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Some Contribution in Construction of Orthogonal Array Testing Approach for Optimizing Test Cases in Diabetic People

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ABSTRACT

We propose a systematic methodology in any experimental design using orthogonal approach technique, which maximizes the coverage by comparatively lesser number of test cases. In such technique we have to balance between the specified time and quality. In this paper we adopt multiple strategy of OATS (Orthogonal array testing Strategies) in diabetic people to asses and compare the practice to optimize the testing efforts and achieve the right balance between diet and medication in urban and rural areas. Here we introduce three case studies of this orthogonal approach **to** reduce the number of test cases under the given software and hence improve the efficiency of the testing.

1. Introduction

In the field of health care where the health practitioners use the most appropriate available possible information, to make decisions for individual patients. It involves complex and conscientious decision-making based not only on the available characteristics, situations, and preferences but also it can help to standardize practice so that outcome data can be analyzed in order to improve the quality and effectiveness of practices.

For this purpose, we are using a technique called Orthogonal Array Testing which involves not only the selection of suitable predictors and outcomes, but plans the delivery of the experiment under statistically optimal conditions given the available resources.

Software testing has now become a very complex and challenging task. To achieve this challenging task, we need to build a proper strategy. The strategy provides a road map that describes the steps to be undertaken as part of testing. It also lays down the effort, time, and resources required to achieve the same. Thus, testing strategy consists of test planning, test case design, test case execution and test result data collection and evaluation. Korel [1] studied that Software testing activity is not just the identification and specification of defects. It covers reporting and also offers suggestions and recommendations for appropriate actions to be taken for improving the software product/solution. Further Clarke [2] discussed that for any given software application, we have a huge number of test cases. We require identifying only those test cases that would lead us to expose maximum number of undetected errors.

Despite the importance of techniques in identifying these test cases, developing the techniques remains one of the most difficult aspects of software testing.

A number of different algorithms have been proposed for constructing orthogonal and nearly-orthogonal arrays; some of these include a Federov exchange algorithm from Miller and Nguyen [3], an interchange algorithm from Nguyen [4], a threshold accepting technique from Ma et al. [5], an algorithm for a mixed level orthogonal array with many 2-level factors from DeCock and Stufken [6], column wise-pairwise algorithms from Li and Wu [7], and a state-of-the-art algorithm from Xu [8] . According to Shishank Gupta [9] with the day to day increasing competition in the market, there is a need to reduce the testing lifecycle so that the desired testing can be performed with high quality and less cost. Considering the fact that time is always at a premium, the need for having an optimized testing process is therefore very essential. When the model of interest is a normal linear regression model, by V. Brayman [10] orthogonal arrays give designs that allow an experimenter to consider a relatively large number of factors in relatively few trials while maintaining desirable statistical properties. For situations when orthogonal arrays do not exist, we consider the concept of nearly-orthogonal arrays. There are a number of ways to measure the "goodness" of orthogonal arrays and nearly-orthogonal arrays, and also a number of ways to actually find them.

2. Orthogonal Array Testing

The Orthogonal Array Testing Strategy (OATS) is a systematic, statistical way of testing pair-wise interactions. It provides representative (uniformly distributed) coverage of all variable pair combinations.

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Orthogonal array testing enables you to design test cases that provide maximum test coverage with reasonable number of test cases. This type of testing can be applied to problems which has relatively small input domain but too large to accommodate exhaustive testing.

Orthogonal array testing is more suitable in finding errors associated with faulty logic within a software component.

Orthogonal arrays are two dimensional arrays of numbers which possess the interesting quality of choosing any two columns in the array you receive an even distribution of all the pair-wise combinations of values in the array.

The benefits of orthogonal array testing includes:

- lower execution time.
- lower implementation time.
- code coverage is high.
- increased overall productivity.
- the analyses of results take less time.

Orthogonal array testing (OAT) helps in optimizing testing by creating an optimized test suite which detects all kind of faults, guarantees the testing of pair wise combinations, less prone to errors, simpler to generate and is independent of platforms and domains.

Runs: the number of rows in the array. This directly translates to the number of test cases that will be generated by the OATS technique.

Factors: the number of columns in an array. This directly translates to the maximum number of variables that can be handled by this array.

Levels: the maximum number of values that can be taken on by any single factor. An orthogonal array will contain values from 0 to Levels-1.

Strength: the number of columns it takes to see each of the Levels Strength possibilities equally often.

Orthogonal arrays are most often named as the pattern $L_{Runs}(Levels^{Factors})$.

