On the control of micro Ball Grid Array (μBGA) production systems

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Abstract: In this paper, two novel control implementations for the production of Ball Grid Arrays (BGA) at the micro scale are presented. The first is a linear control algorithm; the second is an adaptive neural network. The linear control algorithm was developed to manage the key control parameters of the system and to reach the desired performance as fast as possible based on measurements of system's output. The neural network uses an adaptive control architecture for controlling the performance of the system. This architecture dynamically assigns weights to output variables, in current point time as well as in previous points in time, and uses them as control inputs to improve both production performance and stability. Brief theoretical background, experimental validation and a comparison of the two algorithms in terms of performance and stability are provided.

Key-Words: Control software, μBGA, linear control algorithm, neural network, adaptive control architecture

1. Introduction

Ball Grid Arrays (BGAs) systems are designed to produce solder balls and are considered to be expensive equipment that is used for integration purposes in the electronics industry and mainly in the integrated circuit industry. The FP7 ICT micro Ball Grid Array project (μBGA, EC Grant No. 243653), part of which this research work is, targets the creation of a system that will be able to produce such ball grid arrays in the micro scale, that is 50 to 150 μm, and provide a competitive advantage to the E.U. electronics industry. Current trends dictate the constant integration of more electronics into circuits as well as the need for the miniaturization of those integrated circuits. The μBGA system addresses the need for miniaturization by providing spheres in the micro scale level while keeping the advantages of the BGA technology [1]. That is:

- High Density
- Heat conduction
- Low inductance

The scope of this paper is to present the developed control software, within μBGA project, that implements two control solutions:

- a linear control algorithm and
- an adaptive neural network (ANN) [2]

for enabling the stable production of micro ball grid arrays systems at high production rates.

The system (Fig 1) loosely consists of the following:

- a crucible in which liquid solder is placed
- a heater responsible for the increase of the temperature inside the crucible
- a transducer that creates the necessary vibration frequency
- a pressure control system for the introduction of nitrogen into the tank
- a flange with an orifice of specific diameter through which the liquid solder flows and forms the spheres.
- a camera for providing snapshots of the produced spheres
- a computer responsible for controlling the system, storing data and running the HMI.

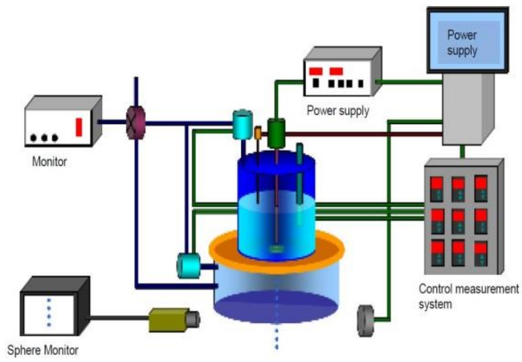

Figure 1: μBGA production system

2. Open and closed loop control

A brief discussion on open- and closed-loop control is presented next.

2.1.Open Loop

An open loop control system is a type of non-feedback control system, i.e. the behavior of the system is based solely on predetermined inputs and any system output is not taken into account when determining the input.. As a result this approach has no learning capabilities and is unable to correct any possible errors or compensated for possible anomalies.

2.2.Closed Loop

A closed loop control system is one that uses feedback control, i.e., the output of the actual production is measured and is used to determine the input of the system. Specifically, the actual output is compared to the desired output and based on the generated differences the input settings are adjusted with the purpose of controlling system output. This process requires defining the control variables beforehand. There are two types of variables: the independent variables, which are the variables that are measured, and the dependent (control) variables, which are the ones that are being adjusted. For instance, in our case the measured (independent) variable is the droplet size and the control input (dependent) variables are frequency, pressure and voltage. In general, a closed-loop system is an automated one.

2.2.1. Linear and Non-Linear Control

Following the closed loop architecture two approaches have been adopted for controlling the system: a linear control approach and a non-linear one implemented by the use of an artificial neural network.

The reason for implementing two distinct approaches is the need to evaluate the performance of system with regards to sphere production, in terms of stability, sphere diameter and production rate. Based on that evaluation we determine the most effective way to control the system.

3. Linear Control Algorithm

Linear control is a procedure where the values of variables in time (t-1), where t is the current time, were used as feedback to adjust the current output of the system aiming at achieving a specific production goal set during the initialization of the algorithm. This production target has been set by the user through software, the human-machine interface. The algorithm is tasked to maintain a stable production rate and specific sphere diameter and roundness.

The algorithm is initiated by initially defining some key inputs. Those are:

1. Desired target ball diameter
2. Orifice diameter
3. Transducer vibration
4. Initial vibration frequency
5. Pressure in the tank

Then the inputs are evaluated and the control parameters are adjusted in order to reach the targeted result. Once that is done the Graphical User Interface (GUI) is updated and the process continues in a loop. Fig 2 is a simple graphical representation of the function of the linear control algorithm.

