International Business Management 10 (Special Issue 4): 6462-6469, 2016
ISSN: 1993-5250

Quality Management Process Optimization

Abdelkader Mazouz and Belkacem Athamena
Department of Mangement Information System, College of Business Administration,
Al Ain University Science and Technology, Abu Dhabi, UAE

Abstract: Improving the quality of a product and manufacturing processes at a low cost is an economic and technological challenge which quality engineers and researchers must contend with. However, when the process is stabilized, it needs to be improved and optimized. This study focuses on identifying the optimization techniques on comparing them and on choosing the most economical one in terms of time and cost. First, the procedure is supported by manufacturing applications used as test bed to validate the procedure undertaken in using first full factorial, Fractional design to identify the key variables that have an effect on the desired response. Second, the Tagushi Orthogonal two step optimization and a natural neural network are used to optimize the process. Finally, the study shows that the Tagushi approach requires less number of experiments while providing the same optimization results as full and fractional factorial designs.

Key words: Design of experiments, Tagushi method, two step optimization, orthogonal arrays, factorial design

INTRODUCTION

Process optimization is to have a process that delivers higher yield, more product or higher return from existing assets. Business activities need process optimization at various stages during manufacturing or services. Business process optimization involves procurement, marketing, research and other business functions. The best companies continue to strive for continuous process optimization exercises throughout their existence. The most important step in process optimization is the “what if” scenario modelling. In an environment of increasing international competition where countries with lower production costs quickly catch up technologically, new thinking is required in order to meet the competition. A proactive way of meeting the increasing competition is to focus on maximizing the utilization of existing technology and faster than the competitors, being able to continuously introduce and make use of new technology. This means much more than just investing in new equipment. The ability to optimize or improve a process is dependent upon the ability to control the process. The ability to control the process is dependent upon the access to reliable and valid measurements.

A successful industrial optimization thus entails a strategic approach encompassing the whole chain: Measuring, controlling then optimizing optimizing is the final stage. Design Of Experiments (DOE) (Chirdchid and Mazouz, 2002) is a data driven optimization approach which translates into time and cost savings andprovides a systematic approach. DOE is the design of any information-gathering exercises where variation is present. It is a way to optimize processes where problems are afflicting operations. It provides information about the interaction of factors and the way the total system works.

This study demonstrates the comparison of the findings in an industrial setting between full factorial, fractional design and the Tagushi orthogonal array two step optimization. The procedures of the findings from the first step are carried out on the second step of the study, where the full factorial and/or fractional factorial design identifies the key and main variables that have an effect on the response, then the Tagushi orthogonal two step techniques will refine the study by optimizing the process are done in the first step, then a neural network is used to optimize the process.

There are several approaches, the objective is to compare several optimization approaches and identify the best technique relevant to the situation. A comparison is made between full factorial design, fractional design and tagushi orthogonal two step design. A platform for the study is considered related to a bioengineering application of a hollow fiber spinning process.

The objective is to optimize a manufacturing process in the bioengineering area. The study in consideration is the optimization of a hollow fiber melt spinning process; the aim is to determine the expected core gas pressure, a measure of the spun fiber quality. First, a full factorial is run, then an analysis of variance is conducted in order to

Corresponding Author: Abdelkader Mazouz, Department of Mangement Information System, College of Business Administration, Al Ain University Science and Technology, Abu Dhai, UAE

determine the main variables that have an effect on the core gas, after that a two-step optimization procedure will be performed using the Tagushi technique.

Literature review: Douglas (2004) and Gupta *et al*. (2011) presents an effective approach as to how to design, conduct andanalyze experiments that optimize performance in products and processes. He provides a thorough description on the design of experiments, full factorial and fractional design andapplications of Analysis of Variance (ANOVA). He shows the used statistically designed experiments in obtaining information for characterization and optimization of systems, the ways to improve manufacturing processes anddesign and develop new processes and products. On the other hand, (Tagushi *et al*., 1992; Hafeez *et al*., 2002), shows that the orthogonal arrays are highly fractional orthogonal. These designs are used to estimate main effects using only a few experimental runs. They are applicable for two level and more experiments, where they can investigate main effects for certain mixed level experiments as factors do not have to have the same number of levels. Some applications are portrayed in the book by Tagushi and elsayed (Han *et al*., 1993).

