A Practical Approach for Performing Multi-response Optimization for Advanced Process Control

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Abstract

In account of the statistical methods used in advanced manufacturing process optimization, multi-response optimization is one of the key areas of focus. Previously multi-response optimization problems were solved by past experiences and engineering judgment by many industries which lead to uncertainty in the decision making & and less confidence in getting optimized process parameters to produce robust products. For identifying the optimal process parameters for a manufacturing a robust product in which multiple CTQ (Critical-to-Quality) characteristics need to be achieved, a systematic statistical optimization approach is required. This paper presents one of the practical systematic approaches for multi-response optimization of advanced manufacturing processes. This statistical methodology uses Taguchi DoE (Design of Experiment) based approach to optimize the process parameters for individual CTQ followed by a multi-response optimization using composite desirability functions to achieve multiple CTQs.

Keywords: Multi-response optimization, Design of Experiments, Critical-to-Quality, Taguchi, Regression

I. Introduction

In general, advanced polymer manufacturing processes require extreme control over multiple process parameters (control factors) to achieve desired quality in the final product. Quality of the product manufactured by different processes like injection molding, blow molding, compression molding, thermoforming, extrusion etc., drastically varies with respect to change in set process parameters like temperature, cooling time, cooling rate, pressure, material flow rate, etc. Therefore, it is important to choose the right settings for each control factor to achieve the right critical-to-quality (CTQ) parameter/properties. As the number of CTQs to be satisfied increases, the processing window becomes narrow. Hence, it is a challenging task for the engineers to arrive at the right process window when multiple CTQs need to be satisfied to achieve the desired quality.

Various Design of Experiment (DoE) based approaches are used in the industry to identify the right process window which would help to achieve the CTQs of the final product. In reality, the overall quality of the product is determined by multiple CTQs. It is almost impossible to achieve multiple CTQs using only one set of control factor values. Therefore, multiple control factors have to be optimized to get a balanced trade-off between all the CTQs, without compromising the overall performance.

Taguchi is one of the popular DoE approaches, where multiple process parameters can be controlled to manufacture a robust product with minimum number of experimental runs [1]. Although Taguchi method helps to optimize multiple process parameters (control factors) to satisfy single CTQ (single response) at a time, it may not optimize the process parameters when multiple CTQs (multiple responses) are to be satisfied simultaneously. Traditionally, Analytical Hierarchical Process (AHP) is used to obtain balanced trade-off when the importance level of multiple CTQs is already known based on engineering judgement. This method might not be a recommended solution for multi-response optimization when the manufacturing process is complex and is very sensitive to minor changes in control factors. Other methods include fuzzy logic [2] which employs grey relational ranking analysis, ridge analysis [3] where single response is maximized while keeping the other responses constrained within certain targeted values, loss function based approach etc. In the present work and alternative approach, where regression functions in combination with Taguchi responses was used to perform multi-response optimization. In this approach a regression functions was generated using Ordinary Least Squares regression (OLS) [4], Generalized Least Squares regression (GLS) [5], or Multivariate regression (MVR) [6] from the responses obtained from the minimum number of runs suggested by Taguchi method. Subsequently multi-response optimization is performed using the output functions obtained from the regression analysis through desirability function approach.

II. Multi-response Optimization Procedure

As described earlier, multi-response optimization is used specifically when there is a need to optimize the control factors in order to satisfy more than one CTQ at a time. It is all about determining a point or range in design space that helps to meet all the CTQ requirements. The system of equations become even more complex when there is interaction between the control factors.

The step-by-step approach employed in this work for multi-response optimization is depicted in Figure 1 using Minitab statistical software. The procedure starts with obtaining responses for every CTQ using Taguchi runs. These multiple responses are fitted into regression models and are fed into desirability functions which perform multiple iterations to arrive at a set of desired control factor values. The desirability function provides a maximum possible desirable value for every CTQ with one set of optimized control factors.

I. Identifications of Control factors

It is very important to understand the process of advanced manufacturing to recognize the effect of control factors on typical CTQs of the product. The parameters which can lead to variations on multiple CTQ characteristics are identified and are used as the control factors in the DoE.

II. Taguchi DoE

Taguchi method is commonly used for optimizing the design parameters with less number of experimental runs [1] as compared to factorial designs. Taguchi DoE uses orthogonal arrays to organize the parameters affecting (control factors) the process and the levels at which they should be varied. Based on the number of parameters and number of levels, appropriate orthogonal arrays can be selected, Table 1.

III. Optimal Process Parameters for Individual CTQs using Taguchi DoE

For example, if we consider a case with 4 control factors to be varied in 3 levels, an L9 orthogonal array with 9 runs is suggested by Taguchi method, Table 2. For each response (CTQ), the optimal control factor setting is obtained from the maximum S/N ratio (Signal–to-Noise ratio) value, while analyzing the DoE using Minitab. Depending upon whether to maximize or minimize the response, S/N ratio value was chosen as either smaller-the-better or larger-the-better or nominal-the-better option, as represented in Figure 2.

