International Journal of Advance Research in Science and Engineering
Vol. No.5, Issue No. 03, March 2016
www.ijarse.com
IJARSE
ISSN 2319 - 8354

REDUCTION OF DEFECTS IN SELECTIVE SOLDERING PROCESSES

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ABSTRACT

Selective soldering process is one of the most complex processes to keep in control in the fabrication of Printed Circuit Boards (PCB). Main reason of this complexity is the number of control variables that affects the quality of solder joints. This paper analyzes the influence of a noise factor in order to propose new control parameters that optimize the mean and reduce the variance. In order to optimize resources, timeand cost of the analysis this research work proposesto perform first a parameter screening, usingdesign of experiments (DOE) thru Taguchi methodology, to identify the most important factors and their corresponding optimal levels, then these factors are used to develop a Modified Central Composite Design (MCCD) using as central values the ones identified in the Taguchi Design. Finally we use the second order adjusted model calculated by the MCCD to apply the Dual Response Surface Methodology (DRSM)and Mathcad to calculate the control variable values that minimize the mean of solder defects and reduces the process variance.

Keywords: Design of Experiments, Dual Response Surface Methodology, Modified Central Composite Design, Selective Soldering Process, Solder Defects, Taguchi Orthogonal Designs.

I. INTRODUCTION

According to an article of the Institute of Printed Circuits (IPC) released on August of 2013 the production of PCBs for North America will grow at an annual rate of 4%. This annual growing rate forecast creates the need to have a better understanding of PCBs production processes so they can be improved and keep in control. Selective soldering is one of the most complex processes in the fabrication of PCBs when it is used Thru Hole Technology (THT). Fig. 1 shows the PPM trend chart of a selective soldering process for a transmission control unit. The purpose of this research work is to show a methodology that minimizes the use of resources, time and cost to calculate robust parameters values that minimize the amount of solder defects and reduces the effect of a noise factor.

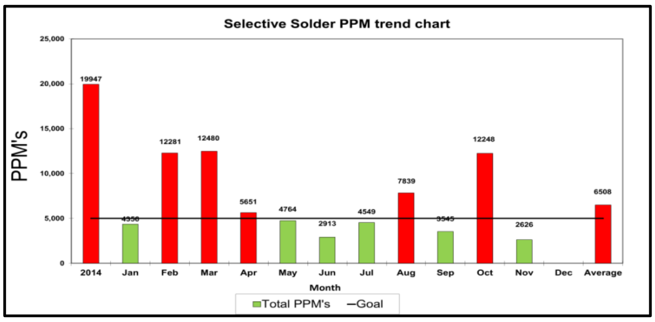

Figure 1 PPM chart for selective soldering process

1.1 Selective soldering process

In our selective soldering process it is used a customized equipment to meet a cycle time of 17 seconds, in order to meet this time the solder pot, nozzles and pallets were designed to process 6 units at the same time. The PCB is 1 ±0.1mm thickness, thru hole finishing (TH) immersion Nickel/Gold 3.0–6.0 µm/0.05-0.15 µm; temperature resistance from -40°C to 153°C; solder mask thickness from 10µm to 40 µm and a glass transition temperature Tg 170. The TH connector to be soldered to the PCB has 58 $CuSn_4$pins, with a thin lead finishing on the solder contact area. The flux used for this application is Alpha RF800 no clean with 5% of solids.The soldering area of the PCB is shown in the Fig. 2; the 58 pin connector is shown in the Fig. 3.