Mazouz, Chirchid and Pantia (John, 2011) approach the design of experiments on using Artificial Neural Network (ANN) and fuzzy logic where a new set of variables and levels are identified andthen the data is generated through the ANN system embedded with fuzzy logic. This will account for the viability between experiments with the same variables and levels. The orthogonal arrays help on minimizing the number of runs without losing the efficiency of the experiments.

In terms of industrial applications, several related study have been identified among which is the one by Hafeez *et al*. (2002) and Kuo and Wu (2009). This study describes the design optimization of a robot sensor used for locating 3D objects employing the Taguchi method in a computer simulation scenario. The location information from the sensor is to be utilized to control the movements of an industrial robot in a ‘pick-and-place’ or assembly operation. The Taguchi method which is based on the ANOVA approach is utilized to improve the performance of the sensor over a wider operating range. A review of the Taguchi method is presented along with step-by-step implementation details to identify and optimize the design parameters of the sensor. The method shows the impact of various interactions present in the sensor system exclusively and permits to single out those factors that have a dominant influence on the overall performance of the sensor. The findings suggest that the Taguchi method is a more structured and efficient approach for achieving a robust design compared with the classical full factorial design approach. The second application set by Han *et al*. (1993) and Angelopoulos and Koukouvinos (2008) is related to Printed Circuit Board (PCB) inspection using ANNs. The challenge is similar to the work done on screen printing, mainly in identifying the main effects. The network is trained to distinguish between correct and faulty PCB assembly boards. The setup consists of a video camera, a robot anda machine vision system along with an IBM PC. The back propagation algorithm is used to train the network.

Another application is that introduced by Gupta *et al*. (2011), it aimed at enhancing system design productivity by exploiting the principle of “design and reuse” to its full potential. A statistical model is set for selecting from a component library the optimal components for a network-on-chip architecture to satisfy certain system performance requirements. Our model is based on regression analysis and Taguchi’s optimization technique. The model estimates the relationship between system performance and component attributes, to help the architect in the component selection process. Having such a model in the system design phase will allow the architect not only to make informed decisions when selecting components but also to exchange components with similar characteristics to fine tune system performance.

Chirdchid and Mazouz (Douglas, 2004) foresees to optimize the parameter and tolerance designs. As it is well documented, parameter and tolerance design are the main key to achieve high quality of products. However, high costs still remain in the process due to reducing the tolerance limit. The objective of this work is to combine the optimization of parameter and tolerance design in one stage into the cost function. This cost function is the sum of tolerance cost function and Tagushi’s quality loss function. Taylor expansion which will be applied in the genetic algorithm, considers close attention regarding its potential as a novel optimization technique for searching the optimization value.

Kuo and Wu (2009) and Nekkanti *et al*. (2015) an approach is developed to determine the overall best parameter setting in design of experiments. It first sets a successive orthogonal array experiments and ends with a full factorial experiment. The setup for the next orthogonal-array experiment is obtained from the previous one by either fixing a factor at a given level or by reducing the number of levels considered for all currently non-fixed factors. An industrial problem with seven parameters at three levels each, translating to 2,187 points. With the new method using 3% of the number of experiments, compared to the Taguchi approach which in this case corresponded to the 366th of the 2,187 possibilities. We conclude the proposed approach would provide an accurate, fast andeconomic tool for optimization using design of experiments and orthogonal arrays approach.

Koukouvinos (Taguchi *et al*., 1987), uses non-isomorphic orthogonal arrays as combined arrays in order to identify a model that contains all the main effects (control and noise), their control-by-noise interactions and their control-by-control interactions with high efficiency. Some cases where the control-by-control-noise are of interest are also considered.

John (2011) and Tagushi *et al.* (1992) demonstrates the variation between the set torque and the actual torque at which the actuator trips can be minimized using Taguchi's robust engineering methodology and shows the application of feature selection approach for the identification of insignificant effects in unreplicated fractional factorial experiments. The effect of five control factors (with two levels each) and two interactions were studied. The experiments were designed using L8 orthogonal array. The findings showed that the factors spring height, spring thickness, star washer position and the interaction between drive shaft length and spring height play a significant role in actuator performance. The implementation of the optimum combination of factors resulted in improving the overall capability indices.

