American Journal of Mechanical Engineering and Automation
2014; 1(6): 60-65
Published online October 10, 2014 (http://www.openscienceonline.com/journal/ajmea)

Analysis of the variables of a production mix in a manufacturing industry (A case of Niger bar soap manufacturing industry Onitsha, Anambra state, Nigeria)

Ezeliora Chukwuemeka Daniel[1], Adinna Boniface O.[2], Umeh Maryrose Ngozi[3], Okpala Chukwunonso Divine[4]

[1]Department of Industrial and Production Engineering, Nnamdi Azikiwe University Awka, Anambra State, Nigeria
[2]Department of Civil Engineering, Nnamdi Azikiwe University Awka, Anambra State, Nigeria
[3]Department of Computer Science, Nnamdi Azikiwe University Awka, Anambra State, Nigeria
[4]Department of Agric and Bio Resource Engineering, Nnamdi Azikiwe University Awka, Anambra State, Nigeria

Email address

cezeliora@gmail.com (E. C. Daniel), adinnaboniface@yahoo.com (Adinna B. O.), rose1chi@yahoo.com (U. M. Ngozi)

To cite this article

Ezeliora Chukwuemeka Daniel, Adinna Boniface O., Umeh Maryrose Ngozi, Okpala Chukwunonso Divine. Analysis of the Variables of a Production Mix in a Manufacturing Industry (A Case Study of Niger Bar Soap Manufacturing Industry Onitsha, Anambra State, Nigeria). *American Journal of Engineering, Technology and Society.* Vol. 1, No. 6, 2014, pp. 60-65.

Abstract

The aim of this research work is to show the interaction and the main effect or impact of the independent variables of a soap production mix materials to the dependent variable of a production quantity. The research shows the dept or the impact of their relationships of the two variables.

Keyword

Interaction, Main Effect, Histogram, Descriptive Statistics, Variables and ANOVA

1. Introduction

In statistics, an interaction [1][2] may arise when considering the relationship among three or more variables, and describes a situation in which the simultaneous influence of two variables on a third is not additive. Most commonly, interactions are considered in the context of regression analyses.

Objective of the study is to understand the effect of independent variables on the dependent variable and to also observe the rate of interaction between the variables.

The presence of interactions can have important implications for the interpretation of statistical models. If two variables of interest interact, the relationship between each of the interacting variables and a third "dependent variable" depends on the value of the other interacting variable. In practice, this makes it more difficult to predict the consequences of changing the value of a variable, particularly if the variables it interacts with are hard to measure or difficult to control.

The notion of "interaction" is closely related to that of "moderation" that is common in social and health science research: the interaction between an explanatory variable and an environmental variable suggests that the effect of the explanatory variable has been moderated or modified by the environmental variable. [3]

An "interaction variable" is a variable constructed from an original set of variables to try to represent either all of the interaction present or some part of it. In exploratory statistical analyses it is common to use products of original variables as the basis of testing whether interaction is present with the possibility of substituting other more realistic interaction variables at a later stage. When there are more than two explanatory variables, several interaction variables are constructed, with pairwise-products representing pairwise-interactions and higher order products representing higher order interactions.

The binary factor *A* and the quantitative variable *X* interact (are non-additive) when analyzed with respect to the outcome variable *Y*.

Thus, for a response *Y* and two variables x_1 and x_2 an *additive* model would be:

$$Y = c + ax_1 + bx_2 + \text{error} \tag{1}$$

In contrast to this,

$$Y = c + ax_1 + bx_2 + d(x_1 \times x_2) + \text{error} \tag{2}$$

is an example of a model with an interaction between variables x_1 and x_2 ("error" refers to the random variable whose value is that by which Y differs from the expected value of Y; see errors and residuals in statistics).

2. Qualitative and Quantitative Interactions

In many applications it is useful to distinguish between qualitative and quantitative interactions.[4] A quantitative interaction between A and B refers to a situation where the magnitude of the effect of B depends on the value of A, but the direction of the effect of B is constant for all A. A qualitative interaction between A and B refers to a situation where both the magnitude and direction of each variable's effect can depend on the value of the other variable.