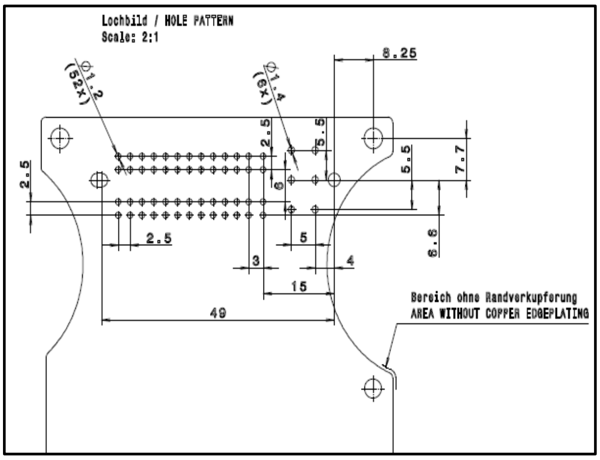

Figure 2 TH soldering area of the PCB

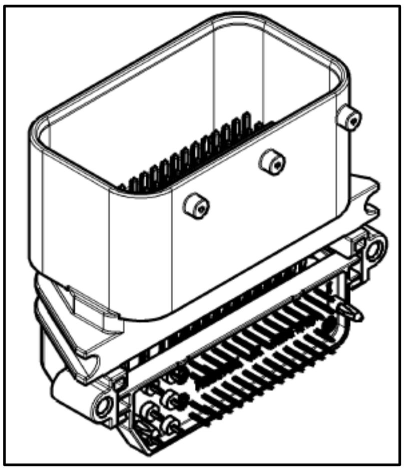

Figure 3 Connector with 58 pins.

1.2 Selection of factors for the experimental design and noise factor.

The control variables and noise factor assigned by the experts of the selective soldering processfor this DOE are shown in table 1 and 2 respectively. Current set-up values are listed in level 1. It is recommended also to define any potential interaction between the factors, and assign the correct sequence in the orthogonal array in order to identify properly the effect in the response, if any,while performing the DOE.

TABLE 1Factors and Levels for Taguchi Orthogonal Array.

Factors	Description	Level 1	Level 2
A	Wave contact time (sec)	6	4
B	Pre-heating temperature (°C)	120	150
C	Flux application speed (mm/sec)	60	40
D	Solder pot temperature (°C)	290	320
E	Separation speed (mm/sec)	3	1

TABLE 2Levels of Noise Factor.

Factor	Description	Level 1	Level 2
M	Relative Humidity Exposure time	40% 20 min	50% 120 min

II. METHOD

2.1 Taguchi orthogonal array.

[1]Taguchi (1986) recommends being careful in determining if the effect of an interaction is important enough to be included in a column in a design of experiment array. Therefore, using Taguchi technique to assign interactions to columns in a L_8array we got the factors and interaction order shown in table 3.

TABLE 3Factors and Interaction Order for L_8 Array.

L8	1	2	3	4	5	6	7
	C	B	CXB	D	CXD	A	E

2.2 Signal to Noise and Mean tables

As we are dealing with one noise factor, which is exposure time to humidity along with relative humidity percentage, Taguchi (1986) recommends using a signal to noise(S/N) relationship. The greater the S/N value, the less variability of the characteristic under analysis. In order to reduce cost of the experiment we are proposing to identify first the significant factors and the optimal levels thru the development of S/N and means tables. Then we will use these significant factors to create a complete MCCD, and the optimal values of each significant factor will be used as central values for the MCCD.

2.3 Modified Central Composite Design.

[2]Myers and Montgomery (2009) indicates that the surface response methodology (SRM) provide statistical techniques that can be used to implement robust parameters design proposed by Taguchi and overcome their limitations. [3]Lucas (1989, 1994) proposed to use the MCCD as an alternative to Taguchi's orthogonal arrays.

In general, thru Taguchi orthogonal arrays the researcher is only able to find out what is the optimal level of a factor with 2 or 3 given levels, but it does not provide any best solution in between. For example, if the researcher is interested to find the best temperature value for a given process, let the 2 levels being 100ºC and 150ºC, and let's assume that the optimal value is 100ºC, thereby the question is, could we have a best response in the output by increasing or decreasing a little bit this level? The SRM gives the answer to this question based on statistical data by developing the second order model (1).

