

Fully Casualized Design: A Brief Literary Review

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Abstract — *The term experimental design is characterized by the manner in which the portions are distributed in a given experiment. The completely randomized design is the most commonly used among experimental designs because the principles of randomization and repetition provide authenticity of the conclusions due to guarantee that the experimental units (plots), even if distinct and exhibit equal probability of being distributed to the groups. It is widely used in experiments have uniform conditions as the experimental conditions are critical in obtaining a good experimental design. It offers a wide experimental application, but must pay attention to the test, that even homogeneous, can present experimental conditions that will harm the experiment. So in order to get a good design, an early collection of information to evaluate the homogeneity of the experimental conditions is critical. This study is a literature review on the DIC, with their main characteristics, mathematical modeling, analysis of variance technique (ANOVA) and analysis of assumptions for ANOVA.*

Keywords— *statistic, experimental design, ANOVA, DIC.*

I. INTRODUCTION

The relevant variables to the object of study that focus on units of a sample or population, we use in statistical analysis, they are obtained from previously planned experiments, known experimental data (BERGAMASCHI, et al., 2011). The implication of factors that may or may not be controllable during experiment necessitates the use of statistical methods of analysis, to verify their prominence in bringing random variation or error experimental (ANDRADE & OGLIARI, 2007).

Among the factors that cannot be controlled stand out environmental heterogeneity not provided by the experimenter and the variations inherent to the experimental material. Thus, in order to minimize the variation of chance, the experimenter you must set the design so that it is possible to isolate the effects of the

factors that, indeed, can be controlled. Thus, the experiment relates to the set of rules that determines the definition of treatment, the arrangement of in the experimental plots and their assignments to treatment and how to analyze the Data from the experiment (DUARTE, 1996).

The completely randomized design (CRD) is the simplest of all experimental designs, it contains only the principle of randomization and repetition. Requiring homogeneity of the material and environmental conditions Experimental since their treatments are distributed in the form of parcels entirely random. The static scope of DIC is given by equation 1 (Silva 2007).

$$y_{ij} = \mu + \alpha_i + e_{ij} \quad (\text{Eq. 1})$$

At where,

y_{ij} is the value observed in experimental plot that received i - in th treatment j th repetition;

μ is a general constant associated with this random variable;

α_i is the effect of the treatment;

and e_{ij} is the error associated with observation y_{ij} , supposed to have normal distribution.

II. EXPERIMENT MODEL DATA BALANCED WITH DIC

According Padovani (2014), the operation of this design since is conditioned to the presence of homogeneous parcels is to designate the treatments to experimental units of pure and simple draw, i.e. without any restriction.

The greater the degree of homogeneity between the experimental units in terms of dependent variables, therefore the design Experimental is more efficient. But for heterogeneous units the same It does not occur. Highlighting the importance of balancing the replicates in treatments employed experimentally.

Therefore, it is an appropriate plan for experiments in laboratory that the parcels may be represented by petri plates or test tubes, as well as in a greenhouse in pots (DUARTE, 1996).

The model indicates that the shape of the biological response of a unit Experimental subjected to the treatments is given by: Biological Response Treatment Average + = Error Casual Biological and described in Equation 2.

$$y_{ij} = \mu + e_{ij} \quad (i = 1, \dots, k \text{ and } j = 1, \dots, r) \quad (\text{Eq. 2})$$

At where,

i the index referring to treatment;

j The experimental unit.

III. STATISTICAL PROCEDURE: ANALYSIS OF VARIANCE

Statistical inference for analysis of variance (ANOVA) is obtained from Distribution F of Snedecor considering two independent random variables, one being

due to other treatments and due to the experimental residue (PADOVANI, 2014).

According to Duarte (1996), if we consider an experiment aimed at test treatment (t) using repetitions (r) for each of the model determines the partition of degrees of freedom and the sum of squares for the variation Total being observed, according to equation 3.

$$y_{1j} = m + t_1 + e_{1j} \quad (\text{Eq. 3})$$

At where,

y_{1j} is the data collected in the experimental unit received at a given treatment repetition;

m is the constant inherent in the overall average;

t₁ is the effect provided by the treatment; and l_j It is the error of the experimental unit.

If the data meets the principles of analysis of variance, then the proposal the model can summarized as shown in Table 1.

Table.1: Scheme for analysis of variance installed in experiments completely randomized design.

FV	GL	SQ	QM	T
Treatment	t- 1	SQ treatment	QM treatment	QM treat/ QM error
Error	t(r - 1)	SQ error	QM error	
Total	tr- 1	Total SQ		

Source: Smith, 2007.

IV. ANOVA TO TEST HYPOTHESES

Duarte (1996) describes that there are some assumptions that must be used to make valid the application of ANOVA because the error greatness experimental and forward answer to the mathematical model assumption guarantee effectiveness and quality of a particular experiment.

These assumptions are: a) additivity, in this condition the effects of the factors that occur in the mathematical model must added together, so do not there interactions; b) independence of errors; c) homoscedasticity of variance and; d) normality of errors (BARBIN, 2003).

Carvalhoet. al., (2010) describe who should use tests to confirm whether the assumptions of the mathematical model are being met. proof these hypotheses should be performed prior to any analysis and testing assumptions including Student's distribution, F Snedecor or chi-square.

