MULTI-STAGE AND MULTI-RESPONSE PROCESS OPTIMIZATION IN TAGUCHI METHOD

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ABSTRACT

Product quality is all about reducing variations of key performance indicators. However, product manufacturing often, requires multiple processes with multiple indicators, which make reducing variation a complex task. There are tools used to optimize a single stage process independently which ensure local optimization only. However, there is no clear approach that leads to system optimization.

The aim of this study is, therefore, to develop a tested approach to optimize multi-stage and multi-response industrial process. For this purpose, a conceptual model with its optimization procedure was developed and then validated by taking Harar Brewery as a case. Variations under each stage were evaluated before and after optimization. As a result, the new model with its optimization procedure is proven to ensure the stability of a process with reduced variation.

Key Words: Taguchi Method, Process Optimization, Brewery

INTRODUCTION

A production process constitutes a set of inputs and outputs as shown in Fig. 1. The inputs X_1, X_2, …, X_n are controllable factors whereas the inputs Z_1, Z_2, …, Z_n are uncontrollable or difficult to control factors (this study deals with the controllable factors). The production process transforms these inputs into outputs that will have several quality characteristics. The output variable 'Y' is measure of process quality. The Taguchi method is an approach for robust experimental design that seeks to obtain a best combination set of factors/levels with lowest variation while the mean is close to the desired target (Liao and Chen, 2002). Initially, the Taguchi method can only be used for single response problem. Since most products have more than one quality characteristics, researchers in the filed proposed methods to solve multi-response problem and a large amount of satisfactory implementation results have been published [2, 5, 7, 10, 12, 13, 14, 17, 18, 19, and 21].

However, previous researches have focused on single-stage optimization. In practice, many industrial processes are multi-stage in nature. Engineers, often, try to optimize individual processes and then expect an optimized system, which is neither systematic nor provides a realistic result. Studies in multi-stage process optimization are limited to:

- a mathematical model which was developed to optimize inspection plans for multi-stage manufacturing systems with the objective to minimize costs while assuring a required output quality [20];
- an optimal inspection policy proposed based on a Particle Swarm Optimization (PSO) algorithm for a serial multi-stage process [3];
- an approach proposed to optimize a multi-stage flash desalination process by using a two-level factorial design through conversion of the multi-stage process in to a single stage and solving with the conventional method. This cannot bring a stabilized robust system [1];
- quality improvement of multi-stage and multi-response grinding processes [8].

The first and the second studies are mainly related with inspection strategies. The third and the forth research have taken the agenda of multi-stage optimization though they procedurally changed the multi-stage process into a single stage. Hence, multi-stage and multi-response process optimization issue is yet to be researched. The aim of this research is, therefore, to develop an approach to solve multi-stage and multi-response problems. First a conceptual model is developed with its optimization procedure and then the model has been validated by taking Harar Brewery Sh.Co. as a case in point.