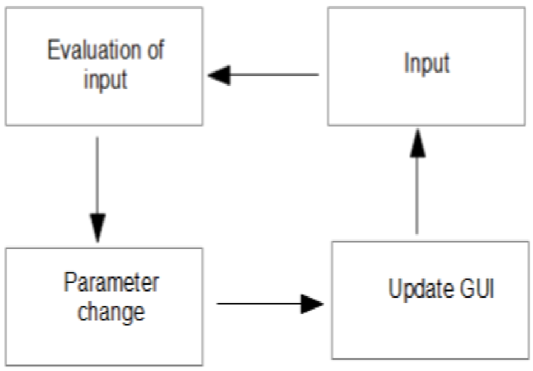

Figure 2: Representation of algorithm's function

The main parameters that contribute to the variation of sphere diameter and roundness are frequency and pressure. In addition, for roundness, temperature levels must also be taken into account. It has been observed that the higher the temperature of the liquid stream is the longer it will take to solidify and the higher the chance for the droplet to get a better spherical shape.

3.1.Radius

According to Rocha J.C [3] the radius of the sphere is approximated by the following equation and can derived by using the work of Eggers J and Villermaux E [4]:

$$d_{drp} = \left(\frac{6A_jV_j}{\pi f}\right)^{\frac{1}{3}}(1)$$

Where:
d_{drp} = the radius of the droplet
V_j = jet velocity
A_j= is the cross section area of the jet
f = frequency of the transducer.

3.2.Diameter control

In order to estimate the diameter of the produced spheres the algorithm is taking data relevant to sphere diameter from snapshots provided by the system's camera module and adjust frequency accordingly. The equation that is used to estimate the diameter of the sphere in comparison to the precompiled dimension is as follows [3]:

$$\varphi_1 = \left|1 - \frac{D_d}{D_t}\right| \quad (2)$$

Where:
D_t = Desirable sphere diameter
D_d = measured diameter
φ_1 = Variation factor

3.3.Frequency control

Based on the work of Rocha J.C [3] for controlling the production of a BGA an algorithm for correcting the frequency of the transducer was developed and it was based on the following equations.

$$f_k = f_{k-1} + f_{k-1} \cdot \varphi_1 \;\; (3)$$

$$f_k = f_{k-1} - f_{k-1} \cdot \varphi_1 \; (4)$$

Where: φ_1 is the sphere variation factor
f_k the adjusted frequency
f_{k-1} frequency at previous moment

The algorithm compares the actual diameter of the sphere with the precompiled one and if the outcome is different than zero then the variation factor is multiplied by the current frequency and as a result a balance frequency is produced. That frequency is either added or extracted from the original frequency depending on the diameter of the actual sphere. If it exceeds the target the vibration frequency increases. If the target size is higher than the output, then the system reduces the vibration frequency and in the case that the size is well into target, vibration frequency remains the same. The process works in a closed loop, as shown in Fig 3.

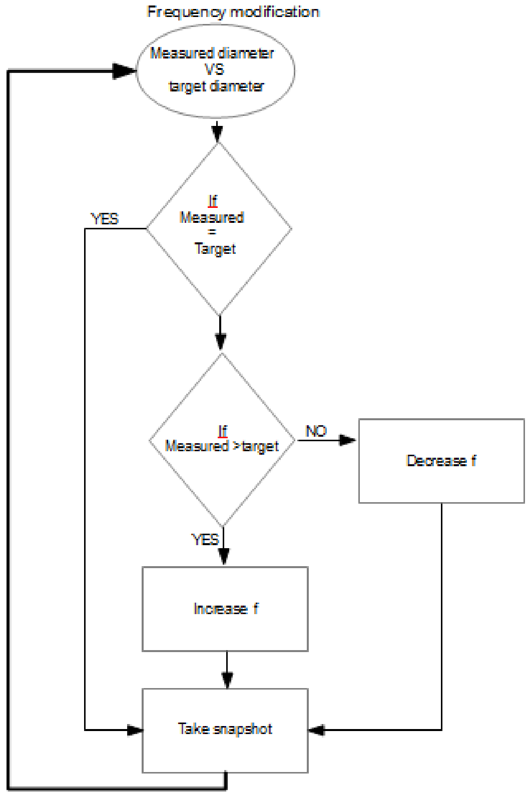

Figure 3: Frequency control

3.4.Pressure control

Besides temperature, the volume of the liquid inside the tank also plays a role in the creation procedure and is closely related to pressure management. If temperature is low, droplets will cool off fast after breaking off the jet stream and thus not enough time will be given for the spheres to get an ideal spherical shape. In terms of liquid's volume it is important to notice that as the liquid decreases the stream's volume and velocity changes too, thus forming droplets of different sizes. In order to control the flow of the liquid and thus control the size of spheres the amount of pressure in the tank must be controlled. To do that the algorithm, calculates the pressure increase needed by knowing the initial height of the liquid and the initial pressure. Below are the equation used for this calculation [3][4].