2.4 Dual Surface Response Methodology.

[4]Myers and Carter (1973) introduce the dual surface response method to analyze the response of the second order model in two separate models, one to analyze the response to the mean(2), in which a SRM is defined, and another one to analyze the response to the variance(3), in which another SRM is generated.

$$y = \beta_0 + \sum_{i=1}^{c} \beta_i x_i + \sum_{i=1}^{c} \beta_{ii} x_i^2 + \sum_{i=1}^{c-1} \sum_{j=i+1}^{c} \beta_{ij} x_i x_j + \sum_{k=1}^{u} \delta_k z_k + \sum_{i=1}^{c} \sum_{k=1}^{u} \delta_{ik} x_i z_k + \varepsilon \quad (1)$$

$$E(y) = \beta_0 + \sum_{i=1}^{c} \beta_i x_i + \sum_{i=1}^{c} \beta_{ii} x_i^2 + \sum_{i=1}^{c-1} \sum_{j=i+1}^{c} \beta_{ij} x_i x_j \quad (2)$$

$$Var(y) = \sum_{k=1}^{u} \left(\delta_k + \sum_{i=1}^{c} \delta_{ik} x_i \right)^2 + \sigma^2 \quad (3)$$

III. RESULTS

3.1Significant factors defined thru Taguchi's orthogonal array.

Table 4 shows the result of the experiment where the outputis measured in amount of solder defects. The result of each run is shown in column M1 for the low level of noise factor, and column M2 for the high level.

TABLE 4 Array L_8 and results of experiment.

							Y	
C	B	BXC	D	CXD	A	E	M1	M2
1	1	1	1	1	1	1	0	7
1	1	1	2	2	2	2	30	42
1	2	2	1	1	2	2	15	41
1	2	2	2	2	1	1	15	40
2	1	2	1	2	1	2	13	13
2	1	2	2	1	2	1	43	53
2	2	1	1	2	2	1	20	48
2	2	1	2	1	1	2	19	36

The analysis of data performed by Minitab® Statistical Softwareis shown in Fig. 4. The main effect plot for S/N ratio and the mean are shown in Fig. 5 and Fig. 6 respectively

```
Columns of L8(2**7) Array

1 2 3 4 5 6 7
Taguchi Analysis: Y1, Y2 versus C, B, BXC, D, CXD, A, E

Response Table for Signal to Noise Ratios
Smaller is better

Level        C       B     BXC       D     CXD       A       E
1       -26.13  -25.27  -26.41  -24.32  -26.63  -23.74  -27.12
2       -29.11  -29.97  -28.84  -30.93  -28.61  -31.50  -28.12
Delta     2.98    4.70    2.43    6.61    1.97    7.77    1.01
Rank         4       3       5       2       6       1       7

Response Table for Means

Level       C      B    BXC      D    CXD      A      E
1       23.75  25.13  25.25  19.63  26.75  17.88  28.25
2       30.63  29.25  29.13  34.75  27.63  36.50  26.13
Delta    6.88   4.13   3.88  15.13   0.88  18.63   2.13
Rank        3      4      5      2      7      1      6
```

Figure 4 Analysis of data calculated by Minitab®

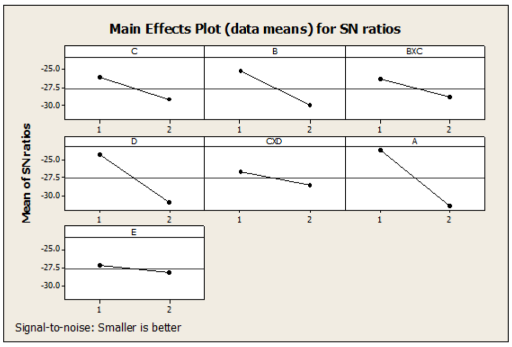

Figure 5 Main effects plot for S/N.

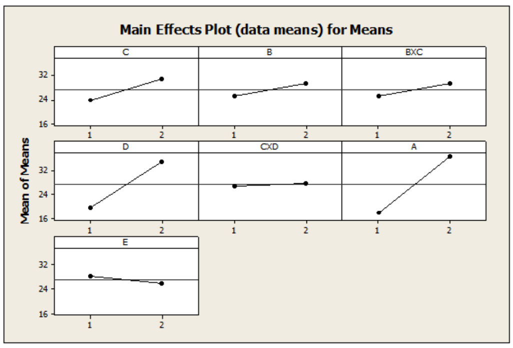

Figure 6 Main effects plot for Means.