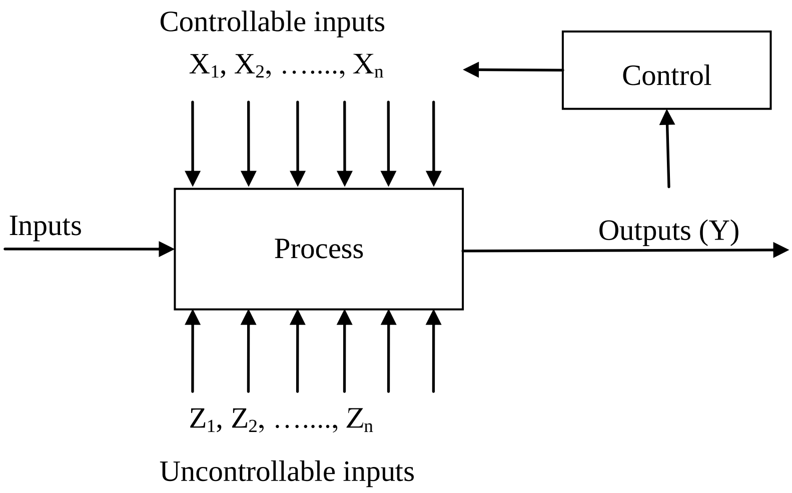

Fig.1: A Process as a System

MULTI - STAGE – MULTI – RESPONSE PROCESS

A system is defined as an entity with input variables and output variables. A multi-stage and multi-response system has input factors, which determine values of their immediate responses in each stage. These response factors, of course, can be the input factors for the succeeding stages. Generally, it is assumed that all inputs in each stage are conceivably controllable by the designer. However, only the input factors in the first stage and new inputs added in the intermediate stages are directly controlled by the designer. The other input factors beyond the first stage are controlled indirectly as an immediate consequence of input factors of their preceding stages and finally the input factors in the first stage (Fig. 2).

Response factors in each stage are assumed as output factors for the stage and denoted them F_{A1}, F_{B1}….F_{M1} for the first stage, F_{A2}, F_{B2}….F_{M2} for the second stage, F_{A3}, F_{B3}….F_{M3} for the third stage, if there is any, and, apparently, Y_1, Y_2 …,Y_Q for the response factors in the final stage. The input factors in the first stage are denoted X_1, X_2….X_M.

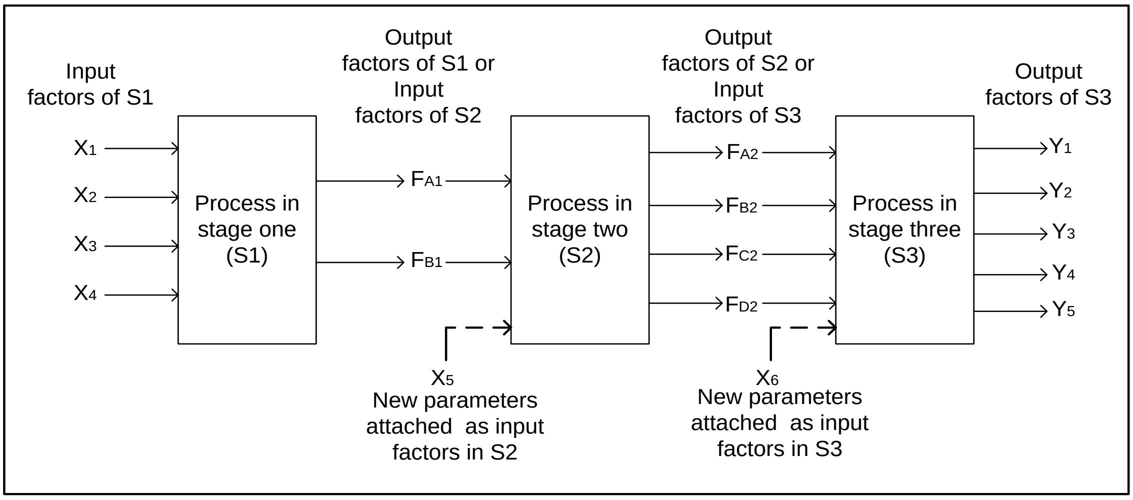

Fig. 2: Multi-stage Multi-response System

In a multi-stage and multi-response process optimization problem, the objective is to determine optimum levels of input parameters in each stage so that the final output quality characteristics result in a least combined quality loss. Unlike the other possible combinations, the combination of control factors levels in each stage will enable the total system to operate under the least possible cost. However, the challenge in this process is the quality characteristics at all stages that need to be optimized are a multiple response type. Furthermore, in a multi-stage process there are intermediate outputs which are inputs for succeeding stages. In effect it enables the propagation of variation from the early stage of the processes to the proceeding stages.

The principle followed to solve multi-stage and multi-response optimization problem is first determining optimal levels of control factors for the product quality characteristics in the final stage, then this process continues for each preceding stages until the optimal levels or values of the design parameters or control factors in the initial stage are determined.

PROPOSED OPTIMIZATION PROCEDURE

The multi-stage and multi-response process optimization proposed in this study has four fundamental steps.