The table of means on the left, below, shows a quantitative interaction — treatment A is beneficial both when B is given, and when B is not given, but the benefit is greater when B is not given (i.e. when A is given alone). The table of means on the right shows a qualitative interaction. A is harmful when B is given, but it is beneficial when B is not given. Note that the same interpretation would hold if we consider the benefit of B based on whether A is given.

	***B* = 0**	***B* = 1**		***B* = 0**	***B* = 1**
A = 0	2	1	*A* = 0	2	6
A = 1	5	3	*A* = 1	5	3

The distinction between qualitative and quantitative interactions depends on the order in which the variables are considered (in contrast, the property of additivity is invariant to the order of the variables). In the following table, if we focus on the effect of treatment *A*, there is a quantitative interaction — giving treatment *A* will improve the outcome on average regardless of whether treatment *B* is or is not already being given (although the benefit is greater if treatment *A* is given alone). However if we focus on the effect of treatment *B*, there is a qualitative interaction — giving treatment *B* to a subject who is already receiving treatment *A* will (on average) make things worse, whereas giving treatment *B* to a subject who is not receiving treatment *A* will improve the outcome on average. [5]

	***B* = 0**	***B* = 1**
A = 0	1	4
A = 1	7	6

3. How to Evaluate and Interpret an Interaction

Let’s use a weight loss example to illustrate how we can evaluate an interaction between factors. We're evaluating 2 different diets and 2 different exercise programs: one focused on cardio and one focused on weight training. We want to determine which result in greater weight loss. We randomly assign participants to both diet A or B and either the cardio or weight training regimen, and then record the amount of weight they’ve lost after 1 month.

4. The Danger of Ignoring Interactions among Factors

Suppose this interaction wasn't on our radar, and we instead focused only on the individual main effects and their impact on weight loss:

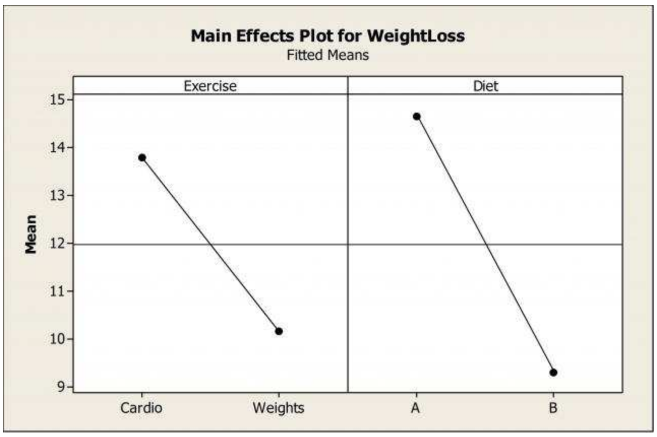

Fig. 1. *Interaction and Main Effect of Weights and Cardio*

Based on this plot, we would incorrectly conclude that diet A is better than B. As we saw from the interaction plot, that is only true if we're looking at the cardio group.

Clearly, we always need to evaluate interactions when analyzing multiple factors. If you don't, you run the risk of drawing incorrect conclusions and you might just get ketchup with your sushi roll.

5. Main Effects

Main effects are differences in means over levels of one factor collapsed over levels of the other factor. This is actually much easier than it sounds. For example, the main effect of Method is simply the difference between the means of final exam score for the two levels of Method, ignoring or collapsing over experience. As seen in the second method of presenting a table of means, the main effect of Method is whether the two marginal means associated with the Method factor are different. In the example case these means were 30.33 and 30.56 and the differences between these means was not statistically significant.

6. Simple Main Effects

A simple main effect is a main effect of one factor at a given level of a second factor. In the example data it would be possible to talk about the simple main effect of ability at method equal blue-book. The effect would be the difference between the three cell means at level a_1 (26.67, 31.00, and 33.33). One could also talk about the simple main effect of method at Ability equal lots (33.33 and 27.00). Simple main effects are not directly tested in this analysis. They are, however, necessary to understand an interaction.

