Comparison of Full and Fractional Factorial Designs in Some Agricultural Experiments Based on TAGUCHI Method

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Abstract: Taguchi method is consisted of statistical and mathematics methods in experimental studies. In this article, we will examine the relative strengths and weaknesses of Full and Fractional Factorial Designs and develop some guidelines for selecting the best approach for solving our specific problems. Thus, present study aimed to access allelopathic effects of three extracts (*Amaranthus retroflexus, Chenopodium album* and *Xanthium strumanium*) with varying levels (control, 20%, 40%, 60%, 80% and 100% on coleorhize and coleoptile length of *Cuminum cyminum, Carum copticum, Foeniculum vulgare.* What and primarily full and Fractional Factorial Designs have in common, then, is that they deal with multiple inputs and how they interact with each other. Taguchi Parameter Design is a powerful, efficient, time saving and accurate method compare to factorial design. In order to meet this purpose in terms of both efficiency and effectiveness, this study will utilize the Taguchi Parameter Design methodology in agricultural studies.

[Saeed Sharafi, Zeinolabedin Jouyban, Somaye Akhlaghi and Hamid Fateh. **Comparison of Full and Fractional Factorial Designs in Some Agricultural Experiments Based on TAGUCHI Method.** *Life Sci J* 2012;9(1s):88-93] (ISSN:1097-8135). http://www.lifesciencesite.com. 15

Keywords*:* TAGUCHI Method, Fractional Factorial Designs, Full Factorial Designs, agricultural experimental design.

Introduction:

Taguchi method is a combination of mathematical and statistical techniques used in an empirical study. Basically, Conventional experimental procedures involve altering of one factor at a time keeping all other factors constant, resulting in assessing the impact of those particular factors; these are time consuming, require more experimental sets, and are unable to provide mutual interacting information of the factors (Mohan et al., 2007, Krishna Prasad et al., 2005).

In an experimental state, the inputs might be settings in some production process. We might be trying to maximize some output (as in throughput or process yield) or minimize some other output to investigate modification of responses (Luftig, 1998). In either type of analysis, production scenario or design situation, we are making decisions on how to do something that will affect what we get as an output. Besides the inputs and outputs described above, they both deal with multiple inputs. That is, we might have two, three, five, or a dozen or more input decisions to make, all affecting some measurable output. It would be nice if we could experiment with these inputs one at a time, optimizing our output for each input in turn, until we've selected ideal values for all input parameters. Unfortunately, this doesn't usually work, because the inputs generally interact with each other to some extent (soltani 2007). If there is three multi level factors; they interact with each other and affect the levels of output together. A more methodical, or experimental, approach to setting parameters should be used to ensure that the operation meets the desired level of quality with given noise conditions and without reducing production accuracy. Unfortunately, in most scenarios, time is limited and design of experiments (DOE) methods tend to be lengthy and cumbersome when considering the complex factors and noise that affect such an operation. The main thing to know about Taguchi technique is that it was developed primarily within the world of statistics. The theory behind the technique comes from the classical world of pure math. Taguchi theory starts with the assumption that all inputs might be interacting with all other inputs. This is a powerful statement. The technique makes no assumptions about some inputs being independent, and therefore can handle any interactions that might be lurking somewhere in your process. Of course this power comes at a price, and that price is lots of experimental runs and lots of calculations. For example, inputs might be 13 factor. Each factor has 3 levels. In these cases, (1594323)3^{13} experiments are required. So long term (91 year) experiments with different treatments should be conducted to establish and test a critical value of factor at which a researchers should optimize yield. In either type of analysis, production scenario or design situation, we are making decisions on how to do something that will affect what we get as an output. But, by using Taguchi theory, 27 experiments are needed. Unfortunately, in most scenarios, time is limited and design of experiments methods tend to be lengthy and cumbersome when considering the complex factors and noise that affect such an operation. In order to optimize such an operation with such restrictions, a more efficient experimental method is needed. An excellent solution to this issue is an approach known as Taguchi Parameter Design. As a type of fractional factorial design, Taguchi Parameter Design is similar to traditional DOE methods in that multiple input parameters can be considered for a given response. There are, however, some key differences, outlined in Table 1, for which Taguchi Parameter Design lends itself well to optimizing a production process [2]. As indicated in Table 1, using the Taguchi Parameter Design method would be ideal for this case, as it would allow for optimization of the Experimental process with a relatively small number of experimental runs. A key idea is the contention that Taguchi Parameter Design uses the non-linearity of a response parameter to decrease the sensitivity of the quality characteristic to variability [3]. Variability in a experimental process can be significant, often uncontrollable, and have varying effects on quality characteristics. Fortunately, according to Roy [4], the very intention of Taguchi Parameter Design is to maximize the performance of a naturally variable production process by modifying the controlled factors.