The first step in optimizing a complex process is modeling and representing the process as a multi-stage and multi-response system. Under this stage all the controllable factors and uncontrollable factors under each stage are established. Moreover, the process inputs, measurable process characteristics, intermediate outputs and final outputs are determined.

The second step is dealing the final stage of the process as an independent process and solving it based on Tong and Su multi-response optimization procedure [18]. This method includes the following four phases: 1) Computing the quality loss, 2) Determining the Multi-Response Signal-to-Noise (MRSN) ratio; 3) Determining the optimal factor/level combination; and 4) Conducting the confirmation experiment.

The third step is by considering the optimal factor/level combination input of the last stage of the process as the outputs of the preceding stage; determine the optimal factor/level combination of the stage in consideration.

The last and the fourth step is repeating step three until the primary inputs' optimal factor/level combination are determined.

To illustrate the procedure proposed above, process industry, Harar Brewery is selected. The brewing process is chosen because of two reasons. First, it is a complex process where there are many intermediate outputs depending one over the other and the second reason is the availability of sufficient data under each process, which is very important for the illustration.

Finally, signal-to-noise ratio of the process before and after the experiment are computed, and compared to validate the significance of the proposed optimization procedure.

CASE STUDY

Harar Brewery Share Company (HBSC) was established in 1984 in the town of Harar, 515 Kilometers from the Capital, Addis Ababa, Ethiopia. In 2011 state owned Harar Brewery became a subsidiary of Heineken International through a buyout.

The brewery's initial design capacity was 200,000 hectoliter (60,000,000 bottles) per annum and it was producing only Harar lager and draught beer. After a period of ten years i.e., since 1994 the brewery diversified its products and introduced two new brands to the market, namely, Hakim Stout—alcohol content 5.5 %W/v (Dark beer), and Harar Sofi—alcohol Free (Malt drink). Since 2005, the Brewery developed and implemented ISO 9000 Quality Management System and got certified. Among other things, it enables an organization to reduce varation in the performance parameter of a product or a process [4].

As far as Harar Brewery is concerned, numerous efforts have been exerted to minimize process variation. However, it is observed that still there is considerable challenge to keep all quality characteristics within customers expectations limit [4]. One potential reason for the problem the company is facing is the complexity of the process to design, monitor and control as it is a multi-stage processes with multiple input, intermediate outputs and final outputs. This study, therefore, is an attempt to devise a means to optimize such a complex system.

PROCESS MODELING

Brewing is the production of beer through steeping a starch source, commonly cereal grains, in water and then fermenting with yeast. Work in the brewery is typically divided into seven processes: mashing, lautering, boiling, fermenting, conditioning, filtering, and filling. In the case of Harar Brewery, the processes are confined into three basic sections where the quality control department always took sample and conduct test in the laboratory. These sections are: Brew-houses, Storage Cellars and Bottling sections. Apart from possession of multiple quality characteristics, brewing processes is a typical example for multistage process.

A multi-stage and multi-response system has input factors which determine values of their immediate responses in each stage; these response factors, of course, can be the input factors for the succeeding stages. We have two kinds of input factors. The first one is an input factor for a certain stage which has acted as an output factor in the preceding stages while the other is a new input factor which is added in the intermediate stages (Fig. 3).

All inputs in each stage are conceivably controllable by the designer. However, only the input factors in the first stage and new factors added in the intermediate stages are directly controlled by the designer in a multi-stage process optimization. The other input factors beyond the first stage are controlled indirectly as an immediate consequence of input factors of their preceding stages and finally the input factors in the first stage. In Harar Brewery, the most critical primary inputs controlled by the designer are T. hard, R.M. PH, and M. value. The response factors in the first stage are W. H. Extract, W. Color and W. PH. The response factors or outputs of stage one are the input factors for stage two in addition with the new factors added into it (this study did not considered addition factors for analysis since it makes the optimization process more complex). The response factors of stage two are A. Extract, W. Color and W. PH. These output factors are considered as the input factors for stage three in addition to the factors included in this stage. Finally, the outputs of stage three are CO2, Apparent Extract, PH, color, haziness, and alcohol.