$$V_j = C_{ori}\sqrt{\frac{2(\Delta p - p_{h(t)})}{\rho}} \quad (5)$$

$$\Delta_p = p - p_{atm} \quad (6)$$

Where:
p= pressure applied in the tank (metallic beam + vessel)
p_{atm} = atmospheric pressure
$p_h(t)$ = hydrostatic pressure at time t (pressure in the tank changes during operation and is measured via the use sensors)
ρ = liquid density
C_{ori} = Drag coefficient

3.5.Voltage Control

In the case of voltage, the control system can adjust the amplitude of the signal by increasing or decreasing voltage. The idea is similar to both frequency adjustment and pressure adjustment. By adjusting the voltage that is introduced we can have control over the diameter of the spheres, roundness and stream. By adjusting voltage we can fine-tune the system, while keeping the rest of the variables constant.

3.6. System stability

In order to have a stable production procedure all parameters are adjusted in a parallel and "cooperative" way. This means that the algorithm is constantly evaluating each parameter not as an individual factor to a problem but as part of a larger system. So, during operation, all adjustments are decided and commanded based on the holistic behavior of the system.

4. Adaptive Neural Network

The second approach for controlling the production of BGA systems is the implementation of an adaptive neural network. The neural network is a non-linear approach for control and by introducing it to the system we can have a dynamic control over each variable [5][6].
The neural network used in our case implements an adaptive control algorithm for the control of the system's functions. The networks architecture is presented in Fig 4. The reason for selecting a more complicated approach for controlling the system is the fact more accurate control may be achieved this way.
The reason for choosing the above architecture is the need for fast adaptation and robust system response. A feedback active control technique with Non Dual Adaptive controller method and Model Reference Adaptive control (MRA) was developed for that purpose.

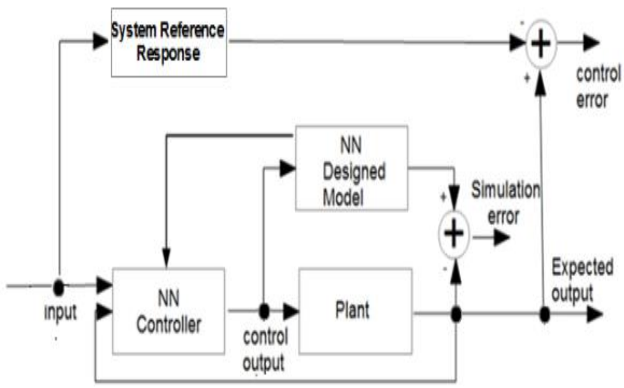

Figure 4:**Neural Control Architecture**

The architecture can be divided into four parts

- Neural Network Controller

The NN controller's responsibility is to adjust the variables of the system (frequency, pressure, voltage) so that their values can reach the values produced by the system reference response. As inputs it accepts data from the system, from the output and the NN designed model. The inputs (frequency, pressure, voltage) are a combination of system variables, in current and previous points in time that are feeding the plant model.

- Plant Model

The Plant model receives inputs from the NN controller. These inputs are multiplied by a factor that varies both in time and for each variable. The output (frequency, pressure, voltage) of the plant is used by the algorithm and also it provides feedback to the NN controller so that it can be readjusted.

- NN Designed Model

The designed model is initiated before the activation of the neural network. It is used to train the controller so that its outputs will follow the outputs of the system reference response and it is utilizes data (frequency, pressure, voltage) both from the controller and the output so that it can provide online training. The output of the controller leads to simulation error where it compares the outputs and inputs in accordance to a predefined target and it produces an error relevant to the deviation from that target.

- System Reference Response

The system reference response is a mathematical model that uses the algorithm's inputs, in terms of variables and it emulates the actions needed to be done by the system in order to produce the desired results. Frequency, pressure and voltage are the received inputs from the system. The simulation's output is compared to the Plant output and an error is produced, when they are not in compliance that error becomes feedback to the NN controller. A more detailed analysis of the adaptive control architecture can be found in Fig 5.

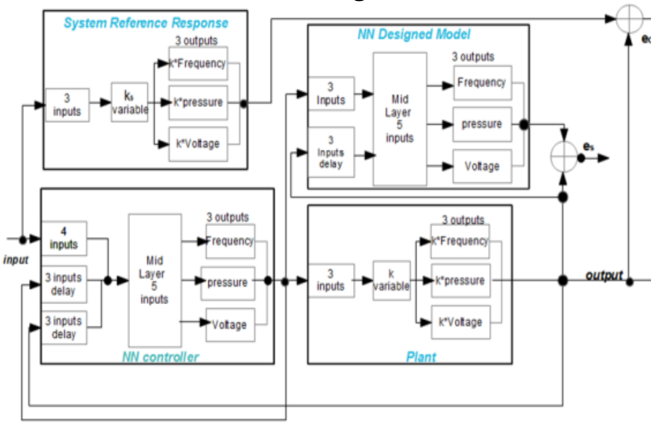

Figure 5:***Analytical Neural Adaptive Control Architecture***

4.1.Dynamic Back Propagation

In order to train the controller, a feedback network that uses adaptive weights for each input parameter is used. Because of that the complexity of the model increases and for the simulation procedure to generate accurate results dynamic back propagation is required. A dynamic back propagation algorithm can manage effectively both the direct and indirect effects that the weights have on the output of the neural network [7][8][9].

