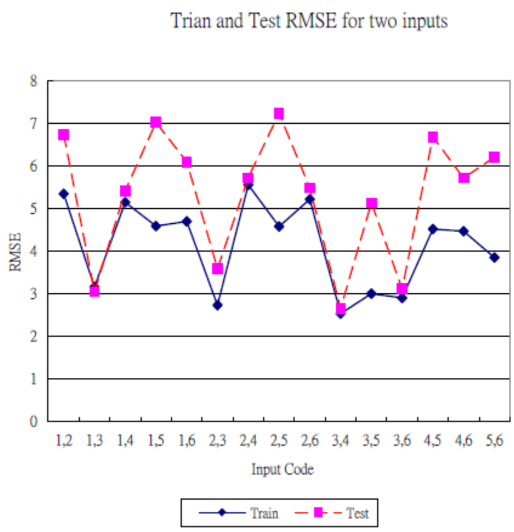


Fig. 7 The performance of selected two inputs for ANFIS estimator

Next, a combination of three inputs and four inputs was tried. The results identify soldering time (2), pre-heating temperature of solder (3), and air flow (4) inputs combination is the most influential three inputs shown in Fig. 8. In the same process, pre-heating temperature of solder (3), air flow (4), probe numbers (5), and probe pressure (6) inputs combination is the most influential four inputs shown in Fig. 9.

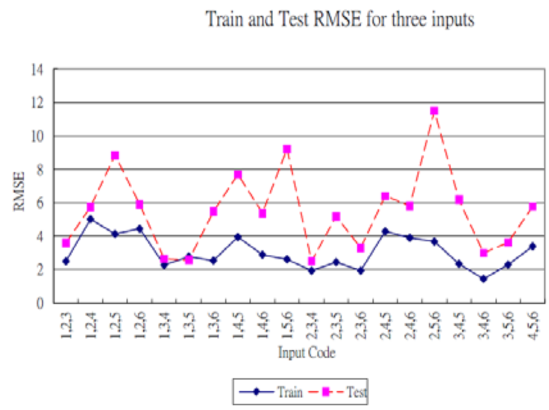


Fig. 8 The performance of selected three inputs for ANFIS estimator

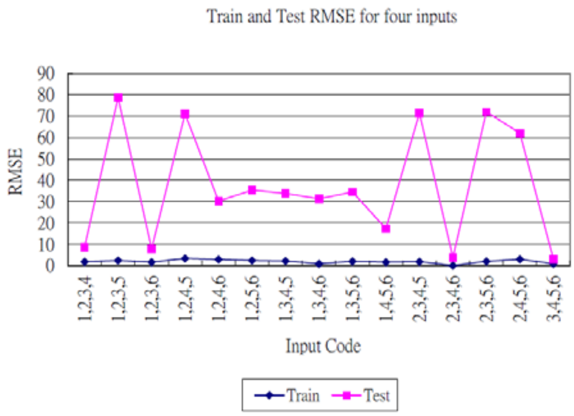


Fig. 9 The performance of selected four inputs for ANFIS estimator

Then testing data and training data are used to test the ANFIS estimator performance for mentioned above different inputs selected. Table 5 presents the comparison of actual values and corresponding output values proposed by the ANFIS estimator.

TABLE V THE PERFORMANCE OF DIFFERENT SELECTED INPUTS ANTIS ESTIMATOR PERFORMANCE EVALUATION

				Selected soldering condition variables						
		Actualvalues	3	3, 4	1, 3, 4	1, 3, 5	2, 3, 4	3, 4, 6	3, 4, 5, 6	1-6(All)
Train	RMSE		3.24	2.53	2.28	2.78	1.94	1.44	0.79	0
	A(%)		98.75	99.05	99.31	98.98	99.5	99.6	99.87	100
Test	RMSE		2.99	2.65	2.65	2.57	2.5	3	3.09	112.43
	A(%)		98.88	98.94	99.16	99.05	99.28	98.94	98.87	55.18
	1	200	200.71	198.75	200	200	200	195	195	102.07
	2	205	211.11	210	210	212.5	209.97	210	210	126.21
	3	205	200.71	203.33	199.83	204.7	202.5	200	200.72	128.88
	4	200	205	210	205.99	205	210	205	204.4	0
	5	200	200.71	203.33	205	202.81	202.5	200	201.46	0
	6	210	200.71	198.75	198.33	200	195	197.5	197.5	195
	7	210	211.11	210	210	213.18	210	210	210	112.58
	8	210	211.11	212	212.5	213.18	210	212.5	210	217.2
	9	210	200.71	203.33	205	201.37	205	200	200.72	111.9
	10	215	211.11	212	210	210.07	210	211.67	210	148.26

The heuristic way was employed to select appropriate inputs. According Table 5, we plot the scatter diagram (Fig. 10) of the actual measured and estimated peel force for the experimental tests. It shows that the estimated values of ANFIS estimator response between 200 and 210 (gf) in a good fashion. In particularly, one of the best performance of ANFIS estimator with soldering time (2), pre-heating temperature of solder (3), and air flow (4) inputs. It was observed the three-input ANFIS estimator provided reasonably low RMSE where beyond this different number of input combinations. As such, the optimum three-input ANFIS estimator was selected. In summary, the ANFIS estimator can be a good option in estimating peel forces value of solar cells soldering ribbon interconnects.

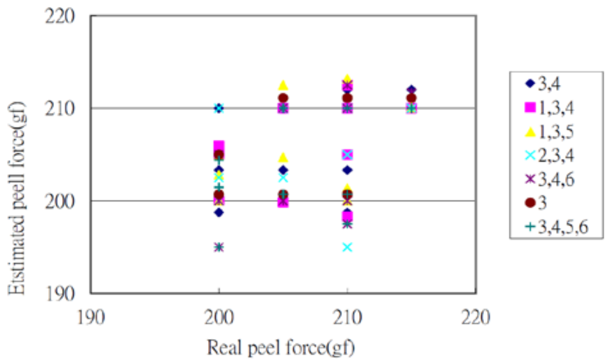


Fig. 10 Scatter diagram of the actual and estimated peel force for the testing data using ANFIS estimator

V. CONCLUSIONS

In this study, the ANFIS estimator was used in estimating the peel force of the hot-air soldering ribbon interconnects. The 30 limited experimental data were used for the estimator training purpose and 10 testing dataset were used for validation. The result showed that the three inputs (soldering time, pre-heating temperature of solder, and air flow) structures of ANFIS estimator gave good estimation accuracy. We see significant differences in soldered performances. Better understanding performance of soldering condition variables will enable optimization of the tabbing/ stringing process and lead to improved solar cells module quality. This work examines performance across a broad range of soldering condition variables. Some technical insights are provided on the reasons for the performance differences that would provide valuable information to the industry.

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