[5]Ross (1996) defines the rules to identify the classification for each factors, the result we got is: Class I: A y D; Class II: B; Class III: C and Class IV: E; therefore the optimal values areA_1 B_1 C_1 D_1 E_1 or $_2$

International Journal of Advance Research in Science and Engineering
Vol. No.5, Issue No. 03, March 2016
www.ijarse.com
IJARSE
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Based on the results of S/N and Means tables we can conclude that the significant factors are A, B and D. The factor C, which is only significant for the mean was not considered because the ratio between the second factor D and third factor C is too large, therefore this factor can be eliminated for the MCCD.

We will use a complete 2^4 MCCD, with 3 control variables x_1, x_2 y x_3 and a noise factor z, three axial points with α = ± 1 and three central runs. The array generated is shown in table 5.

TABLE 5 Complete 2^4 MCCD with 3 central runs.

↓	C1 StdOrder	C2 RunOrder	C3 PtType	C4 Blocks	C5 x1	C6 x2	C7 x3	C8 z	C9 y
1	1	1	1	1	-1	-1	-1	-1	5
2	2	2	1	1	1	-1	-1	-1	4
3	3	3	1	1	-1	1	-1	-1	3
4	4	4	1	1	1	1	-1	-1	5
5	5	5	1	1	-1	-1	1	-1	3
6	6	6	1	1	1	-1	1	-1	2
7	7	7	1	1	-1	1	1	-1	1
8	8	8	1	1	1	1	1	-1	2
9	9	9	1	1	-1	-1	-1	1	11
10	10	10	1	1	1	-1	-1	1	9
11	11	11	1	1	-1	1	-1	1	8
12	12	12	1	1	1	1	-1	1	5
13	13	13	1	1	-1	-1	1	1	6
14	14	14	1	1	1	-1	1	1	4
15	15	15	1	1	-1	1	1	1	4
16	16	16	1	1	1	1	1	1	5
17	17	17	-1	1	-1	0	0	0	0
18	18	18	-1	1	1	0	0	0	0
19	19	19	-1	1	0	-1	0	0	0
20	20	20	-1	1	0	1	0	0	0
21	21	21	-1	1	0	0	-1	0	6
22	22	22	-1	1	0	0	1	0	2
23	25	25	0	1	0	0	0	0	0
24	26	26	0	1	0	0	0	0	0
25	27	27	0	1	0	0	0	0	0

3.2 Converting the parameters in coded units.

Figure 7 shows the values for α = ± 1 and the central points, while the values for the noise factor are the mean μ ± 1σ. Thereby the noise variable is set in coded units (4) and centered in zero with the levels ± 1 defined at ± σresulting in$E(z_j) = 0$ and$\text{Var}(z_j) = 1$ (Myers & Carter, 1973).

Coded units	-1	0	1
Contact time (Seg.)	5	6	7
Pre-heating (°C)	105	120	135
Solder pot temperature (°C)	275	290	305
Exposure to RH (mins.)	60	75	90

Figure 7 Table of variable values in coded units

$$x_1 = Contact = \frac{seg. - 6}{1} \qquad x_2 = \text{Pre}-heating = \frac{°C - 120}{15}$$

$$x_3 = pot = \frac{°C - 290}{15} \qquad z = Exp.RH = \frac{\min s. - 70}{50} \qquad (4)$$

The normal continuous numerical variable was used to determine the mean μ (5)and the standard deviation σ (6) for the noise variable according to the following formulas:

$$\mu = \frac{a+b}{2} \quad \mu = \frac{30+120}{2} = 75\ minutes \qquad (5)$$

$$s = \frac{a-b}{6} \quad s = \frac{120-30}{6} = 15\ minutes \qquad (6)$$

3.3 Calculating the coefficients for the second order model with Minitab

Second order coefficients are shown in Fig. 8.

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Central Composite Design

Factors:        4     Replicates:     1
Base runs:     27     Total runs:    27
Base blocks:    1     Total blocks:   1

Two-level factorial: Full factorial

Cube points:               16
Center points in cube:      3
Axial points:               8
Center points in axial:     0

Alpha: 1

Response Surface Regression: y versus x1, x2, x3, z

The analysis was done using coded units.