7. Interaction Effects

An interaction effect is a change in the simple main effect of one variable over levels of the second. An A X B or A BY B interaction is a change in the simple main effect of B over levels of A or the change in the simple main effect of A over levels of B. In either case the cell means cannot be modeled simply by knowing the size of the main effects. An additional set of parameters must be used to explain the differences between the cell means. These parameters are collectively called an interaction.

The change in the simple main effect of one variable over levels of the other is most easily seen in the graph of the interaction. If the lines describing the simple main effects are not parallel, then a possibility of an interaction exists. As can be seen from the graph of the example data, the possibility of a significant interaction exists because the lines are not parallel. The presence of an interaction was confirmed by the significant interaction.

8. Main Effects and Interactions

Statistical relationships between independent and dependent variables are often referred to as effects. So the difference between the average concentration score in the quiet condition and the average concentration score in the noisy condition can be called "the effect of noise level on concentration." Likewise, the difference between the average intelligence rating in the smile condition and the average intelligence rating in the no-smile condition can be called "the effect of smiling on intelligence ratings." So whenever we manipulate an independent variable, we are interested in its effect on the dependent variable.

9. Main Effects

In a factorial design, a main effect is the overall effect of one independent variable. In an experiment in which both the type of psychotherapy (cognitive vs. behavioral) and the duration of psychotherapy (short vs. long) are independent variables, there is one main effect of type and another main effect of duration. The main effect of type is the difference between the average score for the cognitive group and the average score for the behavioral group … ignoring duration. That is, short-duration subjects and long-duration subjects are combined together in computing these averages. The main effect of duration is the difference between the average score for the short-duration group and the average score for the long-duration group … this time ignoring type. Cognitive-therapy subjects and behavioral-therapy subjects are combined together in computing these averages.

10. The Relationship between Main Effects and Interactions

In a 2x2 factorial experiment, there are two main effects (one for each independent variable) and one interaction (the one between the two independent variables). It gets more complicated with more independent variables. An experiment with three independent variables would have three main effects (again, one for each independent variable) and four interactions. There is an interaction between IV's 1 and 2, 2 and 3, and 1 and 3. There is also something called a three-way interaction, which has to do with whether the interaction between two variables depends on the level of the third. But do not worry about this. Until you understand simple factorial designs, there is no way you will understand more complicated ones.

The important point here is that these effects are all independent of each other. A 2x2 factorial experiment might result in no main effects and no interaction, one main effect and no interaction, two main effects and no interaction, no main effects and an interaction, one main effect and an interaction, or two main effects and an interaction. Your job now is to get good at looking at results presented in a design table or (more importantly) a graph and interpreting what happened in terms of main effects and interactions. [6]

11. The Meaning of an Interaction

When two factors interact, it means that changes in the dependent variable cannot be explained by independent effects of the two factors. Rather, the explanation must be more complicated. The effect of one factor depends on what has happened to the other factor. In the example above, we cannot explain changes in reaction time by stating that responses are slower when the task is more difficult and responses are slower when one is suffering from sleep deprivation. Both of these statements are true, but we must point out also that the effect of sleep deprivation is much greater on difficult tasks than on simple tasks.

As psychologists, interactions complicate life for us, but they also make life more interesting. They suggest that there are multiple psychological processes going on. Indeed, if a theory predicts that two or more processes are involved in explaining some behavior, then testing for an interaction is the best way to test the theory. [7]

The research method used is the analysis of the main effect and the interaction of the independent variables on the dependent variable.