2.1 Uses of OATS.

Implementing OATS technique involves the below steps:

1. Identify the independent variables. These will be referred to as “Factors”.
2. Identify the values which each variable will take. These will be referred as “Levels”.
3. Search for an orthogonal array that has all the factors from step 1 and all the levels from step 2.
4. Map the factors and levels with your requirement.
5. Translate them into the suitable test cases.
6. Look out for the left over or special test cases (if any).

3. Orthogonal Array Approach

3.1 Definition

An Orthogonal Array of strength t with N rows, k columns ($k \geq t$) and based on s symbols is an N x k array with entries 0,1,… , s -1, say, so that every N x t subarray contains each of the s^t possible t-tuples equally often as a row (say **λ** times) N must be a multiple of s^t , and $\lambda = N/s^t$ is the index of the array Notation: OA(N; k; s; t) or sometimes OA(N; s^k; t)

3.2 Mixed orthogonal array

Let S_i be a set of s_i levels denoted by 0, 1. . . $s_{i-1}$for $1 \leq i \leq v$ for some positive integer v ($s_i \geq 2$).We define a mixed orthogonal arrayOA (N, k_j, s_i ,t) to be an array of size N × k such that $k = k_1 + k_2 + \cdots + k_n$ and the first k_1 columns have symbols from S_1, the next k_2 columns have symbols from S_2, and so on, such that given any N ×t sub array, each possible t-tuple appears in the same number of rows. This definition does not require S_1, S_2. . . S_v to be distinct, but for simplicity we generally combine factors with the same number of levels.

The usage of the Orthogonal Array Approach described by S. Banerji[8] is studied in the next section to reduce the number of test cases significantly.

The following terminologies have been used in this approach

1) Factor (f): Those parameters that the tester intentionally changes during testing to study its effect on the output.

2) Levels (p): The different values of factors used in testing.

During testing, we observe the average change in the response when a factor is changed from one level to another level. Hence to achieve the entire test coverage, we should have (f*p) number of test cases. We are using orthogonal array approach to reduce the number of test cases. The following steps are followed to construct the orthogonal array for testing a program with f factors, each factor having p levels:

1. Check if p is a prime number.
2. In case where each factor has different levels, check whether the highest level is a prime number.
3. If the highest level not a prime, identify the next highest prime number.
4. Check if $f \leq p+1$.If not, check if f is a prime number, else identifies the next highest prime number.
5. There exists an OA (Orthogonal Array) with p_2 rows and (p+1) columns.
6. When p=3, we have an OA with 9 rows and 4 columns.
7. We construct “p - tuples” (e_1, e_2….e_p) as follows:

$e_1 = (0, 1, 2,…., p-1) = (0,1,2)$ (3.1)

$e_2 = (1, 2,……, p) = (1,2,3)$ (3.2)

$e_i=(e_{i-1} + e_1) \bmod p$, for i= 3 to p

$e_3 = (e_2 + e_1) \bmod 3 = (1, 3, 2)$ (3.3)

8. With p = 3, let us now construct the OA with 9 rows and 4 columns. The 9 rows represent the 9 test cases.

The 1^{st} column is constructed as shown in Table 3.1.

Table 3.1.

ROWS	1	2	3	4
1	1			
2	1			
3	1			
4	2			
5	2			
6	2			
7	3			
8	3			
9	3			

9. The 1^{st} p (p=3) rows are constructed and is shown in Table 3.2

Table 3.2.

ROWS	1	2	3	4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2			
5	2			
6	2			
7	3			
8	3			
9	3			

Now we will make use of the tuples constructed in (3.1), (3.2), and (3.3) at step 10.

10. Insert e_i's in $[((i-1)*p) +1]^{th}$ rows, ¥ i = 2, 3..., p. In our case, p =3, so for $[((2-1)*3) + 1]^{th}$ row ,that is, 4^{th} row; and $[((3-1)*3) + 1]^{th}$ row, that is, 7^{th} row; we can compute e_2 and e_3 as

$e_2 = (1,2,3)$ (3.4)

$e_3 = (1,3,2)$ (3.5)

Using (3.4) and (3.5), Table 3.2 is further developed and is shown in Table 3.3.

Table 3.3.