In dealing with multi-stage multi-response process optimization problems, we are trying to determine optimum levels of selected parameters in each stage so that the final output quality characteristics result in a least combined variation. In this way, unlike the other possible combinations, the combination of selected levels of control factors in each stage will enable the total system to operate under the least possible variation.

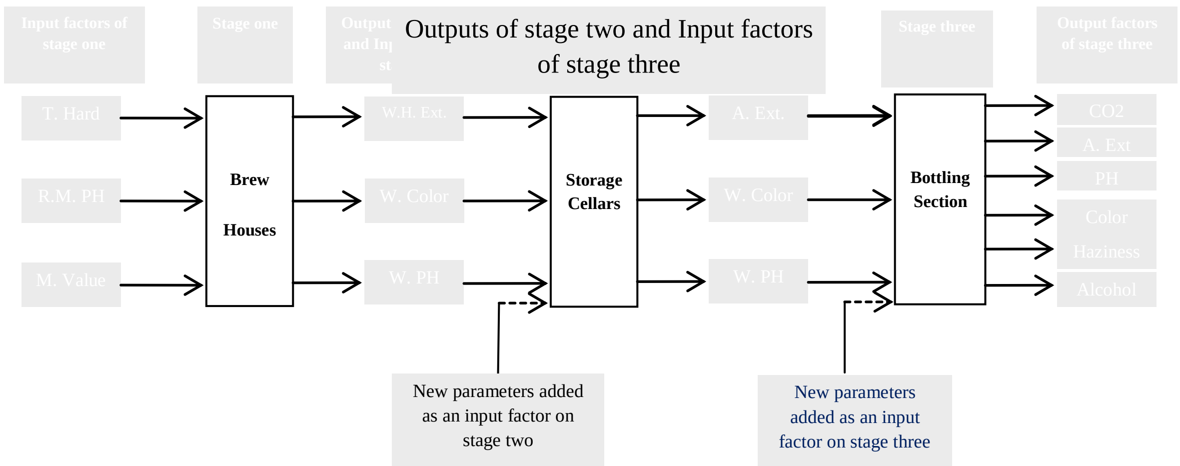

Fig. 3: Harar Brewery's System

DESIGN OF EXPERIMENT WITH TAGUCHI METHOD

A system as an entity with input variables and output variables has to be defined as stated in the process modeling section above. A multi-stage and multi-response system has input factors, which determine values of their immediate responses in each stage.

It is assumed that the system in each stage is associated with more than one output variables of prime interest in relation to the effects of input variable changes. Key input variables, in contrast, are selected based on the effect they bring on the key output factors when they are changed.

Determined factors in each stage and their corresponding values are T. hard, Raw Mash PH and M. value for stage one; H.W. Extract, Wort Color, and Apparent Extract for stage two; Apparent Extract, Wort Color and Wort PH for stage three. Based on these, important output quality characteristics of the third stage or the final output in this case are; CO2, Apparent Extract, Color uniformity, PH level, Haziness and alcohol. Accordingly, levels and their values of each control factors in all stages are developed and shown in Table1.

The degrees of freedom for each stage under investigation and that for each factor in the stage are computed and presented in Table 2. Based on the number of factors and their number of levels Orthogonal Arrays (OA) for each stage is also selected (Table 2). The Orthogonal Array selected complies with the rule that the total degree of freedom available in an Orthogonal Array must be greater than or equal to the degree of freedom for the stage.

Table 1: Values of Levels of Control Factors

Stages	Control factors	Selected level	Values of levels of factors			
			Level 1	Level 2	Level 3	Level 4
Stage 1	T. hard	4	2.80	3.30	3.80	4.30
	Raw mash PH	4	5.60	5.70	5.75	5.85
	M. value	2	1.80	2.00		
Stage 2	H.W. Ext.	4	11.60	11.80	11.90	12.00
	Wort color	4	10.50	11.50	12.00	12.50
	Wort PH	2	5.60	5.70		
Stage 3	App. Ext.	3	2.00	2.15	2.40	
	Wort color	3	7.50	9.00	9.50	
	Wort PH	3	4.20	4.35	4. 45	