MATERIALS AND METHODS

The porposed approach: In both experimental cases, the study of the effect of four factors on process is conducted. In the case, these factors are varied at three levels each as part of a 3^4 full factorial design. Through the analysis of variance, we test the hypothesis that the factors have or don't have any effect on the output response. A one half fractional resolution 4 design is also analyzed and compared to the full factorial model for the study and one way ANOVA is conducted on each factor, to state whether there is a difference between the levels for each factor. A regression analysis and a multivariate model are developed. Then a two step Tagushi orthogonal array is performed.

The key critical input variables that have an impact on the output response are selected mainly from past experience coming from engineer's knowledge on hollow fiber spinning optimization process. The ongoing work concentrates on pre-selected critical process variables and through the use of DOE, the current setting is validated or determine new optimal ones. Finally, making sure that there is correlation between both pieces of equipment with identical settings is of course a must. The objective is to determine the expected core gas

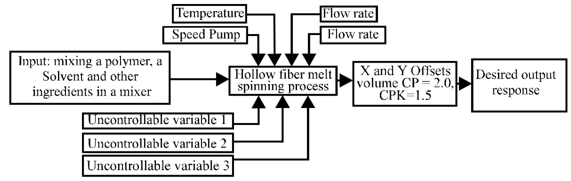

Fig. 1: The hollow fiber melt spinning process I/O block diagram with controllable and some uncontrollable variables

pressure, a measure of the spun fiber quality. First a full factorial is run, an ANOVA is conducted in order to determine the main variables that have an effect on the core gas as depicted in Fig. 1.

RESULTS AND DISCUSSION

The core gas process considers four factors: Temperature, flow rate, cooler level and speed of pump, the response, the desired is pressure. Each factor is set at three levels as shown in Table 1-4.

The ANOVA for the full factorial is shown in Table 5. All the main variables are significant, temperature, cooler, flow rate and speed. Moreover, some interaction like temperature and flow rate and temperature and speed are significant at both level of 5 and 1%. However, the interaction between flow rate and cooler and between flow rate and speed are significant at 5% but not at 1%. At 5%, F critical at $\alpha = 0.05$ is 2.37 and F critical at $\alpha = 0.01$ is 3.32 which all of combinations specified above are greater than the F table. Other combinations are not significant. The $R^2 = 0.990$ and the adjusted $R^2 = 0.984$. If we look at R^2 which is 99% and also at adjusted R^2 which is still very high, equals to 98.4%. These could prove that all variables that we have are good enough to use for evaluating and that they do contribute to the variability of the output response. The next step a one way ANOVA is run for each factor. The objective is to check if there is difference between levels for each factor or not as shown in Table 6-9.

The ANOVA of temperature is summarized in the Table 6. comparing the F value to the F table at $\alpha = 0.05$, $V1 = 2$ and $V2 = \infty$ which provide $F = 3.00$. This indicates that the temperature means are not equal. More formally, the F value that we get from data is more than F table which means the null hypothesis has to be rejected and conclude that the temperature means differ, so that the Temperature significantly affects the mean pressure. The ANOVA of speed is summarized in Table 7. Comparing

Table 1: Factors, level and number of runs

Factors	Level	No. of runs
Temperature	344	81
	347	81
	350	81
Flow rate	85	81
	88	81
	91	81
Cooler	10	81
	11	81
	12	81
Speed	23	81
	24	81
	25	81

Table 2: Runs with 3 replicates, speed level = 23

	Cooler level = 10 (flow rate level)			Cooler level = 11 (flow rate level)			Cooler level = 12 (flow rate level temperature)		
Temperature	85	88	91	85	88	91	85	88	91
344	0.481	0.496	0.509	0.476	0.491	0.510	0.475	0.487	0.504
	0.481	0.490	0.510	0.478	0.492	0.506	0.472	1.490	0.509
	0.477	0.491	0.513	0.474	0.494	0.508	0.476	0.492	0.508
347	0.490	0.502	0.520	0.483	0.498	0.514	0.482	0.502	0.516
	0.486	0.506	0.514	0.488	0.502	0.518	0.480	0.496	0.514
	0.487	0.507	0.517	0.485	0.504	0.516	0.481	0.498	0.512
350	0.499	0.509	0.521	0.499	0.510	0.520	0.496	0.510	0.518
	0.496	0.513	0.524	0.495	0.507	0.523	0.492	0.506	0.521
	0.500	0.511	0.526	0.496	0.509	0.519	0.497	0.508	0.519