Estimated Regression Coefficients for y

Term          Coef  SE Coef       T      P
Constant   -0.1871   0.3861  -0.484  0.638
x1         -0.2778   0.2146  -1.295  0.222
x2         -0.6111   0.2146  -2.848  0.016
x3         -1.5000   0.2146  -6.990  0.000
z           1.6875   0.2276   7.414  0.000
x1*x1       0.3273   0.5487   0.597  0.563
x2*x2       0.3273   0.5487   0.597  0.563
x3*x3       4.3273   0.5487   7.886  0.000
x1*x2       0.4375   0.2276   1.922  0.081
x1*x3       0.1875   0.2276   0.824  0.428
x1*z       -0.4375   0.2276  -1.922  0.081
x2*x3       0.3125   0.2276   1.373  0.197
x2*z       -0.3125   0.2276  -1.373  0.197
x3*z       -0.3125   0.2276  -1.373  0.197

S = 0.9104    R-Sq = 96.0%    R-Sq(adj) = 91.3%


Analysis of Variance for y

Source           DF   Seq SS   Adj SS   Adj MS      F      P
Regression       13  218.883  218.883  16.8372  20.31  0.000
  Linear          4   94.174   94.174  23.5434  28.41  0.000
  Square          3  113.335  113.335  37.7782  45.58  0.000
  Interaction     6   11.375   11.375   1.8958   2.29  0.111
Residual Error   11    9.117    9.117   0.8288
  Lack-of-Fit     9    9.117    9.117   1.0130      *      *
  Pure Error      2    0.000    0.000   0.0000
Total            24  228.000


Unusual Observations for y

Obs  StdOrder      y    Fit  SE Fit  Residual  St Resid
 12        12  5.000  6.594   0.743    -1.594    -3.03 R

R denotes an observation with a large standardized residual.