Table 2: Selected Degree of Freedom

Stages	Factors	Selected level	DOF for each factor (Df)	DOF for each stage (Dm)	Selected OA	DOF available in OA selected
Stage 1	Raw mash PH	4	3		L16	15
	M. value	2	1	7		
	T. hard	4	3			
Stage 2	Wort PH	2	1		L16	15
	Wort color	4	3	7		
	H.W.Ext.	4	3			
Stage 3	Wort PH	3	2		L9	8
	Wort color	3	2	6		
	App. Ext.	3	2			

MULTI - RESPONSE SIGNAL – TO - NOISE (MRSN) RATIO

The selected Orthogonal Array for the first two stages is L16 and, hence, the designations set for the control factors in these stages is the same. For this reason, 16 experimental trials are there to see the effects of different level combinations of the control factors in these stages on the respective outputs (response factors). Apparently, L9 Orthogonal Array is selected for stage three and designation of control factors in the stage is set accordingly.

The response values in each stage observed from the experiment conducted according to the designations set are summarized in Table 3 as follows. The target value for the last stage, CO2, Apparent extract, PH, Color, Haziness and Alcohol are 0.6, 2.1, 4.4, 7.5, 0.35 and 3.9

respectively. According to Taguchi, any deviation from the target value is a loss to the society [16]. Based on a discussion made with the factory workers a failure cost is assumed to be 2.5 Ethiopian Birr per bottle of Beer. Therefore, based on the above equation the average quality losses under each experimental run for all the stages are computed. Only the average quality loss in stage three is summarized in Table 4 below. Then, the scale of quality loss of each response should be normalized in order to reduce the variability. For this reason, the quality loss at each trial is divided by the maximum quality loss in the j trials for each response. Then the normalized quality loss for the i^{th} response and j^{th} trial is; $NL_{ij} = L_{ij} / L_{imax}$.

Dealing with the multi-response problem in this way, the value of the normalized quality loss always ranges between 0 and 1 and the smaller the normalized value implies the smaller the quality loss. Normalized quality losses for stage three are summarized in Table 5.

The relative weights for each quality characteristics need to be assigned. Assignment of relative weights is according to their relative impact to product or process quality. The sum of the weights assigned to each quality characteristics is made to give a value of 1. The relative weight given from the experience of the factory for CO2, Apparent extract, PH, Color, Haziness and Alcohol are 0.15, 0.2, 0.2, 0.15, 0.2 and 0.1 respectively. The normalized combined quality loss for each trial is calculated by multiplying the normalized quality losses in the row by the corresponding weights and adding them together. The combined normalized quality losses and the multi-response signal-to-noise ratio are calculated and presented in Table 6. Determining the optimal levels of the control parameters which is the important part of robust parameter design is done by following a two-step optimization procedure; first reducing variation and then adjusting the mean on target.

Table 3: Experimental Results found in the Three Stages

Trial	**Stage 1**			**Stage 2**			**Stage 3**					
	H.W. Extract	**Wort Color**	**Wort PH**	**App. Ext.**	**Wort color**	**Wort PH**	**CO2**	**App. Ext.**	**PH**	**Color**	**Haziness**	**Alcohol**
1	11.70	12.00	5.71	2.30	8.00	4.15	0.6	2.15	4.23	7.50	0.43	3.94
2	11.90	11.50	5.65	2.20	9.50	4.31	0.58	2.10	4.72	7.50	0.37	3.92
3	11.80	12.00	5.62	2.30	9.00	4.30	0.62	2.10	4.29	7.50	0.38	3.92
4	11.70	12.00	5.73	2.35	9.50	4.35	0.61	2.15	4.44	7.50	0.30	3.89
5	11.60	12.00	5.71	2.10	9.00	4.47	0.61	2.15	4.43	7.50	0.26	3.90
6	11.65	10.50	5.72	2.40	9.00	4.40	0.62	2.10	4.30	7.50	0.29	3.90
7	12.20	12.00	5.45	2.00	9.00	4.47	0.6	2.05	4.21	8.00	0.38	3.84
8	12.35	12.00	5.49	2.20	9.00	4.60	0.61	2.10	4.29	7.50	0.47	3.87
9	11.65	10.50	5.66	2.20	9.00	4.51	0.62	2.20	4.41	7.50	0.28	3.86
10	11.85	12.00	5.60	2.00	9.00	4.15						
11	11.80	11.00	5.55	2.25	8.50	4.38						
12	12.65	12.00	5.60	2.35	10.5	4.38						
13	11.85	11.50	5.51	2.00	10.0	4.48						
14	12.10	12.00	5.85	2.00	10.0	4.45						
15	12.10	12.00	5.79	2.10	9.00	4.40						
16	11.60	12.00	5.36	2.20	9.00	4.51						