Table 3: Runs with 3 replicates, speed level = 24

	Cooler level = 10 (flow rate level)			Cooler level = 11 (flow rate level)			Cooler level = 12 (Flow rate level temperature)		
Temperature	85	88	91	85	88	91	85	88	91
344	0.460	0.472	0.495	0.455	0.478	0.488	0.450	0.470	0.488
	0.464	0.471	0.491	0.452	0.476	0.485	0.458	0.480	0.487
	0.459	0.471	0.495	0.451	0.472	0.487	0.456	0.468	0.489
347	0.472	0.494	0.504	0.465	0.488	0.500	0.464	0.485	0.500
	0.474	0.489	0.502	0.471	0.484	0.498	0.469	0.481	0.498
	0.478	0.491	0.499	0.469	0.482	0.502	0.466	0.487	0.496
350	0.486	0.495	0.508	0.480	0.494	0.507	0.479	0.488	0.502
	0.483	0.499	0.512	0.485	0.497	0.510	0.480	0.492	0.507
	0.480	0.497	0.509	0.482	0.492	0.504	0.482	0.495	0.504

Table 4: Runs with 3 replicates, speed level = 25

	Cooler level = 10 (flow rate level)			Cooler level = 11 (flow rate level)			Cooler level = 12 (Flow rate level temperature)		
Temperature	85	88	91	85	88	91	85	88	91
344	0.443	0.460	0.480	0.440	0.459	0.476	0.437	0.459	0.475
	0.445	0.458	0.478	0.439	0.455	0.476	0.435	0.451	0.474
	0.446	0.460	0.476	0.435	0.458	0.478	0.434	0.457	0.475
347	0.458	0.475	0.488	0.453	0.468	0.487	0.452	0.471	0.486
	0.461	0.471	0.493	0.456	0.472	0.482	0.454	0.466	0.482
	0.456	0.469	0.491	0.458	0.474	0.485	0.455	0.469	0.484
350	0.468	0.479	0.494	0.466	0.480	0.492	0.464	0.482	0.496
	0.472	0.482	0.498	0.464	0.485	0.496	0.460	0.479	0.493
	0.470	0.484	0.496	0.467	0.483	0.494	0.461	0.476	0.490

Table 5: Tests of between-subjects effects, dependent variable-pressure

Source of variation	Type 3 sum of squares	df	Mean square	F-values	Sig.
Corrected model	9.487E-02	80	1.186E-03	191.986	0.000
Intercept	57.129	1	57.129	9248673.770	0.000
TEMP	1.683E-02	2	8.415E-03	1362.264	0.000
FLOW	3.706E-02	2	1.853E-02	2999.667	0.000
COOLER	8.958E-04	2	4.479E-04	72.514	0.000

Table 5: Continue

Source of variation	Type 3 sum of squares	df	Mean square	F-values	Sig.
SPEED	3.881E-02	2	1.941E-02	3141.574	0.000
TEMP×FLOW	4.551E-04	4	1.138E-04	18.419	0.000
TEMP×COOLER	2.318E-05	4	5.794E-06	0.938	0.443
FLOW×COOLER	6.737E-05	4	1.684E-05	2.727	0.031
TEMP×FLOW×COOLER	6.961E-05	8	8.702E-06	1.409	0.196
TEMP×SPEED	2.995E-04	4	7.489E-05	12.124	0.000
FLOW×SPEED	7.352E-05	4	1.838E-05	2.976	0.021
TEMP×FLOW×SPEED	6.932E-05	8	8.665E-06	1.403	0.199
COOLER×SPEED	1.545E-05	4	3.862E-06	0.625	0.645
TEMP×COOLER×SPEED	2.998E-05	8	3.748E-06	0.607	0.771
FLOW×COOLER×SPEED	2.527E-05	8	3.158E-06	0.511	0.847
TEMP×FLOW×COOLER×SPEED	1.493E-04	16	9.331E-06	1.511	0.101
Error	1.001E-03	162	6.177E-06	-	-
Total	57.225	243	-	-	-
Corrected total	9.587E-02	242	-	-	-

Table 6: One way ANOVA for temperature-pressure

Variables	Sum of squares	df	Mean square	F-value	Sig.
Between groups	1.585E-02	2	7.925E-03	22.455	0.000
Within Groups	8.470E-02	240	3.529E-04	-	-
Total	0.101	242	-	-	-

Table 7: One way ANOVA for speed-pressure

Variables	Sum of squares	df	Mean square	F-value	Sig.
Between groups	4.047E-02	2	2.024E-02	80.846	0.000
Within groups	6.007E-02	240	2.503E-04	-	-
Total	0.101	242	-	-	-