Estimated Regression Coefficients for y using data in uncoded units

Term           Coef
Constant  -0.187050
x1        -0.277778
x2        -0.611111
x3         -1.50000
z           1.68750
x1*x1      0.327338
x2*x2      0.327338
x3*x3       4.32734
x1*x2      0.437500
x1*x3      0.187500
x1*z      -0.437500
x2*x3      0.312500
x2*z      -0.312500
x3*z      -0.312500
```

Fig 8 Second order coefficients calculated with Minitab

3.4 Interpretation of the MCCD result

1. Based on the value of P = 0.000 for S/N we can conclude that there is notenough data to reject the null hypothesis, therefore it is accepted:

   x_0 = Exposure time to humidity is a noise factor. **ACCEPTED**

   x_1 = Exposure time to humidity is not a noise factor

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2. As R-Sq = 91.3% we can assume that the second order model describes very well the process behavior.
3. The significant factors according to P value are x_2 and x_3.
4. For the development of dual surface response methodology only will be considered the significant values, therefore the second order adjusted model is $y = -0.61x_2 - 1.5x_3 + 1.69z + 4.33x_3^2$
5. The equation for the surface response for mean is $E(y) = -0.61x_2 - 1.5x_3 + 4.33x_3^2$
6. The equation for the surface response of variance is $V(y) = (1.69)\sigma_z^2 + \sigma^2$

Using the response optimizer tool from Minitab we get the preliminary results shown in Fig. 9.

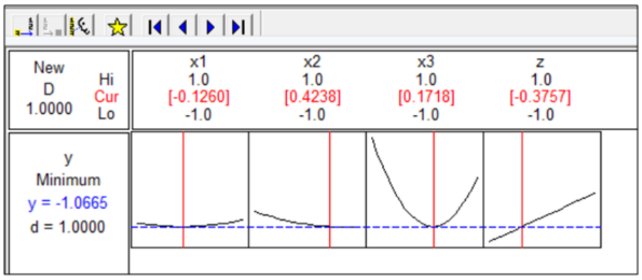

Figure 9 Minitab optimizer tool, values shown are in coded units.

Thecoded values for control variableswhere we get the minimum response for y are $x_1 = -0.126,\ x_2 = 0.4238\ and\ x_3 = 0.1718$, the uncoded values are:

$$x_1 = contacttime = \frac{seg. - 6}{1}; \qquad seg. = 6 - 0.126 = 5.9$$

$$x_2 = preheating = \frac{^\circ C - 120}{15}; \qquad ^\circ C_{preH} = 15(0.4238) + 120 = 126.4$$

$$x_3 = Pot = \frac{^\circ C - 290}{15}; \qquad ^\circ C_{Pot} = 15(0.1718) + 290 = 292.6$$

3.5Optimizing simultaneously the mean and the variance for an optimal solution

In this chapter we will show the methodology to obtain the equation that provide the values for the control variables that will minimize the mean of defects, and another equation to minimizethe variance. In our design we have 3 control variables and 1 noise factor. Fig. 10shows the code in Mathcad to define the surface response to the mean.

Objective: Minimize defects	
(Up to 3 control variables and 1 noise factor)	
Surface Response Equation for Mean	
Constant	$a := -0.187$
Coefficient of x1	$b := -0.278$
Coefficient of x2	$c := -0.61$
Coefficient of x3	$d := 4.327$
Coefficient of x1 square	$e := 0.327$
Coefficient of x2 square	$f := 0.327$
Coefficient of x3 square	$g := 4.33$
Coefficient of x1x2	$h := 0.437$
Coefficient of x1x3	$i := 0.187$
Coefficient of x2x3	$j := 0.312$

$E(x_1,x_2,x_3) := a + b\cdot x_1 + c\cdot x_2 + d\cdot x_3 + e\cdot x_1^2 + f\cdot x_2^2 + g\cdot x_3^2 + h\cdot x_1\cdot x_2 + i\cdot x_1\cdot x_3 + j\cdot x_2\cdot x_3$

Finding the best mean $\quad x_1 := 0 \quad x_2 := 0 \quad x_3 := 0$

Restriction to the experimentation zone

Given

$x_1 > -1.0 \quad x_1 < 1 \quad x_2 > -1 \quad x_2 < 1 \quad x_3 > -1 \quad x_3 < 1$

The solution to the equation is:

$minM := Minimize(E, x_1, x_2, x_3) \qquad minM = \begin{pmatrix} -0.091 \\ 1 \\ -0.534 \end{pmatrix}$

The best mean is

$E(minM_0, minM_1, minM_2) = -1.715$

Figure 10 Code in Mathcad to calculate control variables values that minimize defects.

The Fig. 11 shows the code in Mathcad that minimize the variance.

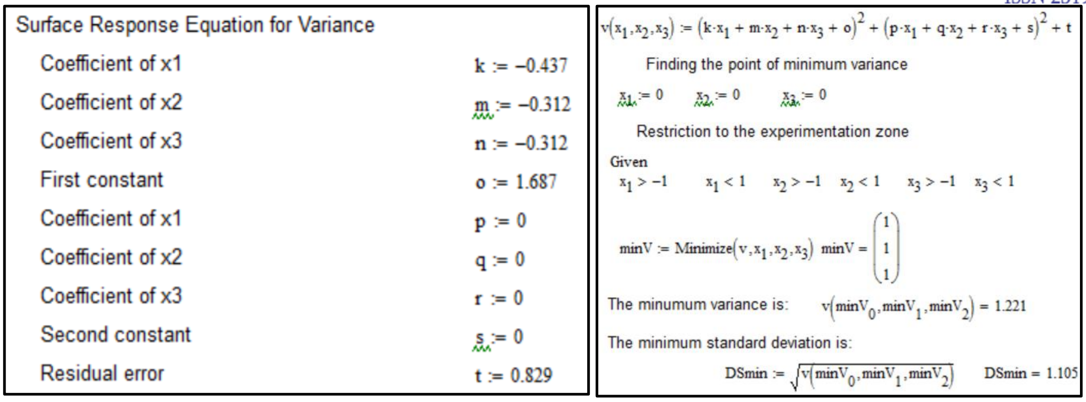

Figure 11 Code in Mathcad to calculate control variables values that minimize variance.