Table 4: Average Quality Losses in Stage Three

Experimental Trial	Average quality losses of response factors (L_{ij})					
	CO_2	APP. Ex	PH	Color	Haziness	Alcohol
1	0.037599	1.052772	2.5	1.530842	2.758173	0.625239
2	0.137104	0.43037	2.5	1.530864	1.264059	0.326467
3	0.137199	0.430272	2.096902	1.530842	1.388673	0.326439
4	0.062499	1.052772	1.445902	1.530842	1.787073	0.251739
5	0.062499	1.052772	1.402502	1.530842	2.5	0.226839
6	0.137199	0.430272	1.966702	1.530842	2.060973	0.226839
7	0.037599	1.052772	2.5	2.5	1.388673	1.123239
8	0.062499	0.430272	2.096902	1.530842	2.5	0.450939
9	0.137199	2.5	1.352902	1.530842	2.384673	0.625239
L_{imax}	0.137199	2.5	2.5	2.5	2.5	1.12

Table 5: Normalized Quality Losses of Response Factors in Stage Three

				Normalized quality losses of response factors (NL_{ij})					
Experimental Trial	A	B	C	CO_2	APP. Ex	PH	Color	Haziness	Alcohol
1	1	1	1	0.27405	0.421109	1	0.612337	1.103269	0.558249
2	1	2	2	0.99931	0.172148	1	0.612346	0.505624	0.291488
3	1	3	3	1.00000	0.172109	0.838761	0.612337	0.555469	0.291463
4	2	1	2	0.45554	0.421109	0.578361	0.612337	0.714829	0.224767
5	2	2	3	0.45554	0.421109	0.561001	0.612337	1	0.202535
6	2	3	1	1.00000	0.172109	0.786681	0.612337	0.824389	0.202535
7	3	1	3	0.27405	0.421109	1	1	0.555469	1.002892
8	3	2	1	0.45554	0.172109	0.838761	0.612337	1	0.402624
9	3	3	2	1.00000	1	0.541161	0.612337	0.953869	0.558249

Table 6: Stage Three MRSN Values of Response Factors in Different Experiments

Experimental Trail	Designation of control factors			$NCLj$ $\sum_{1}^{n} Wi * NLij$	MRSNj $-10\log(NCLj)$
	A	B	C		
1	1	1	1	0.638495	1.948427
2	1	2	2	0.58117	2.356968
3	1	3	3	0.556491	2.545417
4	2	1	2	0.489776	3.100027
5	2	2	3	0.526856	2.783079
6	2	3	1	0.57752	2.384327
7	3	1	3	0.658938	1.811552
8	3	2	1	0.552617	2.575756
9	3	3	2	0.748988	1.255252

REDUCING VARIATION AND ADJUSTING MEAN ON TARGET

For nominal-best case, the level of the control parameter that results in maximum signal-to-noise ratio is selected as optimal. In this case, the combination of levels of control parameters that give maximum value of MRSN is selected as optimal. In other words, levels of parameters that minimize variation should be identified and chosen as optimal.

As shown in Fig. 4, the optimal setting of the control factors in stage three is A2B2C3 (Apparent Extract should be set at 2.2 (2^{nd} level), Wort Color at 9 (2^{nd} level) and Wort PH at 4.45 (3^{rd} level)). The main effects on the average MRSN is Apparent Extract, Wort Color and Wort PH in their order of appearance (Table 7).