The purpose of this study is to efficiently determine the optimum turning operation parameters for achieving the lowest surface roughness in that range of parameters, while considering a noise factor. This study will include the following features in order to meet this purpose and distinguish it from the reviewed literature:

♦ The use of an array with the fewest experimental runs possible.
♦ Relationships between the control parameters and the response parameter.
♦ the use of damaged chuck jaws as a noise factor.
♦ Effects of the noise parameter on the response parameter.
♦ To determine effects of extract concentration on germination status of seeds

Methods and material:

Experimental Design and Setup:

Conventional approach to investigate the influence of some parameters on a system, involve altering of one factor at a time keeping all other factors constant. This approach requires numerous experimental runs to fully explore the entire parameter space. In this respect, the experimental design approach including Taguchi method can reduce the number of experiments while retaining data collection quality.

Taguchi method with a special design of orthogonal arrays can be used to study the entire process parameter space and the optimal conditions of factors with a small number of experiments (Roy et al. 2001).

The first important step in design of experiment is the proper selection of factors and their levels (Mahmoodian, et al., 2007). In this study, three treatment (extract concentration, medicinal plant type, and type of weed extract), were considered in several levels (Table 2). The root length and shoot length is used as a measure of germination rate of medicine plant. Table 3 indicates the Taguchi experimental design and the results of experiments with three replications. In order to avoid the systematic bias, the sequence in which these runs were carried out was randomized (Roy et al., 2001).

Statically Analysis of experimental design

The results are statistically analyzed using analysis of variance (ANOVA) to determine the partial contribution of each operating factor on the response. The strategy of ANOVA calculation is to statistically analyze the variation that each factor cause relative to the total variation observed in the results. Furthermore, the main effects of factors are also determined using average values of response at each level (Roy, 2001). In Taguchi method the main effect of a control factor indicate the trend of influence of a factor on response. The analysis of the results is carried out using Qualitek-4 (Nutek, Inc.) and Minitab (Minitab, Inc.) software. In the following, ANOVA analysis and the trend of influence of each factor is discussed.

3.2.1.1 Analysis of Variance

ANOVA can estimate the effect of a factor on the characteristic properties, and an experiment can be performed with the minimum replication using the table of orthogonal array (Kim et al., 2005). ANOVA table with percentage of contribution of each factor are shown in table 5 and 6. It is evident from P percentage, which only two factors extract concentration and medicine plant type considered in the experimental design had statically significant effects at 95% confidence limit. The variability of the experimental data was explained in terms of significant effects.

The F-ratio, defined as the variance of each factor dividing by variance for the error term (Ve) and has very important role for obtaining the significant of factors on response (table 5 and 6).

Table 1. Comparing DOE and Taguchi methods

Aspect	method	Taguchi method
Knowledge of the process being studied	required	In-depth knowledge required
Number of test runs	Relatively large; all combinations of inputs	Much smaller number of combinations
Variability of system being studied	Ignored; only used to look for most effective combination of inputs	Looks at both level and variability of output to select input combinations
Confirmation runs	required, as all combinations of inputs	Advisable; selected combination of inputs may not have been tested
Noise factors	Usually not included	Included in the basic design

Table 2 - Factors affects root length and shoot length of plants and level of each factor

	level					factor
	1	2	3	4	5	6
extract concentration (A)(v/v)%	0	20	40	60	80	100
Medicinal Plant type (B)	*Cuminum cyminum*	*Carum copticum*	*Foeniculum vulgar*	-	-	-
Type of weed extract (C)	*Amaranthus retroflexus*	*Chenopodium album*	*Xanthium strumanium*	-	-	-

The array selected to meet these criteria is a modified table 2. Note that this is based on table 1 and according to full factorial design $3^2 \times 6^1$ experiments is needed, whereas according to tagucchi method no more than 18 experiments are needed which is fractional factorial design. To curtail systematic or experimental error three replications were chosen to boost reliability of experiment.