Table 8: One way ANOVA for cooler-pressure

Variables	Sum of squares	df	Mean square	F-value	Sig.
Between groups	6.727E-04	2	3.363E-04	0.808	0.447
Within groups	9.987E-02	240	4.161E-04	-	-
Total	0.101	242	-	-	-

Table 9: One way ANOVA for flow rate-pressure

Variables	Sum of squares	df	Mean square	F-value	Sig.
Between groups	3.691E-02	2	1.845E-02	75.323	0.000
Within groups	5.880E-02	240	2.450E-04	-	-
Total	9.570E-02	242	-	-	-

the F value to the F table at $\alpha = 0.05$, V1 =2 and V2 = ∞ which provide F = 3.00. This indicates that the speed means are not equal. More formally, the F value that we get from data is more than F form table which means the null hypothesis has to be rejected and conclude that the speed means differ, so that the speed significantly affects the mean pressure.

The ANOVA of cooler is summarized in Table 8. comparing the F value to the F table at $\alpha = 0.05$, V1 = 2 and V2 = ∞ which provide F = 3.00. This indicates that the Cooler means are equal. More formally, the F value that we get from data is less than F form table which means the null hypothesis cannot be rejected and conclude that the cooler means are the same so that the cooler are not significantly affects the mean pressure.

The ANOVA of flow rate is summarized in Table 9. Comparing the F value to the F table at $\alpha = 0.05$, V1 = 2 andV2 = ∞ which provide F = 3.00. This indicates that the Flow rate means are not equal. More formally, the F value that we get from data is more than F form table which means the null hypothesis has to be rejected and conclude that the flow rate means differ, so that the flow rate significantly affects the mean pressure.

A L9 Orthogonal array with 3 replicates is used; this has reduced the number of combination runs. The results from both techniques, Tagushi orthogonal array two step procedure and full factorial yielded the same results. Table 10 shows all data, mean and S/N computations.

Then the two step procedure is done by computing the means and S/N ratios in order to come up with the response tables for the mean Table 11 and S/N ratio Table 12 to eventually generate the two step (Table 13):

$$S/N = 10\log\left(\frac{S_m - V_0}{V_0}\right)$$

And:

$$S_m = \frac{\text{Total}^2}{m} = \frac{\left(Y_1 + Y_2 + Y_3\right)^2}{4}$$

$$V_0 = \sum_{i=1}^{3}\frac{\left(Y_i - \bar{Y}\right)^2}{n-1}$$

In Table 11, X_4 has the most effect to the mean, the results show in Table 12 which could see that X_3 has the most effect to the S/N. X_2 is the second one and the last group which include X_1 and X_4, they have almost the same value. Therefore, the conformation runs bases on the optimum combination. Comparing the result with the full factorial design both give the same answer that all main factors are significant to the data set.

Neural network is a maintain tool for controlling the quality or the value of the data set. This technique will be applied after we finish setting up the parameter by using those all kinds of technique to help. The Neural network uses the data it gets from all combination to train the system and let the system learn by itself. The best system of neural network depends on how good the data and how many the data are. For this experiment the data set will be divided into three sets: 70% will be used for

Table 10: L9 Layout and computations

Temperature (X1)	Flow (X_2)	Cooler (X_3)	Speed (X_4)	Metrics Y1	Y2	Y3	Mean (Y)	Signal to noise ratio
1	1	1	1	0.480	0.480	0.477	0.47967	46.349
1	2	2	2	0.478	0.476	0.472	0.47533	43.839
1	3	3	3	0.475	0.474	0.475	0.47467	58.299
2	1	2	3	0.453	0.456	0.458	0.45567	45.156
2	2	3	1	0.502	0.496	0.498	0.49867	44.256
2	3	1	2	0.504	0.502	0.499	0.50167	45.992
3	1	3	2	0.479	0.480	0.482	0.48033	44.784
3	2	1	3	0.479	0.482	0.484	0.48167	45.638
3	3	2	1	0.520	0.523	0.519	0.52067	47.963

Table 11: Mean respond table

Level	X1	X2	X3	X4
1	0.48	0.472	0.488	0.50
2	0.49	0.485	0.484	0.49
3	0.49	0.499	0.485	0.47
Delta	0.01	0.027	0.004	0.03
Rank	3	2	4	1