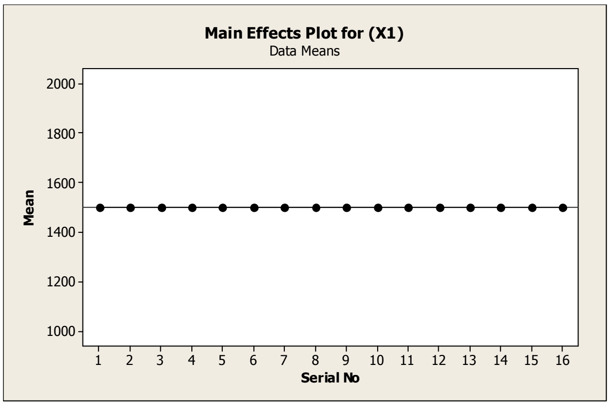

Fig. 2. *Main Effects Plot for (X1)*

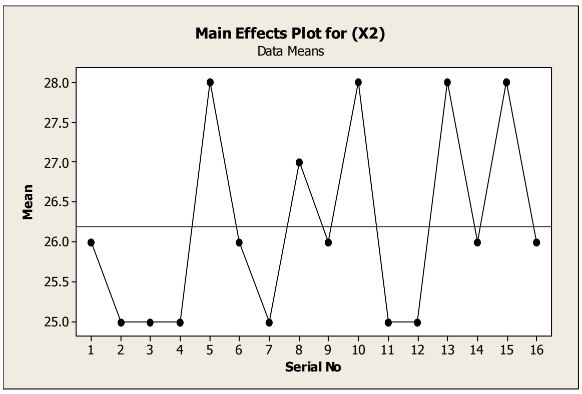

Fig. 3. *Main Effects Plot for (X2)*

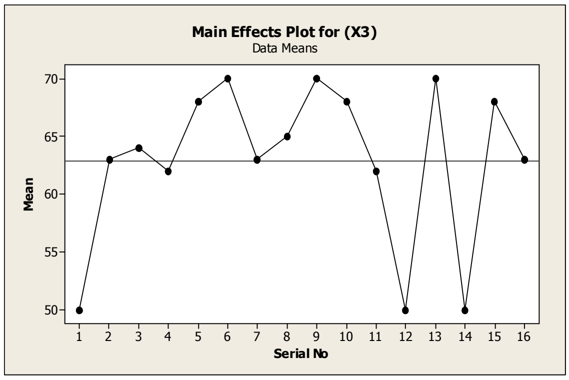

Fig. 4. *Main Effects Plot for (X3)*

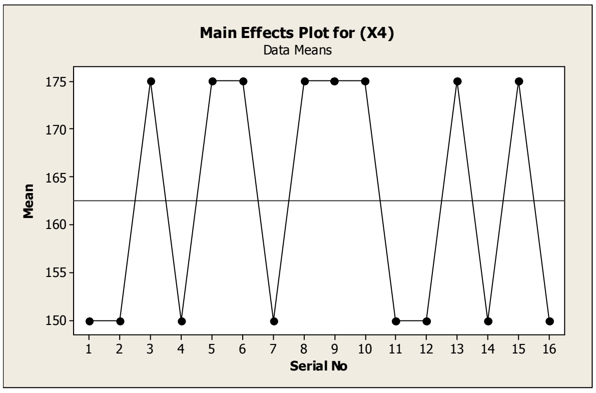

Fig. 5. *Main Effects Plot for (X4)*

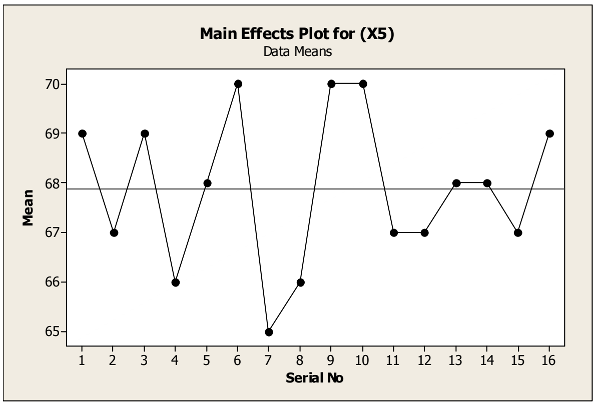

Fig. 6. *Main Effects Plot for (X5)*

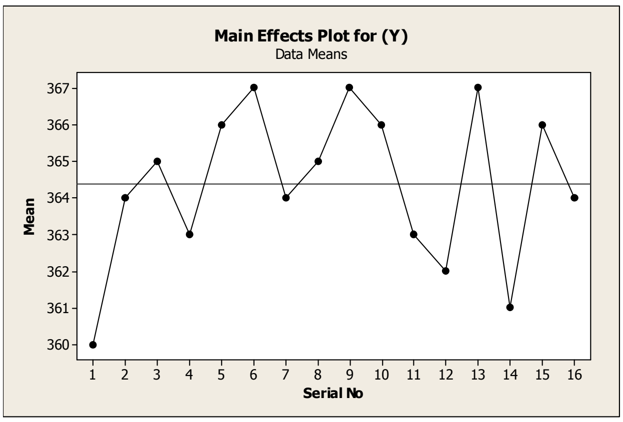

Fig. 7. *Main Effects Plot for (Y)*

Descriptive Statistics: (X1), (X2), (X3), (X4), (X5), (Y)

Variable	N	N*	Mean	SE Mean	StDev	CoefVar	Minimum	Q1	Median
(X1)	16	0	1500.0	0.000000	0.000000	0.00	1500.0	1500.0	1500.0
(X2)	16	0	26.188	0.306	1.223	4.67	25.000	25.000	26.000
(X3)	16	0	62.88	1.75	7.00	11.14	50.00	62.00	63.50
(X4)	16	0	162.50	3.23	12.91	7.94	150.00	150.00	162.50
(X5)	16	0	67.875	0.386	1.544	2.27	65.000	67.000	68.000
(Y)	16	0	364.38	0.539	2.16	0.59	360.00	363.00	364.50

Variable	Q3	Maximum
(X1)	1500.0	1500.0
(X2)	27.750	28.000
(X3)	68.00	70.00
(X4)	175.00	175.00
(X5)	69.000	70.000
(Y)	366.00	367.00