Table 3- designed table to optimize germination of medicine seed plant using Qualitek-4 software

Runs	extract concentration (A)(v/v)%	Medicinal Plant type (B)	Type of weed extract (C)	Root length			Shoot length		
				Rep(1)	Rep(2)	Rep(3)	Rep(1)	Rep(2)	Rep(3)
1	0	*Cuminum*	*Amaranthus*	1.100	1.200	1.080	0.910	0.970	0.960
2	0	*Carum*	*Chenopodium*	1.020	1.140	1.170	0.350	0.350	0.240
3	0	*Foeniculum*	*Xanthium*	2.330	3.780	2.120	1.140	1.170	1.140
4	20	*Cuminum*	*Amaranthus*	1.100	1.000	1.000	0.750	0.750	0.710
5	20	*Carum*	*Chenopodium*	6.320	8.210	7.710	3.170	5.640	3.210
6	20	*Foeniculum*	*Xanthium*	6.140	6.350	6.120	3.510	4.140	3.720
7	40	*Cuminum*	*Chenopodium*	3.600	3.900	3.870	1.560	1.390	1.200
8	40	*Carum*	*Xanthium*	1.120	1.160	2.000	0.840	0.970	1.000
9	40	*Foeniculum*	*Amaranthus*	0.010	0.000	0.000	0.030	0.048	0.052
10	60	*Cuminum*	*Xanthium*	4.340	4.140	4.210	3.120	2.970	3.100
11	60	*Carum*	*Amaranthus*	0.000	0.000	0.000	0.000	0.000	0.000
12	60	*Foeniculum*	*Chenopodium*	4.450	5.650	4.740	3.000	2.970	2.910
13	80	*Cuminum*	*Chenopodium*	0.000	0.000	0.000	0.000	0.000	0.000
14	80	*Carum*	*Xanthium*	0.000	0.000	0.000	0.000	0.007	0.000
15	80	*Foeniculum*	*Amaranthus*	1.020	1.030	1.000	0.120	0.165	0.098
16	100	*Cuminum*	*Xanthium*	0.000	0.000	0.000	0.000	0.001	0.000
17	100	*Carum*	*Amaranthus*	1.200	1.300	1.200	1.170	1.010	1.000
18	100	*Foeniculum*	*Chenopodium*	1.000	0.980	1.001	0.000	0.000	0.000

Results:

All traits were analyzed using full factorial design. Since all traits were also differed significantly from another at 5, 1% level.

Table 4. variance analysis (ANOVA) in full factorial method (SAS)

Factor	df	RL	SL
extract concentration (A)(v/v)%	5	**	**
Medicinal Plant type (B)	2	**	*
A×B	10	**	*
Type of Weed extract (C)	2	**	**
A×C	10	**	**
B×C	4	**	*
A×B×C	20	**	**
Error	108	-	-
CV	-	12.41	18.8

* and ** significant difference at P< 0.05 and 0.01; n.s, not significant.

Table 5. variance analysis (ANOVA) in Taguchi method (response:RL)

Factors	DOF	Sum of squares	F-ratio	P
extract concentration (A)(v/v)%	5	38.699	2.35	0.135
Medicinal Plant type (B)	2	1.8470	0.28	0.762
Type of weed extract (C)	2	11.812	1.80	0.227
Error and others effect of factors	8	26.292		
Total	17	78.620		

Table 6. variance analysis (ANOVA) in Taguchi method (response:SL)

Factors	DOF	Sum of squares	F-ratio	P
extract concentration (A)(v/v)%	5	13.731	2.30	0.141
Medicinal Plant type (B)	2	0.444	0.19	0.834
Type of weed extract (C)	2	3.214	1.35	0.313
Error and others effect of factors	8	9.543		
Total	17	26.933		

Influence of Individual

Conventional statistical experimental design can determine the optimal condition on the basis of the measured values of the characteristic properties, while Taguchi method can determine the experimental condition having the least variability as the optimum condition (Kim et al., 2005). The variability of a property is due to 'noise factor', which is a factor difficult to control. On the contrary, the factor easy to control is called 'control factor'. The variability can be expressed by signal to noise (S/N) ratio (Kim et al., 2005). In order to evaluate the influence of each selected factor on the responses: The signal-to-noise ratios S/N for each control factor had to be calculated. The signals have indicated that the effect on the average responses and the noises were measured by the influence on the deviations from the average responses, which would indicate the sensitiveness of the experiment output to the noise factors. There are three standard S/N ratios, i.e., bigger-is-better, smaller-is-better, and nominal-is-better quality characteristics, which are generally applicable in strength (or yield), contamination, and dimension, respectively (Nikbakht et al., 2007). The appropriate S/N ratio must be chosen using previous knowledge, expertise, and understanding of the process (Anawa & Olabi, 2007). For example in the case that bigger characteristics are better, as in this study, the S/N ratio is defined as (Daneshvar et al., 2007).