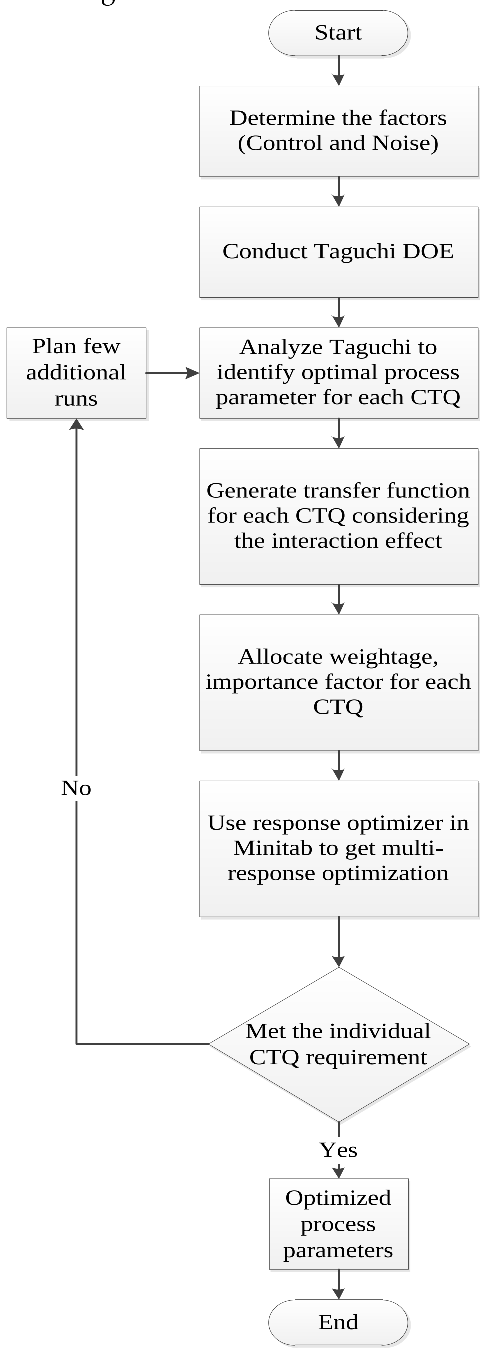

Figure 1: *Multi-Response Optimization Procedure*

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Table 1: *Orthogonal Array selector for Taguchi*

Parameter# Level#	2	3	4	5	6	7	8	9	10	11	12	13
2	L4	L4	L8	L8	L8	L8	L12	L12	L12	L12		
3	L9	L9	L9	L18	L18	L18	L18	L27	L27	L27	L27	L27
4	L16	L16	L16	L16	L32	L32	L32	L32	L32			
5	L25	L25	L25	L25	L25	L50	L50	L50	L50	L50	L50	

Table 2: *L9 (32) Orthogonal Arrays*

	Independent Variables			
Exp#	Var 1	Var 2	Var 3	Var 4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

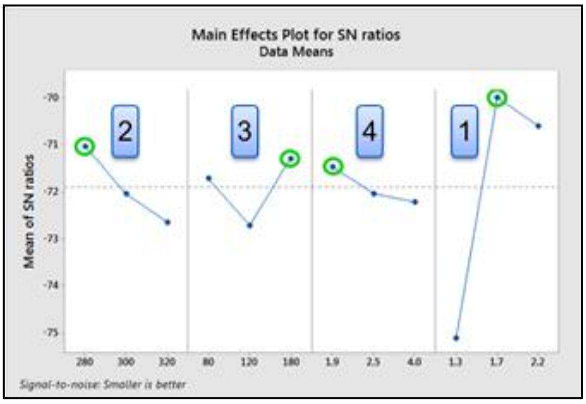

Figure 2: *Signal-to-Noise (S/N) Ratio (Smaller the Better)*

V. Transfer Function for Each CTQs using Regression

In general the transfer function generated from the Taguchi DoE analysis is a Taylor Series approximation. In order to obtain an analytical transfer function, the optimal control factor value obtained for individual CTQ responses from Taguchi method is used to generate transfer function by regression analysis, using Minitab. Each regression based transfer function is validated with the parameter effects and responses of the CTQs.

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VI. Allocation of the Weightage and Importance to Each CTQ

The regression based transfer functions are allocated with weightages and importance based on the CTQs criticality. This will help in providing priority to certain CTQs over the other during the optimization process.

VII. Multi-Response Optimization using Minitab

Multi-response optimization is performed using the optimizer function inbuilt in the Minitab. The importance level of each CTQ is fed into the optimizer function [7]. This optimizer function performs iteration over the control factors and identifies an appropriate most favorable range which satisfies desired multiple responses using desirability function in the Minitab. Desirability in the response optimizer suggests the best combination of control factors which will satisfy the goals that are defined for the multiple CTQs. Individual desirability indicates how well single CTQ is satisfied whereas Composite desirability indicates how the requirements for multiple CTQs are satisfied simultaneously. Desirability has a range of 0 to 1 where 1 is the most favorable case and 0 indicates that one or more CTQ's are outside acceptable limits. The desirability function depends upon the weightage and important index given for each CTQ. The optimizer has a very important feature of visualizing the effect of each parameters on the CTQs which can be varied and cross verified; the below Figure 3 shows the response optimizer in Minitab as an example.

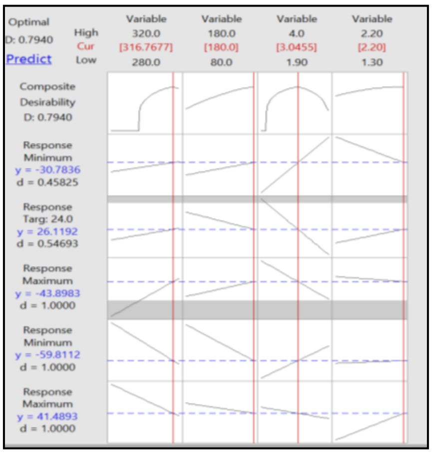

Figure 2: *Sample Response Optimizer in Minitab*

IV. Conclusion

The approach described in the work was found to be more practical and simpler one which can be adopted for optimizing new manufacturing processes, where the process history is not fully known. Especially when the process is very complex, where more process parameters to controlled, which involves higher lead time and considerable budget for identifying the right process setting, this approach would be simpler to adapt.

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