Once that the equations that minimizes the mean and the variance have been determined we have to calculate the best solution that optimizes both the mean and variance. For this purpose we will make iterations using different values for the "weight" of the standard deviation. In order to calculate the optimal value of the weight we can vary the values from 1/100 to 100, then for every value used the percentage of difference from the best mean and best standard deviation is calculated. Weight values below 0 means that we are given more importance to the mean, values above 0 means that we are given more importance to the standard deviation. The Fig. 12 showsthe code in Mathcad to calculate the optimal value of the weight. The best solution is when we get the lowest value for total percentage.

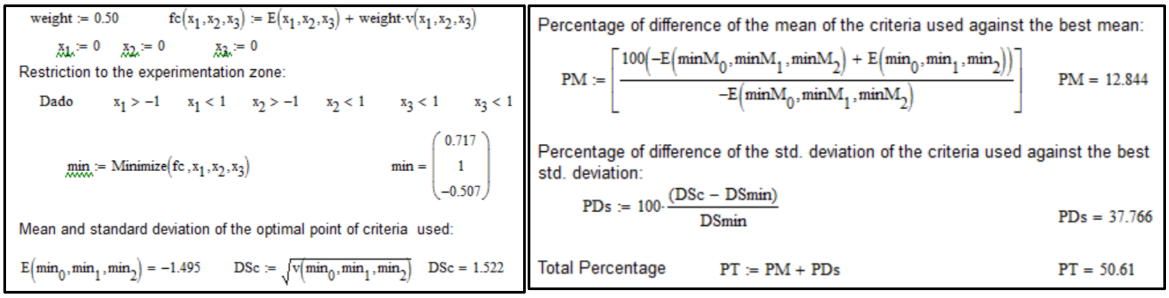

Figure 12 Code in Mathcad to calculate the weight for the standard deviation.

The table 6 shows the iterations performed to find out the optimal weight ofour research work. The table 7 shows the summary of the solutions.

TABLE 6 Iterations to Calculate the Optimal Weight of the Standard Deviation.

Weigth of σ	Percentage from the best mean	Percentage from the best variance	Total Percentage
0.01	0.01	64.39	64.40
0.30	5.60	46.80	52.40
0.40	9.03	42.04	51.06
0.45	10.90	39.84	50.74
0.50	12.84	37.77	50.61
0.55	14.86	35.80	50.65
0.60	16.92	33.93	50.85
0.70	21.14	30.48	51.61
1	24.08	28.36	52.44
2	28.47	26.74	55.21

TABLE 7 Summary of the Solutions.

Criteria	x	x	x	Mean	Stadard deviation
Optimizing Response Surface for the Mean.	-0.09	1.00	-0.53	-1.72	3.33
Optimizing Response Surface for the variance.	1.00	1.00	1.00	9.17	1.11
Combined (*m + 0.5s*)	0.72	1.00	-0.51	-1.50	1.52

Based on the best solution that minimize the mean ant the variance for x_1, x_2 and $x_3$the values of the parameters in uncoded units are:

x_1= Contact time = 6.7 seconds, x_2= preheating temp. = 135°C, x_3 = pot temp. = 282.4 °C.

With these values the minimum number of defects expected is zero, due that Mathcad calculated -1.5, and it is not possible to get defects below 0. The maximum number of defects at 3σ is 5. In summary the new values proposed for the variables that have main effects of the response and that minimize the effect of the noise factor are shown in the table 8.

TABLE 8 Proposed values for main effect factors that will minimize the effect of RH.

Variable	Current value	New value
Contact time	6 seconds	7 seconds
Preheating temperature	120 °C	135 °C
Pot temperature	290 °C	282 °C

IV. CONCLUSIONS

Taguchi orthogonal designs have demostrated to work well in experimental research works, however this technique lacks of means to find out the best solution at the surrounding area of experimentation under the influence of a noise factor. Due to this reason Taguchi was used in this research work only to perform a screening of the factors along with signal to noise methodology. In this way the main effect factors and their corresponding levels were determined, these "optimal" levels were used further as central values to perform a complete 2^4MCCD, which provide more accurate data for the analysis and overcome the limitations of Taguchi design. Response surface methodology was used to define robust process parameters using two techniques: 1-Optimizer of Minitab and, 2-Combined solution to minimize the mean and the variance with Mathcad. From a manufacturing point of view it is better to have a solution that optimizes the mean and reduce the variance. In general we can conclude that by applying these 3 steps sequence we get the best solution with minimum scrap generated due to experimental runs and less time and effort invested.

V. ACKNOWLEDGMENTS

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