Table 12: S/N respond table

Levels	X1	X2	X3	X4
1	49.50	45.43	33.78	46.19
2	45.13	44.58	45.65	44.87
3	46.13	50.75	49.11	49.70
Delta	4.361	6.174	15.33	4.826
Rank	4	2	1	3

Table 13: Two step optimization

Factors	Effect S/N	Effect Y	Effect only S/N	Effect S/N and Y	Effect only Y
X_1	-	-	-	-	$X1_{1,2\ or\ 3}$
X_2	*	*	-	$X2_3$	-
X_3	*	-	$X3_3$	-	-
X_4	-	*	-	-	$X4_3$

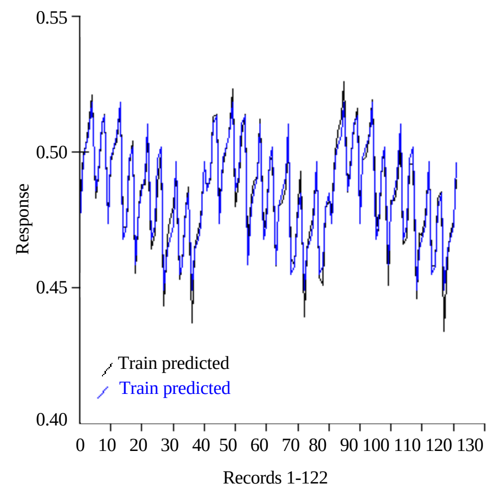

Fig. 2: Predicted vs. desired, neuro genetic optimizer

training, 20% for testing and another 10% for validation. This data set is also applied into neuro genetic optimizer.

Figure 2 shows the closeness between the predicted values of Pressure and the desired ones. The graphs are very close together which indicates that the neural network provided a good learning process from the past data taken. This is another window as shown in Fig. 3. It identifies the best network which shows that R^2 is very high. The summary results of neuro genetic optimizer system is.

Summary results of neurogenetic optimizer

Source data file:

- Project DOE.csv
- File contains 243 records and 5 fields
- Every 2 records were split to create
- 122 training records and 121 testing records

Parameters used in this run:

- Generations run: 10
- Population size: 30
- The minimum network training passes for each network were 20
- The cutoff for network training passes was 50
- The input neural node influence factor used was 0
- The hidden neural node influence factor used was 0
- The limit on hidden neurons was 8
- Selection was performed by the top 50% surviving
- Refilling of the population was done by cloning the survivors
- Mating was performed by using the TailSwap Technique

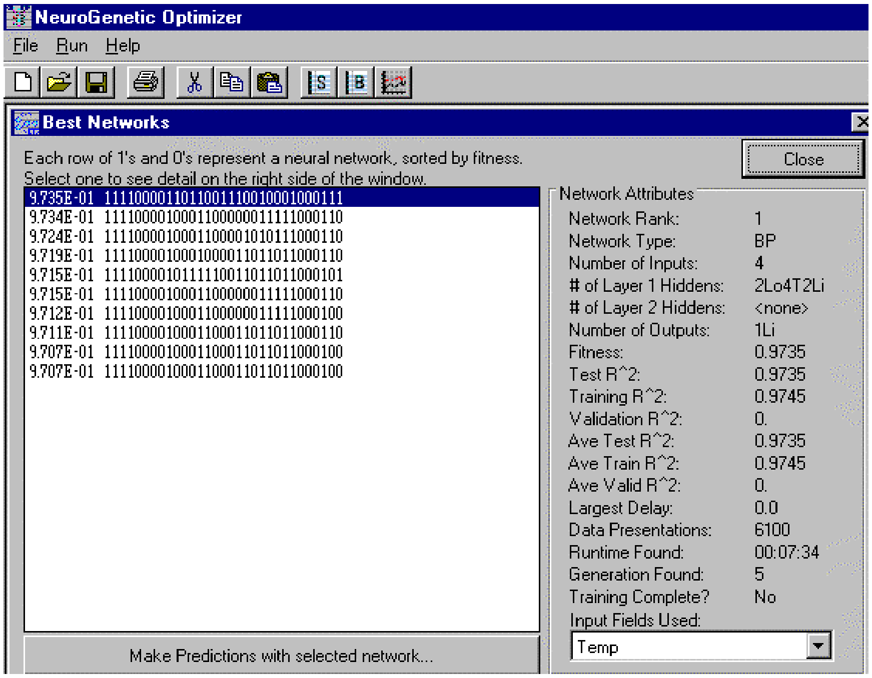

Fig. 3: Neural network best outputs

Mutations were performed using the following technique (s):