Once variation is reduced by determining the optimal level combination of the control parameters, the mean of the response factors needs to be adjusted on target. To do this an adjustment factor has to be selected. For the nominal-the-best case, a factor that has no significant effect on MRSN, a significant effect on the mean response for its quality characteristic, and no significant effect on the mean response for the other quality characteristics can be selected as an adjustment factor.

The response tables need to be examined for each control factor in order to identify the appropriate adjustment factors for adjusting mean of responses on target. The response tables of the final stage are examined the effect of the control factors on each quality characteristics shown in Table 7.

As it can be clearly seen from the table, factor C (Wort PH) has no significant influence on the average MRSN, CO2, PH, Color, and Alcohol but a more significant influence on the mean values of the response factors Apparent Extract and Haziness. Factor B (Wort Color) has slight influence on the average MRSN and the mean values of the response factors Apparent Extract and Haziness but a significant influence on CO2, PH, Color, and Alcohol. Hence, Factor C can be chosen as adjustment factor for Apparent Extract and Haziness while Factor B for CO2, PH, Color, and Alcohol.

In a similar way the iteration proceed to remaining stages until the optimized combination of the primary inputs in stage one are ensured. As it is summarized in Table 8, the control parameters in stage one, Raw Mash PH, T. Hard and M. Value, should be set in 3^{rd}, 1^{st} and 2^{nd} level respectively.
The control parameters in stage two, Hot Wort Extract, Wort Color and Wort PH, need to be set in 4^{th}, 3^{rd} and 1^{st} level respectively.

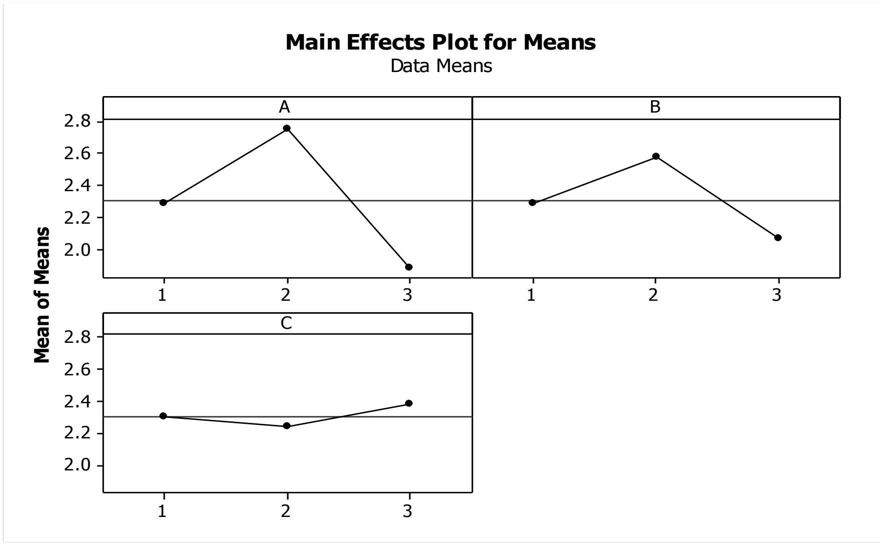

Fig. 4: MRSN versus Apparent Extract, Wort Color, and Wort PH

Table 7: Summary of Effect of Control Factors on the Stage Three Mean Response and MRSN

Conditions	Control factors	Level 1	Level 2	Level 3	Delta
Main effects on the average of CO2	App. Ext.	0.114	0.096	0.086	0.027
	Wort Color	0.050	0.096	0.150	0.100
	Wort PH	0.086	0.123	0.086	0.036
Main effects on the average of App. Ex	App. Ext.	0.051	0.068	0.106	0.055
	Wort Color	0.084	0.051	0.090	0.039
	Wort PH	0.051	0.106	0.068	0.055
Main effects on the average of PH	App. Ext.	0.189	0.128	0.159	0.061
	Wort Color	0.172	0.160	0.144	0.028
	Wort PH	0.175	0.141	0.160	0.034
Main effects on the average of Color	App. Ext.	0.092	0.092	0.111	0.019
	Wort Color	0.111	0.092	0.092	0.019
	Wort PH	0.092	0.092	0.111	0.019
Main effects on the average of Haziness	App. Ext.	0.1082	0.1270	0.1255	0.019
	Wort Color	0.1187	0.1253	0.1167	0.007
	Wort PH	0.1464	0.1087	0.1055	0.041
Main effects on the average of Alcohol	App. Ext.	0.038	0.030	0.065	0.044
	Wort Color	0.060	0.030	0.035	0.030
	Wort PH	0.039	0.036	0.050	0.014
Main effects on the average of MRSN	App. Ext.	2.284	2.756	1.881	0.875
	Wort Color	2.287	2.572	2.062	0.510
	Wort PH	2.303	2.237	2.380	0.143