A back propagation procedure can be described as a feedback loop that connects the output of the neural network to its input using a delay line. Our approach implements feedback from:

- Output
- NN designed model
- System reference response

In the initial stage all weights and biases are set to zero. In this first step we start from the last layer of the neural network and we compute the initial static derivatives that will be used for the calculation of the dynamic ones. After initialization all weights and biases of that layer are calculated using a devised function. In order to calculate the explicit derivatives of the layers outputs all outputs should be taken under consideration. The next step is for the algorithm to initialize the output for every weight and bias and compare to see if the output of the first layer is a time delayed input. If "yes" all weights and biases are calculated if "no" the layer is incremented. In the case that this is the last layer the function is used to calculate weights and biases for that layer. Fig. 6 presents the flow chart of the dynamic back propagation algorithm.

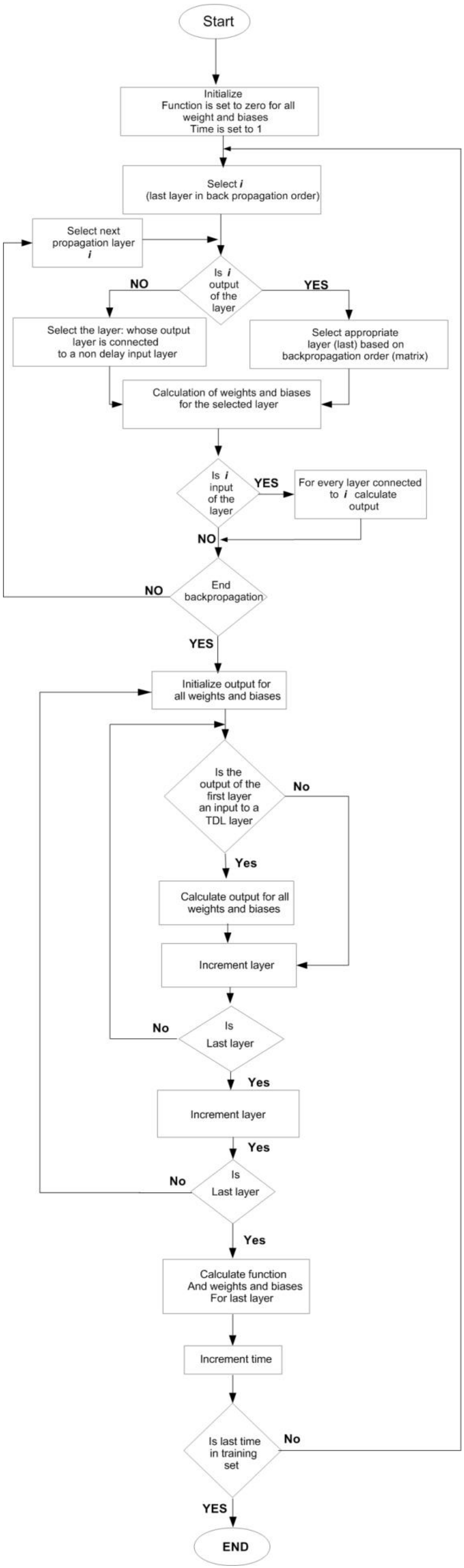

Figure 6: Dynamic back propagation Algorithm

4.2. ANN Simulated results

In order to test the performance of the developed artificial neural network before its actual implementation to the system, a series of simulations were performed with the ANN activated. The simulations were performed by using system defined inputs as well as random noise parameters and the acquired results included output data (diameter, error) from all the components of the neural network.

By initially training our neural network to produce spheres of 160μm stable diameter we then inserted the random noise.

In Fig. 7 the performance of the neural network in relevance to diameter control is presented.

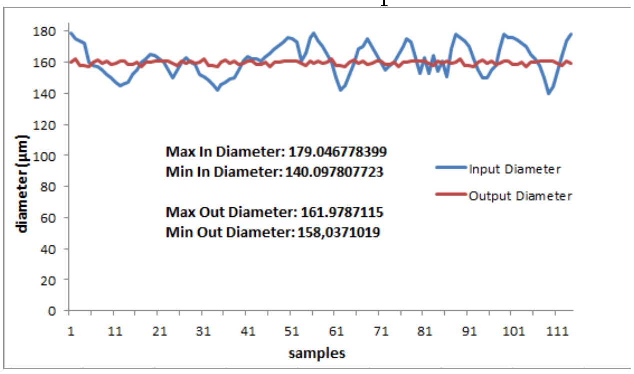

Figure 7: Simulated input and output diameters

It was observed that the ANN was able to adjust the control variables effectively to enable a stable, on target output.