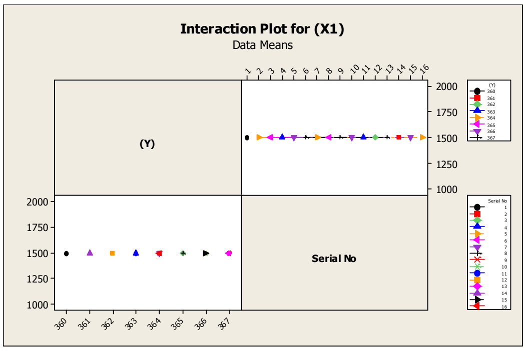

Fig. 8. *Interaction Plot for (X1)*

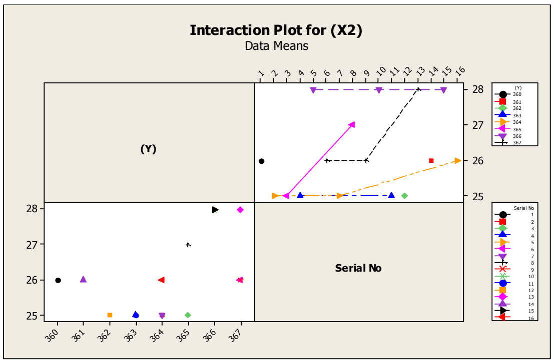

Fig. 9. *Interaction Plot for (X2)*

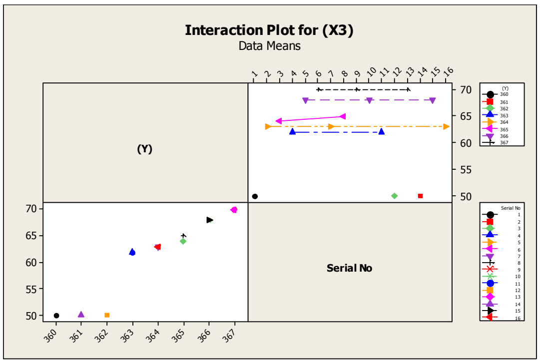

Fig. 10. *Interaction Plot for (X3)*

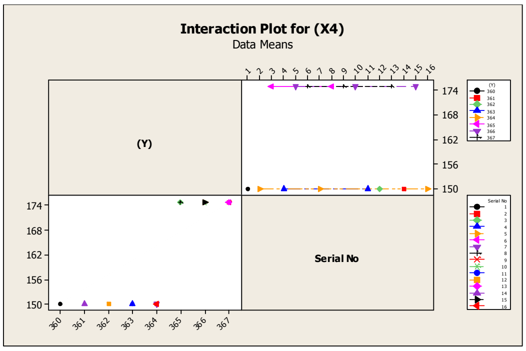

Fig. 11. *Interaction Plot for (X4)*

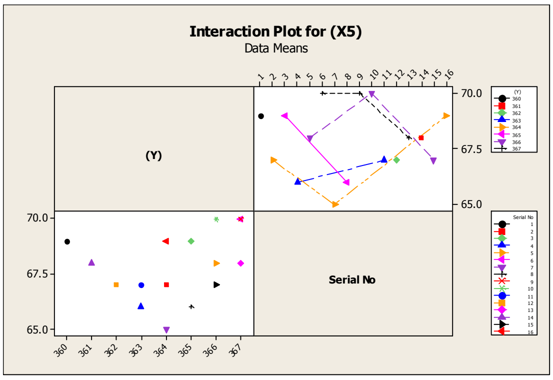

Fig. 12. *Interaction Plot for (X5)*

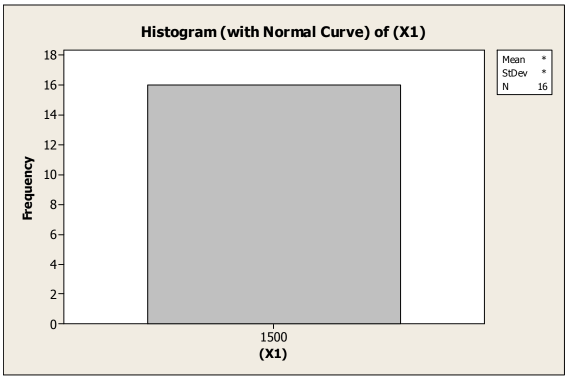

Fig. 13. *Histogram (with Normal Curve) of (X1)*

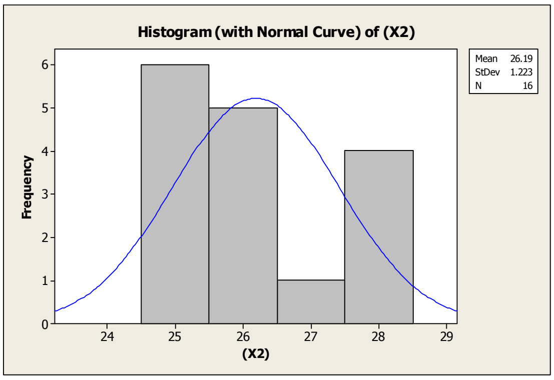

Fig. 14. *Histogram (with Normal Curve) of (X2)*

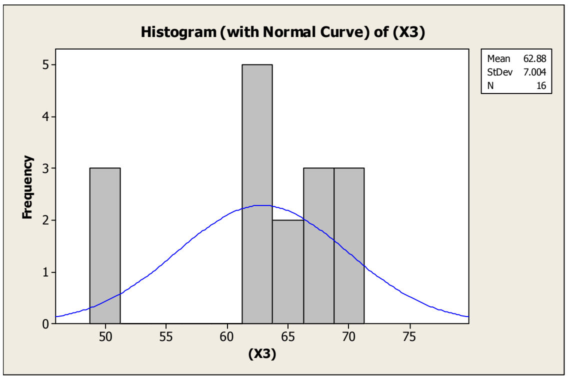

Fig. 15. *Histogram (with Normal Curve) of (X3)*

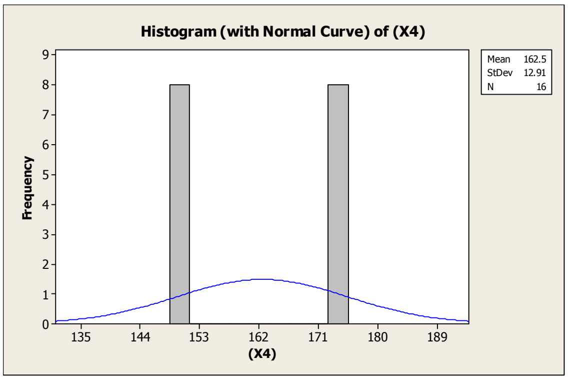

Fig. 16. *Histogram (with Normal Curve) of (X4)*

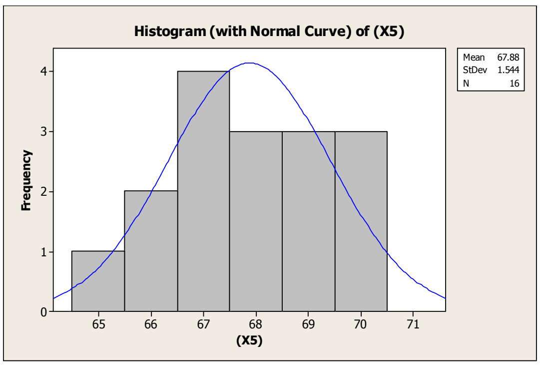

Fig. 17. *Histogram (with Normal Curve) of (X5)*

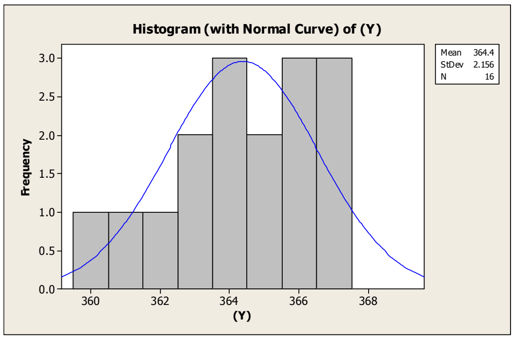

Fig. 18. *Histogram (with Normal Curve) of (Y)*

12. Discussion and Conclusion

From the results, the main effect of the independent variables show that there is no effect on X1, why on the other hand there is an effect on X2, X3, X4, X5 and the dependent variable Y. In factorial design, this shows that a new design for X1 cannot be created because it has no effect. A new design can be created for X2, X3, X4, X5 and the dependent variable Y because they have an effect. Similarly, we also observe that there is no interaction between