ROWS	1	2	3	4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2			
6	2			
7	3	1	3	2
8	3			
9	3			

For the remaining few rows, we carry out steps 11discussed below

11. Fill $[(i*p) + 2]^{th}$ row as $(e_{(i+1)} + 1) \bmod p$, i = 1,2,……,p. In our case p =3, so levels for different factors in 5^{th} row is given by

5^{th} row = $(e_2 + 1) \bmod 3 = ((2, 3, 4) \bmod 3) = (2, 3, 1)$. (3.6)

Again with i = 2, levels for different columns in 8^{th} row is given as

8^{th} row = $(e_3 + 1) \bmod 3 = ((2, 4, 3) \bmod 3) = (2, 1, 3)$ (3.7)

Next we filled up the 5^{th} and 8^{th} row of Table 3.3 using (3.6) and (3.7) and is shown in Table 3.4.

Table 3.4

ROWS	1	2	3	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				
7	3	1	3	2
8	3	2	1	3
9				

For the final rows, that is, 6^{th} and 9^{th}, we proceed to step 12.

12. Fill $[(i*p) + 3]^{rd}$ row as $(e_{(i+1)} + 2) \bmod p$ ¥ i = 1, 2… p. In our case, p =3, so with i = 1,

6^{th} row = $(e_2 + 2) \bmod 3 = ((3, 4, 5) \bmod 3) = (3, 1, 2)$ (3.8)

And with i = 2, 9^{th} row = $(e_3 + 2) \bmod 3 = ((3, 5, 4) \bmod 3) = (3, 2, 1)$ (3.9)

Finally using (3.8) and (3.9), we can filled up the 6^{th} and 9^{th} rows of Table 3.4 which is shown in Table 3.5

Table 3.5.

ROWS	1	2	3	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

Here Table 3.5 gives a OA with 4 factors each at 3 levels in 9 runs.

4. Application of orthogonal array testing

When the goal in a statistical study is to understand cause and effect, experiments are the only way to obtain convincing evidence for causation. We use a hypothetical example of an experiment to illustrate the concepts. In an experiment, we deliberately impose some treatment on individuals and then observe the response variables. When the goal is to demonstrate cause and effect, experiment is the only source of convincing data.

In the data below cross-sectional, study was conducted on urban and rural diabetic patients. Demographic data and knowledge of participants was recorded regarding various aspects of diabetes type II. There is a need to enable the patients to understand the causes, risk factors, symptoms, signs, complications and various treatment modalities. Out of 1000 patients we observed with the help of descriptive statistics that majority of the patients (42%) were male and (58%) female, 74% vegetarian and only (26%) were non vegetarian. During medication we observed that weight of the 42% patients decreased, weight of the 12% patients increased and there was no change in the weight of 46% patients. During treatment 32% of patients were skipping the tablets and 68% of the patients were taking the tablets regularly. During treatment 68% of the patients were skipping mid-day meal 24% of the patients were skipping evening meal and 8% were skipping breakfast. During treatment 66% of the patients were doing exercises daily and 34% were not doing the exercises. Clinical sign and symptoms were observed like mouth ulcer, dry skin, dry throat, night blindness, memory loss, depression, hair fall etc. were observed during the treatment.

To investigate the relationships between participants, household, community level characteristics and diabetes awareness we used test design using Orthogonal Array which creates an efficient and concise test suite with fewer test cases without compromising test coverage. The experiments described in these examples are double-blind, meaning that both the subjects and the experimenters do not know which treatment any subject has received.

In sections 4 and 5, we apply three case studies of orthogonal array testing strategies.

In case study_1 using $L_9(3^4)$ array, we consider a system which has 4 parameters (Age, Type of exercise, Diet rating, weight observed) and each of them has 3 levels. The permutations of factor levels comprising a single treatment are so chosen that their responses are uncorrelated between treatments and therefore each treatment gives a unique piece of information.

In case study _2 we consider optimality criterion of orthogonal design using the system of OA (8, 4, 2, 3). The optimality criterion used for any design, $|X'X| \leq 1$ and $|X'X| = 1$, if the original design d is an orthogonal array.

In case study _3 using mixed orthogonal array approach we add 1 more level in age and diet rating to this combination. This will help the practitioners to be more effective and efficacy in their practice. The net effects of organizing such experimental treatments is gathered with the minimum number of experiments.

4.1 Case Study 1: In our study best fit would be $L_9(3^4)$. The factors and various levels for each of the factors are listed below in Table 4.1:

Table 4.1. Factors and Levels listed for the Compatibility Testing

Factors	Level 1	Level 2	Level 3
Age	Below40	40-55	55-70
Type of exercise	No exercise	Walk daily	Yoga
Diet rating	Poor	Good	Excellent
Weight observe	Decrease	Remain same	Increase

Here the highest level =3, which is a prime number. Hence the OA with p=3 are constructed as follows in Table 4.2:

For 4 Factors, each with 3 levels, the total number of test cases = 3^4 = 81.With the Orthogonal Array Approach, we have been able to reduce it to 9 Test Cases. Thus we have been able to reduce the testing effort to 11.11% of the total effort. Hence, Effort Saved = 88.89%.