Furthermore, by comparing the system reference response with the plant output; and the designed model output with the plant output a series of error relevant data were produced.

Errors were recorded for all types of variables (frequency, pressure, voltage) in order to evaluate the control performance of the neural network. Fig. 8 displays an example of frequency error in the controller.

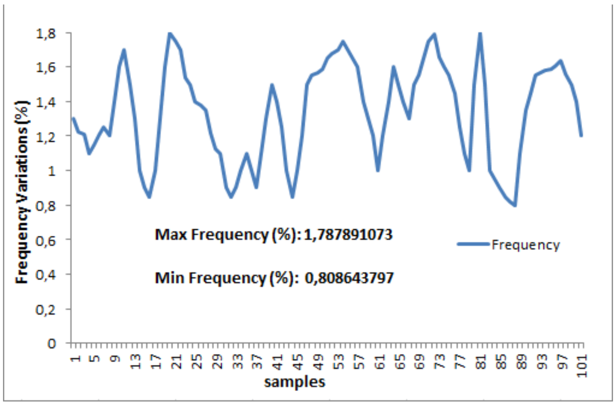

Figure 8: Control Error: Frequency

The range of errors measured, in comparison to the standards accepted by industry, was minimal both in the controller and the designed model and is presented in the Tables 1 and 2 respectively.

Table 1: Control error

Control error	Min error (%)	Max error (%)
Frequency	0.81	1.78
Pressure	0.81	1.79
Voltage	0.81	1.79

Table 2: Model Error

Model error	Min error (%)	Max error (%)
Frequency	1.01	1.98
Pressure	1.01	2.00
Voltage	1.00	1.96

5. Experimental measurements

The target of the experimental procedure was to validate the stable production rate of BGA spheres with diameter in the range of 152 – 168 μm. The performed experiments were divided into three phases:

- Initialization Tests. During these tests the variables were manually adjusted.
- Linear Control Tests. The linear algorithm was introduced to the system and its control functionalities were tested
- Implementation of ANN. The artificial neural network was introduced to the system and its control functionalities were tested.

5.1.Initialization tests

During the initialization procedure, we investigated the effects of frequency, pressure and voltage variables to the performance of the BGA system. A stable production rate was achieved through open loop system operation and the manual adjustment of each individual parameter, while the rest were kept constant.

Fig. 9 displays the behavior of the system based on frequency alterations. The optimal operational range is defined to be between the two markers.

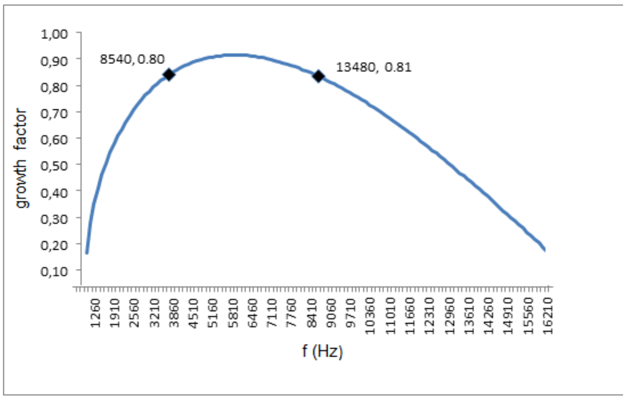

Figure 9: System's behavior graph

The initial experimentation procedure followed the principle of maintaining two variables stable while manually adjusting the third one. Fig. 10, 11 and 12 graphically present the outcome of this experimentation procedure.

Based on these experiments we observed that for a frequency of 11.8 kHz, a voltage of 22.4 V(peak to peak) and a pressure of 22kPa the system had a stable response and by using the data acquired we calculated that the production accuracy of the manually controlled system reached a level of 96% with a ±5% tolerance.