the dependent variable Y and X1 but there is an interaction between X2 and Y, X3 and Y, X4 and Y and X5 and Y. furthermore, from the statistical description of the data, it was observed that the X1 was a constant why X2, X3, X4, X5 and Y varies and grows at different frequencies.

In conclusion, there is always a need to analyze data statistically, to observe the statistical relationships and statistical description of the data. This will help to have a good understanding of the data and a better conclusion of the research.

References

[1] Bailey, R. A. (2008). *Design of Comparative Experiments*. Cambridge University Press. ISBN 978-0-521-68357-9. Pre-publication chapters are available on-line.

[2] Cox, David R. (1958) *Planning of experiments* ISBN 0-471-57429-5

[3] Cox, David R. and Reid, Nancy M. (2000) *The theory of design of experiments*, Chapman & Hall/CRC. ISBN 1-58488-195-X

[4] Hinkelmann, Klaus and Kempthorne, Oscar (2008). *Design and Analysis of Experiments, Volume I: Introduction to Experimental Design* (Second ed.). Wiley. ISBN 978-0-471-72756-9.

[5] Kempthorne, Oscar (1979). *The Design and Analysis of Experiments* (Corrected reprint of (1952) Wiley ed.). Robert E. Krieger. ISBN 0-88275-105-0.

[6] http://psych.csufresno.edu/price/psych144/mainint.html

[7] Halford, G. S., Baker, R., McCredden, J. E., & Bain, J. D. (2005) How many varables can humans process? *Psychological Science*, 16, 70-76.