$$\frac{S}{N} = \frac{-10\log\left(1/y_1^2 + 1/y_2^2 + 1/y_3^2 + \ldots + 1/y_n^2\right)}{n}$$

Where y_i is the characteristic property, n is the replication number of the experiment.

In addition analysis of variance run using ratio of each component to mean response (figure 2, 4) or includes the Signal-to Noise (S/N) ratio of the Individual runs (figure 3,5), which is calculated as:

$$\text{S/N} = -10\log\left(\frac{\sum_{i=1}^{n}\frac{1}{Y_i^2}}{n}\right)$$

Where; n = the number of replications, Y_i and Y_0 represents response value and optimal response value. The S/N ratio is a Summary statistic which indicates the value and dispersion of the response variable with the given noise factors [19]. In this case, the S/N ratio equation is based on the Taguchi smaller-the better loss function, as the idea is to minimize the response.

Terminal column indicates "Others/error" parameter which is consisted of uncontrollable elements such as experimental error or temperature variations. Freedom degree is an assessment of data which is obtainable with input data. Sum of square is a sign of data variation. F is magnitude of each factor.

The data in Table 1, 2 can then be analyzed using informal and statistical methods. This begins with determining the effects of each treatment level on the response and S/N ratio. The effects are merely the means of the response and S/N ratio at each level for each. These values can then be graphically analyzed (Figures 2 through 4), to look for relative effects on the response.

A steeper slope in the graphed response and S/N ratio effects indicates a greater effect of the parameter on the response. This can also be statistically tested, using analysis of variance (ANOVA), to analyze the effects of parameters on the response. Fowlkes and Creveling 1995 suggest looking at the F-ratios calculated in the ANOVA for each parameter to determine this, with the following criteria:

♦ F < 1: Control factor effect is insignificant (experimental error outweighs the control Factor effect).

♦ F ≈ 2: Control factor has only a moderate effect compared with experimental error.

♦ F > 4: Control factor has a strong (clearly significant) effect.

Conducting an effective Taguchi Parameter Design study requires review of literature regarding Coleoptile and root length parameters and similar studies (mahmodiyan et al., 2007).Table 5 and 6 shows the results of this process, which can be interpreted in terms of germination of this experiment. These studies all supported the idea that medicinal plant extracts has a strong influence on seed germination. Several medic weed extracts found to have differing levels of effect in each study, often playing a stronger role as part of an interaction. Some very informative studies were found that were conducted using the Taguchi Parameter Design method for the purpose of optimizing extract concentration parameters. These studies made use of various medic extract materials and controlled parameters to optimize seed germination, Coleoptile and root length parameters. In both experiment, weed extract was provided to increase coleoptile and root length, at which weed medic extract was shown to be similar to that in seeds growing in medic extract medium (table 5 and 6). Extract concentration has an F-ratio which is just a little greater than two, indicating only a moderate effect in this setup.

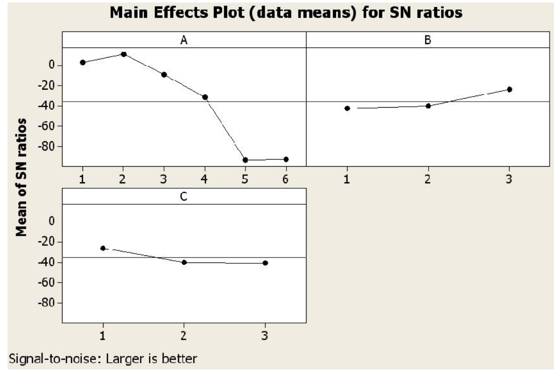

Figure 1. The effect of processing factors on RL increasing on base of S/N.