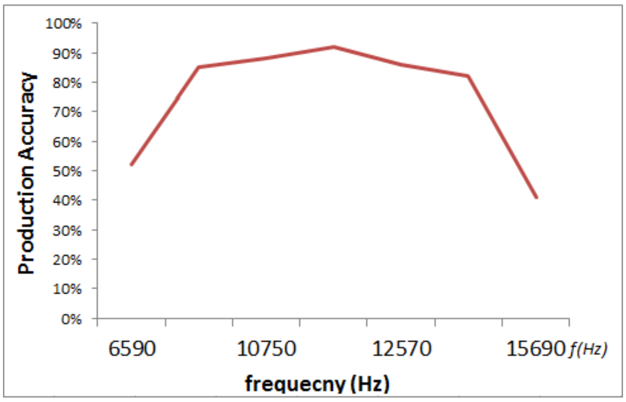

Figure 10: Production Accuracy – frequency alterations

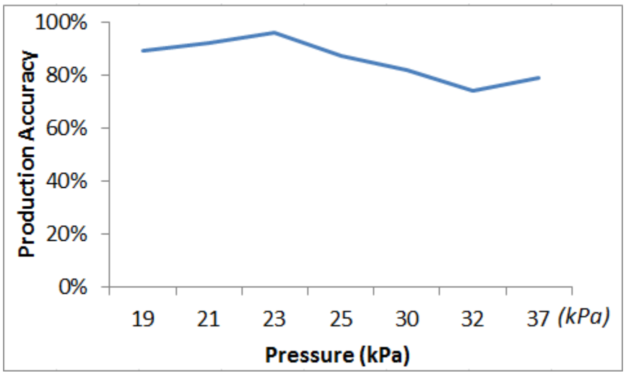

Figure 11: Production Accuracy – Pressure alterations

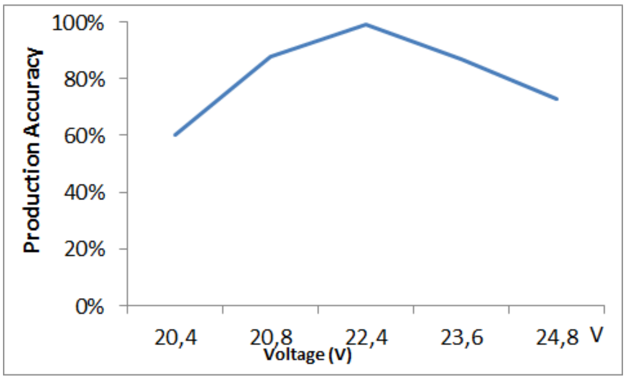

Figure 12: Voltage VS Roundness

5.2.Linear Algorithm

In terms of the linear algorithm we observed that after activation, the algorithm worked and the system started producing spheres of relative stable diameter. Fig. 13 is a comparison of sphere diameter versus sample number.

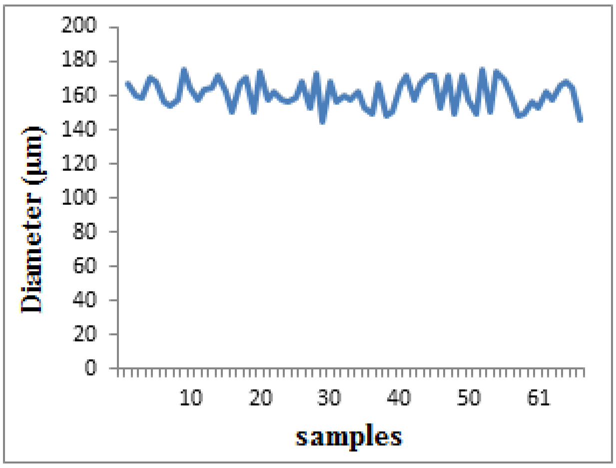

Figure 13: Linear Algorithm – Diameter VS Samples

Based on the results shown above we calculated that the accuracy level of our system with the introduction of the linear control algorithm rose to 98.2%. The average sphere diameter was 162 μm with a ±5% tolerance. This proves that the algorithm can improve the performance of our system in comparison to manually adjusting variables. The greatest advantage of the linear algorithm is that it is not time consuming and it can quickly adapt the variable values in order to reach a predefined target. The disadvantage is its inability to sustain for long periods of time the targeted production. The latter has to do with the experimental setup used, for example the tank with the liquid solder was emptying faster than in real conditions due to small size, thus affecting the tank pressure.

5.3.Adaptive Neural Network

The implementation of the proposed neural network in our system is acomplex procedure. The neural network must initially train based on a series of simulated data as well as data acquired from previous operation circles. Once training is over it can start the actual control of the system.

The performance of the neural network as it was recorded during experimentation, in terms of sphere diameter is presented in Fig. 14.

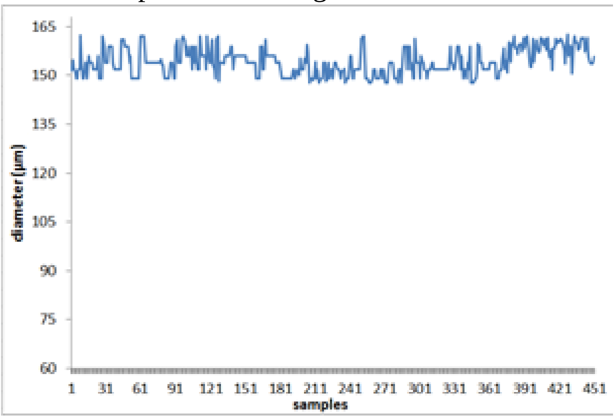

Figure 14: Neural Network – Diameter VS Samples

We observed that the accuracy level of the system with an active ANN rose to 99.4%. The average sphere diameter was 155μm with a ±5% tolerance.