Table 8: Summary of Selected Optimal Setting of Control Factors in Each Stage

Conditions	Stage 3			Stage 2			Stage 1		
	App. Ext.	Wort Color	Wort PH	H. W. Ext.	Wort Color	Wort PH	T. Hard	R.M. PH	M. Value
Order of significance of control factors on MRSN	1st	2nd	3rd	1st	2nd	3rd	2nd	1st	3rd
Optimal setting of the control factors	2nd level	2nd level	3rd level	4th level	3rd level	1st level	1st level	3rd level	2nd level
Optimal value of control factors	2.15	9.0	4.45	12.0	12.0	5.60	2.8	5.75	2.0

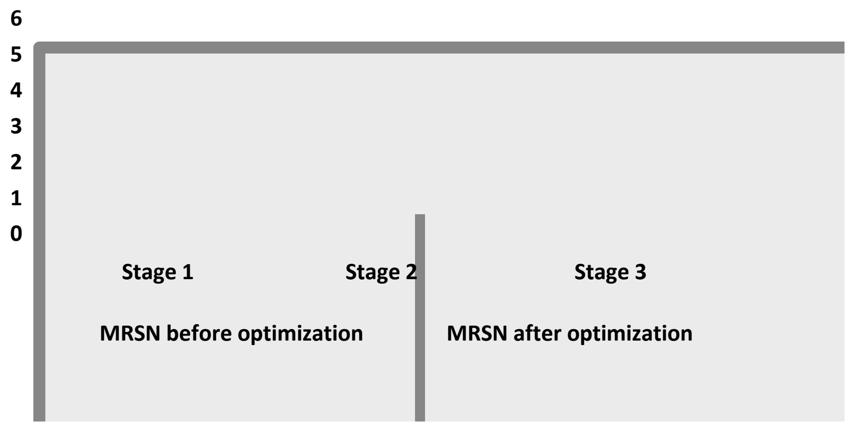

Fig. 5: MRSN Values before and after Optimization

VALIDATION

Once the optimal level of each parameter has been selected, the final step is to predict and verify the improvement of the quality characteristic using the optimum level of the parameters. The multi-response signal-to-noise ratio in each stage for the optimized setting are calculated to show the difference in variation created before and after the optimal setting is determined. The result is summarized in Fig. 5 which proofs that the MRSNs of the optimized process in each stages have significant improvement.

CONCLUSION

This research has dealt with a multi-stage and multi-response process optimization problem by developing a new and easy to use method. The method showed that optimization of such problems should start from determining the optimal levels of the control factors in the final stage. Once, the final stage control factors are determined in such a way that their optimal setting ensures robustness of the quality characteristics of the stage, the next step will be determining the optimal levels of the control factors of the preceding stage. At this time, however, the control factors in the final stage are taken as output factors for the stage. Determining the optimal levels of the control factors in this stage, hence, ensures the optimal values of these output factors and consequently the optimal levels of the quality characteristics of the final stage. This process continues until the optimal levels (values) of the control factors in the initial stage are determined. The new model developed has been tested and has shown improvement in MRSN. Future research could be undertaken by considering additional inputs in the intermediate stages. These will make multi-stage and multi-response process optimization complete. Moreover, this model could be tested and adapted in a wider area of process optimization problems. Comparing Taguchi method with other methods shall also be taken as a future research field.

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