Table 4.2. Orthogonal Array constructed for the Compatibility Testing of treatments in patients.

Test Number	Age	Type of exercise	Diet rating	Weight observed
1	Below40	No exercise	Poor	Decrease
2	Below40	Walk daily	Good	Remain same
3	Below40	Yoga	Excellent	Increase
4	40-55	No exercise	Good	Increase
5	40-55	Walk daily	Excellent	Decrease
6	40-55	Yoga	Poor	Remain same
7	55-70	No exercise	Excellent	Remain same
8	55-70	Walk daily	Poor	Increase
9	55-70	Yoga	Good	Decrease

5. Optimality criterion of orthogonal design

D-optimal design are straight optimizations based on a chosen optimality criterion and the model that will be fit.The optimality criterion results in minimizing the generalized variance of the parameter estimates for pre-specified model. The reasons for using optimal designs instead of standard classical design generally fall into two categories:

1. Standard factorial or fractional factorial designs require too many runs for the amount of resources or time allowed for the experiment.
2. The design space is constrained(the process space contains factor setting that are not feasible or are impossible to run).

Often the goal of experiment is to study the impact that factors have on a response variable of interest. At the beginning of an experiment, there may be a large number of factors which can impact the response. By Ryan Lekivetz [14] before continuing study on these factors, it is useful to "screen" out the inert variables and identify the important factors. If the set of (potentially) important factors can be reduced, more time can be spent studying the effect of the active factors. For a general factorial design, we consider the standard normal regression model for a design d,

$y = x_0 \alpha_0 + x_1 \alpha_1 + \cdots + x_m\alpha_m + \varepsilon$ (5.1)

Where, Y is the vector of observations, α_j the vector of j-factor interactions, X_j the matrix of coefficients for α_j (column i corresponds to the coefficient for the i^{th} effect) and ε the vector of independent random errors which are distributed as $N(0, \sigma^2)$. When using a full factorial design, the main effects and j-factor interactions can be estimated independently of each other. We refer to X as the model matrix. For a response vector y with values corresponding to observations for the level settings of the factors in each row, the vector of estimated main effects and interactions, can be calculated a $=1/2^{n-1}$ X' y the covariance matrix for model (5.1) is diagonal matrix, so the effects can be estimated independently of each other.

5.1 Case Study 2: Consider the following OA (8, 4, 2, 3)

Table 5.1 shows the Orthogonal Array, OA (8, 4, 2, 3) constructed for the Compatibility Testing of treatments in patients.

Table 5.1.

Test Number	Age	Area	Weight observe	Diet
1	Below55	Rural	Decrease	light
2	Below55	Rural	Increase	heavy
3	Below55	Urban	Decrease	heavy
4	Below55	Urban	Increase	light
5	55-70	Rural	Decrease	heavy
6	55-70	Rural	Increase	light
7	55-70	Urban	Decrease	light
8	55-70	Urban	Increase	heavy

Wang and Wu (1992) proposed the D criterion $D = |X'X|^{1/m}$

In trying to estimate the effects $\beta_1, \ldots, \beta_m$, then the variance of the least squares estimator of β_i is minimized when x_i, the vector of x_i values for the N runs is orthogonal to the other columns of X.For any design, $|X'X| \le 1$ and $|X'X| = 1$, iff the original design d is an orthogonal array.Then the D criterion measures the efficiency of estimating $\beta_1, \ldots, \beta_m$.

$$X'X = \begin{bmatrix} 4 & 2 & 2 & 2 \\ 2 & 4 & 2 & 2 \\ 2 & 2 & 4 & 2 \\ 2 & 2 & 2 & 4 \end{bmatrix}$$

$D= |X'X|^{1/m} = [-16]^{1/4}=-2$

$D= |X'X|^{1/m} = -2$ the original design d is an orthogonal array.

The estimate $\hat{\alpha} = (X'X)^{-1} X' \hat{y}$ for model (5.1) in Case Study 2: OA (8, 4, 2, 3)

In our study we need to enter the variable symptom score of diabetic as the dependent variable and the age, area of residence, observe weight and diet rating as independent variables.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.619	.383	.340	.543

The above table shows the multiple linear regression model summary and overall fit statistics. We find that the adjusted R^2 of our model is 0.340 with the R^2 = .383that means that the linear regression explains 38.3% of the variance in the data.