The neural network was able to show a robust and stable performance for long periods of time and was able to produced better results than the simulated ones.

The disadvantage was the significant time it required for the training process to be completed. This training must be repeated every time the setup is radically changed as the training data set is connected to a particular setup.

6. Result Comparison

The advantages of the linear approach are as follows:

- Simpler design
- Not time consuming
- Doesn't require training
- Less demanding in terms of resources

The main disadvantage of the linear approach is:

- Not stable for long periods of operational time.

The advantages of the non-linear approach are:

- Extremely stable in time
- More accurate results
- More stable production rate

The disadvantages are:

- Higher complexity
- Requires training
- Time consuming

Table 3 is a comparison between the results produced by each approach.

Table 3: Result Comparison Table

Parameter	ANN	Linear control algorithm	Simulation	Open Loop (initialization)
Proportion (>=95%)	99,40%	98,20%	98,00%	96,00%
Mean (μm)	155	163	160	161
Standard error	0,93	2,93	3,20	6,44
C.I'. (95%) lower	153,14	157,13	153,60	148,12
C.I. (95 %) upper	156,86	168,87	166,40	173,88
Acceptance level (lower – 152μm)	YES	YES	YES	NO
Acceptance Level (upper – 168 μm)	YES	NO	YES	NO

Fig 15 is a representation of the sphere size distribution for both algorithm as well as the expected results based on simulation.

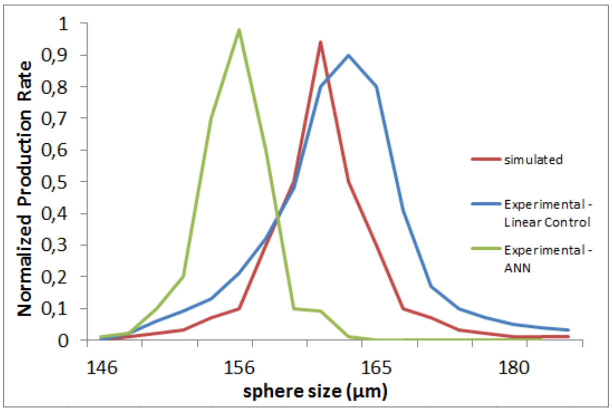

Figure 15Experimental and simulated distribution sphere size.

The performance of the linear control algorithm was very close to the expected results produced by the simulation process whereas the results of the ANN actually showed improvement in production rates and stability in comparison even to the simulated outcome.

Considering now the fact that the end target is for such systems to be used by the industry for mass production of BGAs it has become clear that the neural network is better suited for the intended control purpose.

6.1.Validation

In order now to validate the performance of both control approaches, as presented above, and verify their functionalities we have randomly selected sphere samples created during the production procedure and measured their diameter and roundness by taking snapshots of the spheres using

the installed camera module and by inserting them to a custom-developed image processing software. Furthermore actual samples were collected and examined under a digital microscope to further evaluate the results generated by the algorithms.
While the control of the system was performed by the linear control algorithm the following samples were randomly selected and a small part of them can be previewed in Figs 16 and 17.

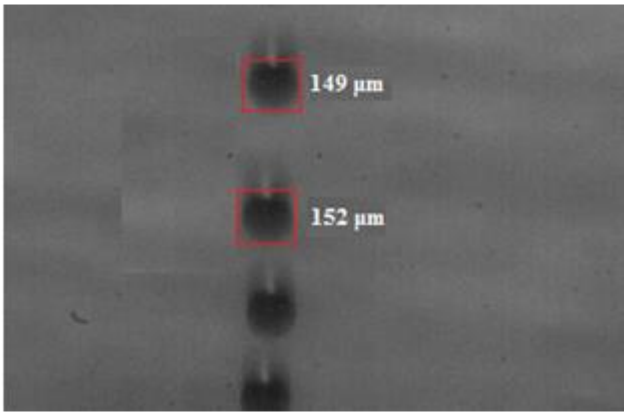

Figure 16: Camera Snapshot – Linear Control

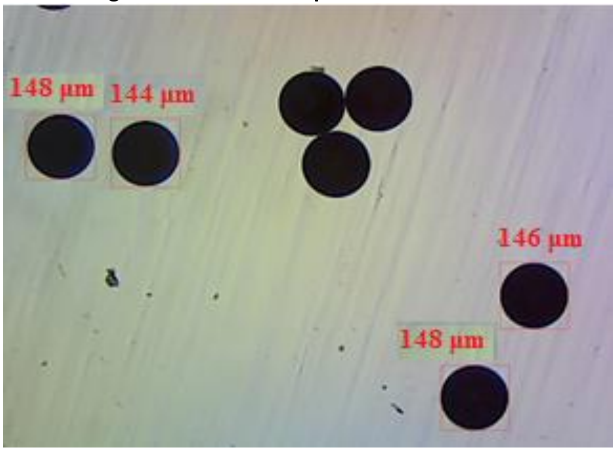

Figure 17: Microscope – Linear Control

Based on the above results we verified the correct operation of the algorithm. A comparison between the average values of the logged results and the results from both the snapshots and the microscope can be viewed in table 4.