- Random exchange technique at a rate of 25%
- Information on network rank 1 that evolved
- Found on generation 1 after a runtime of 00:00:03
- Training of this network is considered complete
- R^2 on training set: 0.9719
- Max.R^2 on test set: 0.9704
- R^2 on validation set: 0.00
- This network is a fast-back propagation neural network
- The network employed 4 inputs and 1 hidden layer with 3 logistic 3 Tanh and 3 linear neurons
- There were 1 output neurons using the logistic transfer function
- Four columns in the data file were used: temperature, flow rate, cooler and speed

As we can see the results show very high the R^2 and this indicates that the system is able to predict the right of >90% for the new combination of data which is very good. So, this system is ready to test and be used for maintaining the system.

CONCLUSION

This study demonstrates the comparison of the findings in an industrial setting between full factorial, fractional design and the Tagushi orthogonal array two step optimization. The procedures of the findings from the first step of the study are carried out, where the full factorial and/or fractional factorial design identifies the key and main variables that have an effect on the response andthen the Tagushi orthogonal two step techniques will refine the study by optimizing the process. The key critical input variables that will impact the output response were selected mainly from past experience coming from engineers knowledgeable of the process. The ongoing work concentrates on pre-selected critical process variables and through the use of DOE, validate its current settings or determine new optimal ones. Four factors were varied at three levels each as part of a 3^4 full factorial design. The full factorial will set the pace in identifying key variables affecting the response; the second step is carried by the Tagushi orthogonal array two step optimization to optimize the process. The analysis has been used to set the pace for the procedure. This approach has been proven to be time and cost efficient at the token optimizing the process where quality is achieved and maintained at the desired level.

REFERENCES

Angelopoulos, P. and C. Koukouvinos, 2008. Some robust parameter designs from orthogonal arrays. J. Appl. Stat., 35: 1399-1408.

Chirdchid, S. and A.K. Mazouz, 2002. A genetic algorithm for combined parameter and tolerance design optimization. Proceeding of the International Conference on Industrial Technology, ICIT'02, December 11-14, 2002, IEEE, Florida, USA., ISBN:0-7803-7657-9, pp: 1223-1228.

Douglas, C.M., 2004. Design and Analysis of Experiments Solutions Manual. 6th Edn., Wiley and Sons Inc., USA., ISBN-13: 978-0-471-73304-1, pp: 280.

Gupta, V., A. Mazouz, A. Agarwal and G. Hamza-Lup, 2011. A statistical model for system components selection. Proceedings of the 2011 IEEE International Systems Conference (SysCon), April 4-7, 2011, IEEE, Boca Raton, USA., ISBN: 978-1-4244-9494-1, pp: 1-6.

Hafeez, K., H. Rowlands, G. Kanji and S. Iqbal, 2002. Design optimization using ANOVA. J. Appl. Stat., 29: 895-906.

Han, C., K. Mazouz and N. Saravanan, 1993. A printed circuit board inspection system using artificial neural network. Proceeding of the 25th Southeastern Symposium on System Theory SSST'93, March 7-9, 1993, IEEE, Boca Raton, Florida, ISBN:0-8186-3560-6, pp: 238-242.

John, B., 2011. Optimization of actuator performance using robust engineering and feature selection methodologies: A case study. Int. J. Prod. Perform. Manage., 60: 642-652.

Kuo, H.C. and J.L. Wu, 2009. A new approach with orthogonal array for global optimization in design of experiments. J. Global Optim., 44: 563-578.

Nekkanti, V., A. Marwah and R. Pillai, 2015. Media milling process optimization for manufacture of drug nanoparticles using design of experiments (DOE). Drug Dev. Ind. Pharm., 41: 124-130.

Taguchi, G., S. Konishi and S. Konishi, 1987. Taguchi Methods Orthogonal Arrays and Linear Graphs: Tools for Quality Engineering. American Supplier Institute, Nasr City, Cairo, Egypt, ISBN-13: 9780941243018, pp: 8-35.

Tagushi, G ., A. Elsayed and T. Hsiang, 1992. Quality Engineering in Production Systems. 3rd Edn., McGraw Hill Publisher, California, USA., ISBN: 9780070628304, Pages: 173.