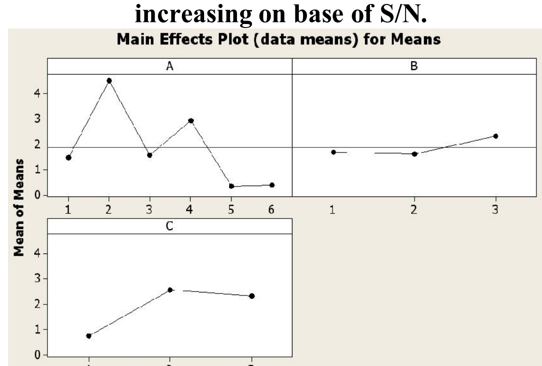

Figure 2. The effect of processing factors on RL increasing on base of responses average.

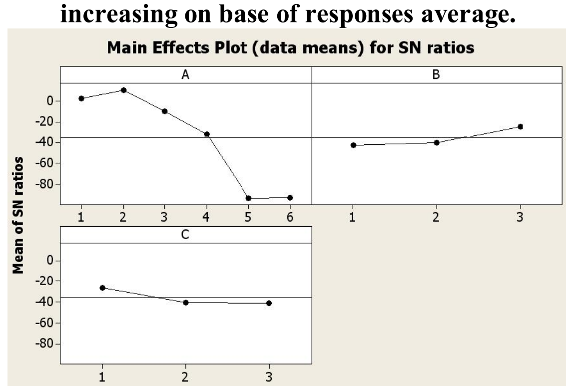

Figure 3. The effect of processing factors on SL increasing on base of S/N.

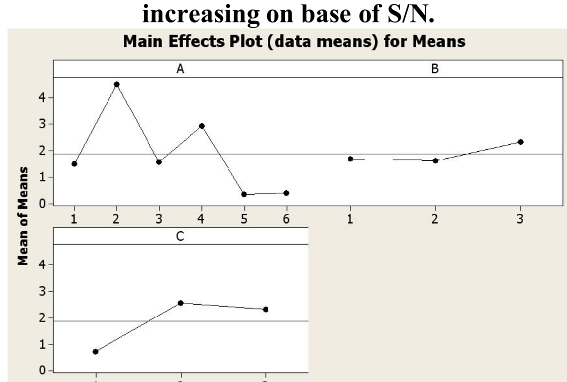

Figure 4. The effect of processing factors on SL increasing on base of responses average.

Germination status of three seed type significantly decreased in circumstance which extracts concentration was higher than 20 % (Figure 2 -5). In such treatment optimum germination may be achieved. Dissimilarly in weed concentration was seen which indicates C*henopodium* and *Amaranthus* extract importance. This area of research would benefit from future studies taking place in a controlled environment. Additionally, the addition of more representative conditions and materials, such as several medic extract would provide a more robust and applicable study. Addressing issues such as numerous uncontrolled error factors and laboratory constraints for experimentation and implementation would be important in demonstrating Taguchi Parameter Design as a valuable and manageable tool for germination studies and seed production optimization.

We can pointed out that infusing weed extract into *Carum copticum* seeds caused germination lessening, also this results showed that *Carum copticum* extract on its seed germination had a similar effect.

Contour plot

The counter plot is the locus of the responses with equal values. It is a projection of three dimensional response surface plots on a plane. The contour plot is commonly given as a graph drawn for pairs of most important factors. Consistent with results, extract concentration and weed extract type strongly affects RL response. Accordingly, optimum responses were occurred when two factors were at mean condition. In contrast, Responses were more conspicuous whilst mean factors value were established (figure 6). Throughout wide range of factor level, responses were nearly upper limit position.

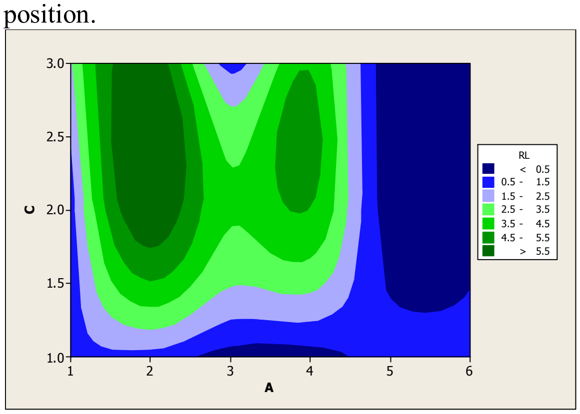

Figure 5. The contour plot graph of Wed extract concentration and Kind of weed extract in improvement of condition of medicine plant germination.

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12/15/2012