Table 4: Sphere comparison – Linear

Average values	**Logged Results**	**Snapshot Images**	**Microscope**
Diameter	151.66μm	146μm	141μm
Roundness	94.89%	97%	96%

While the control of the system was performed by the Artificial Neural Network the following samples were randomly selected. A small part of them can be previewed in Figs 18, 19 and 20.

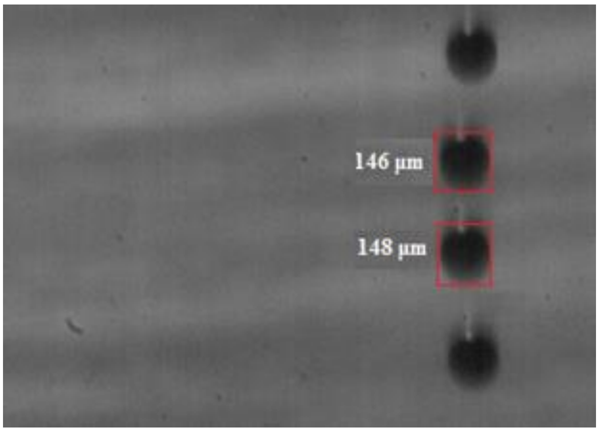

Figure 18: Camera Snapshot -- ANN

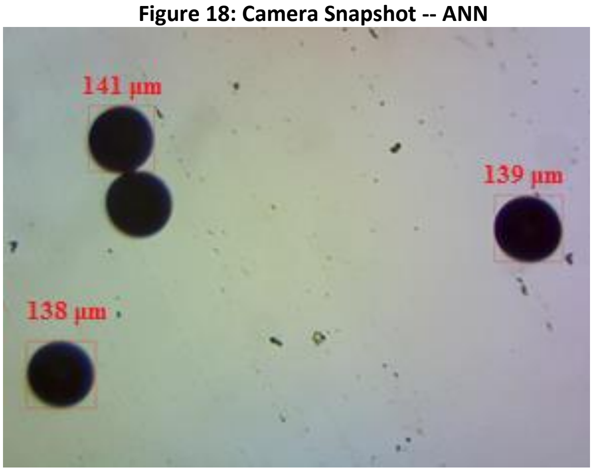

Figure 19: Microscope – ANN

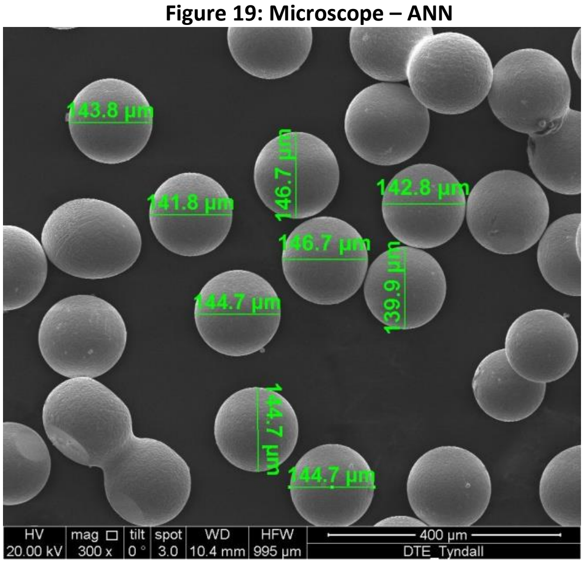

Figure 20: SEM Results – ANN

Based on the above results we verified the correct operation of the ANN. A comparison between the average values of the logged results and the results from both the snapshots and the microscope can be viewed in table 5.

Table 5: Sphere comparison – ANN

Average values	**Logged Results**	**Snapshot Images**	**Microscope**
Diameter	144.52μm	146μm	143μm
Roundness	95.11%	98%	97%

The validation procedure for both algorithms was conducted based on the examination of a few hundreds of spheres. Considering now that both algorithms have to evaluate the results of millions of spheres it is understandable to have a ±7% variation between the results produced by the algorithms and the results measured manually. The validation process proved that both algorithms are able to operate efficiently and verified the superior control capabilities of the neural network.

7. Conclusions

Two control algorithms for enabling the stable production of a μBGA system, which are also able to control a plethora of BGA production systems, were developed and presented. The first was based on linear architecture and the second was the implementation of a neural network (a non-linear approach).

Based on simulation data and the actual experimentation carried out using both algorithms it has been demonstrated that both were able to control effectively the system. Yet, the linear algorithm could not maintain a stable production rate for long periods of time. On the other hand, the neural network offered a more robust mechanism for controlling the system and maintain stable production rates.

8. Acknowledgments

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