The next table is the F-test, the linear regression's F-test has the null hypothesis that there is no linear relationship between the variables (in other words R^2=0). The F-test is highly significant, thus we can assume that there is a linear relationship between the variables in our model.

ANOVA

Model	Sum of Squares	D f.	Mean Square	F	Sig.
Regression	10.623	4	2.656	8.995	.000
Residual	17.124	58	.295		
Total	27.746	62			

The next table shows the estimates including the intercept and the significance levels. The b value tells us about the relationship between symptom score of diabetic and predictors.

If the value is positive we can tell that there is positive relationship between predictors and the outcome whereas negative coefficient represents negative relationship. If t-test associated with a b value is significant then the predictors are making a significant contribution to the model

Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.691	.489		5.504	.000
Age	-.028	.007	-.442	-4.165	.000
Area of residence	.457	.159	.342	2.880	.006
Weight observed	-.030	.114	-.030	-.264	.793
Diet rating	.074	.077	.109	.960	.341

In the above table we find that age and area of residence are significant predictors.

The estimated regression coefficients for the model can be obtained as:

$$\hat{\alpha} = (X'X)^{-1} X' \hat{y} = \begin{bmatrix} 2.691 \\ -.028 \\ .457 \\ -.030 \\ .074 \end{bmatrix}$$

Therefore, the fitted regression model is:

$\hat{y}$=2.691-0.028 age+0.457area-0.030 observe weight+0.074 diets

5.2 Case Study 3

Extending with our approach and suggested us to add 1 more level in age and diet rating to this combination. Hence, the factors and various levels for each of the factors are now as follows in Table 5.2: Factors and Levels listed for the Compatibility

Table 5.2. Mixed Orthogonal Array constructed for the Compatibility Testing of treatments in patients.

Factors	Level 1	Level 2	Level 3	Level 4
Age	Below 30	30-40	40-50	Above 50
Type of exercise	No exercise	Walk daily	yoga	
Diet rating	Poor	Average	Good	Excellent
Weight observe	Decrease	Remain same	Increase	

Here the highest level =4, which is not a prime number. The second highest level =3, which is a prime number. Hence we can construct the Orthogonal Array with 4*3= 12 rows and 4 (3+1) columns. The OA is constructed as follows in Table 5.3:

Table 5.3. Orthogonal Array constructed for the Compatibility Testing with 1 more variable and 1 more level added.

Test Number	Age	Diet rating	Typeof exercise	Weight observe
1	Below 30	Poor	No exercise	Decrease
2	Below 30	Average	Walk daily	Increase
3	Below 30	Good	yoga	Remain same
4	30-40	Excellent	Walk daily	Remain same
5	30-40	Poor	yoga	Decrease
6	30-40	Average	No exercise	Increase
7	40-50	Good	yoga	Increase
8	40-50	Excellent	No exercise	Remain same
9	40-50	Poor	Walk daily	Decrease
10	Above 50	Average	No exercise	Remain same
11	Above 50	Good	Walk daily	Decrease
12	Above 50	Excellent	yoga	Increase

Benefit shown to the combinations of test cases:

For 4 Factors, 2 factors with 3 levels and the other 2 factors with 4 levels, the total number of test cases = 144. With the Orthogonal Array Approach, we have been able to reduce it to 12 Test Cases. Thus we have been able to reduce the testing effort 8.33% of the total effort. Hence, Effort Saved = 91.67%

6. Conclusion

Strategy is a systematical statistical way of testing pairwise interaction by deriving suitable small set of test cases from a large number of scenarios. OAT should be used to reduce the no. of combinations and provide maximum coverage with a minimum no. of test cases. Furthermore, for compilation, it has been found that the new technique is the least time-consuming among the existing technique.

Table 3.1 to 5.3 illustrates the results from the above 3 Case Studies.

These case studies focuses on many test reduction technique using OA approach and mixed orthogonal approach in the area of diabetic people . This technique leads to filter the important requirement in clinical trial and thus efficient system is achieved.

Case Study 1 shows the reduction of total test cases from 81 to 9 with the use of this algorithm 88.89% efforts have been saved.

Case study 2 measure the efficiency for design $|X'X| \leq 1$ the original design d is an orthogonal array. For model (5.1), we estimate $\hat{\alpha}$ using $\hat{\alpha} = (X'X)^{-1} X'Y$. Therefore, the fitted regression model is:

$\hat{y}$ =2.691-0.028 age+0.457area-0.030 observe weight+0.074 diets

Case Study 3 shows the reduction of total test cases from 144 to 12 with the use of this algorithm 91.67% efforts have been saved.

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