The main tests are: Test not Tukey additivity, to ascertain the additivity; random testing, to verify the randomness of the errors on the Experimental map; Lilliefors test to verify the normality of the provision of and errors; Bartlett test to analyze the homogeneity of the errors between the treatments (CONAGIN et al., 1993).

4.1 ANOVA Applicability

The main objective of the trial is to analyze alternatives (treatment) in order to identify among them those of greater biological return, agronomic and even economic (DUARTE, 1996). In this sense, all experiments aim for transparent and clear results in the environmental field need means efficient statistical.

As an example of the applicability of completely randomized design for scientific nature of experiments, Angels (2005) brings the following question:

"Consider the following experiment was conducted considering a design randomized. Nine Strains of fungi were compared by measuring growth rates in microns / hour. "

Table.2: Strains growth rates of fungi in microns / hour

Strains	Reps						Total
	I	II	III	IV	V	VI	

L1	385	323	417	370	437	340	2272
L2	406	385	444	443	474	437	2589
L3	354	292	389	312	432	299	2078
L4	271	208	347	302	379	264	1762
L5	344	292	354	354	401	306	2051
L6	354	354	410	453	448	417	2436
L7	167	115	194	130	240	139	985
L8	344	385	410	437	437	410	2423
L9	385	385	396	453	458	417	2494
Total							19090

The hypotheses for this experiment are therefore the following:

$$H_0: T_1 = T_2 = T_3 = \dots = T_9$$

$$H_1: T_1 \neq T_i \text{ 'to at least one pair with } i \neq i'$$

Assuming that one or more treatments have difference significant with regard to the efficiency of the same, is used for ANOVA check this difference.

It has been that

$$\sum_{i=1}^i \sum_{j=1}^j y_{ij} = 385 + 323 + \dots + 417 = 19090$$

$$\sum_{i=1}^i \sum_{j=1}^j y^2_{ij} = 385^2 + 323^2 + \dots + 417^2 = 7168788$$

$$I_i = 1 \quad I = 9 \text{ degrees of freedom treatments} = I - 1 = 8$$

$$J = 6 \text{ degrees of freedom residue} = I (J - 1) = 9 (6 - 1) = 45$$

$$N = IJ = 9 \times 6 = 54, \text{ degrees of freedom} = \text{Total } IJ - 1 = 53$$

From these results, based on the ANOVA formula, they have the sum of squares are as follows:

$$SQ \text{ Total} = 420,119.5$$

$$SQ \text{ Treatment} = 332,918.1$$

$$SQ \text{ Residue} = 87201.4 \text{ (SQ Total - SQ Treat)}$$

With these results, it is possible to obtain the values of the mean squares and F and calculated by ANOVA formula being:

$$QM \text{ Treat} = 41614.763$$

$$QM \text{ Res} = 1937.8089$$

$$F \text{ calculado} = QM \text{ Treat} / QM \text{ Res} = 21.48$$

Table.3: Filling the table with the obtained data, we have:

FV	GL	SQ	QM	T
Treatment	8	332.918,1	41.614,763	21.48
Error	45	87.201,4	1937.809	
Total	53	420,119.5		

Once you get all of these values, compares it with the F calculated F tabulated (1%, as called for example, the value is 2.9475).

According to the F test was significant difference between treatments, and therefore, this calculation allows us to reject the null hypothesis (H₀). That way, it means that one of the fungal strains is more efficient with respect to the rate of growth, and this is the basis for the next steps for obtaining data Statistical through the use of some means comparison test or contrasts.

4.2 Independence of errors

Padovani (2014) describes that the independence of errors is guaranteed by principle of randomization. If the errors of the independence assumption is satisfied, on graph-standardized residuals versus the order of data collection, the waste must be casually distributed around zero, without following a pattern.

In the graph construction is considered the ordinary residue (and ij): residue on the jth observation of the i-th group (i = 1, ..., K; j = 1, ..., r) (Equation 4) and residue standardized (z ij): standardized residue on the jth observation of the ith group (Equation 5). The graphical conformation of waste enables confirm that hypothesis independence errors can be accepted (LIMA and LIMA, 2014).

$$(e_{ij}) = y_{ij} - y_i \tag{Eq. 4}$$

$$(z_{ij}) = e_{ij} / \sqrt{QM \text{ Res}} \tag{Eq. 5}$$

At where, QM Res It is the Mean Square Residual

$$QM \text{ Res} = S^2 = \frac{\sum_{i=1}^k (n_i - 1) S_i^2}{(n - k)}$$

4.3 Homocedasticity

It can be verified by the Bartlett test, Levene and Hartley (F_{max}) in which errors must submit a variance (δ

2) in common. THE homogeneity of variance has two hypotheses from data groups obtained from a given experiment, as the assumptions below, and δ^2 The variance of each of the data groups (LIMA, 2014).

$$H_0: \delta_1^2 = \delta_2^2 = \dots = \delta_n^2$$

H_1 : one of δ^2 'S is different from the others

Box (1953) recommends that the results of an ANOVA are considered valid, the largest variance should not exceed four times the smaller. . Dean et al, (1999), discloses that in a more analytical decision tests: Cochran, Hartley, Bartlett and Levene were highlights for the homogeneity of variances.

Based on further in the example cited by Angels (2005), for the homoscedasticity, realized by the following figure (Figure 1), there is heterocedasticity between treatments, because some of them are showing different behavior regarding the distribution of errors.

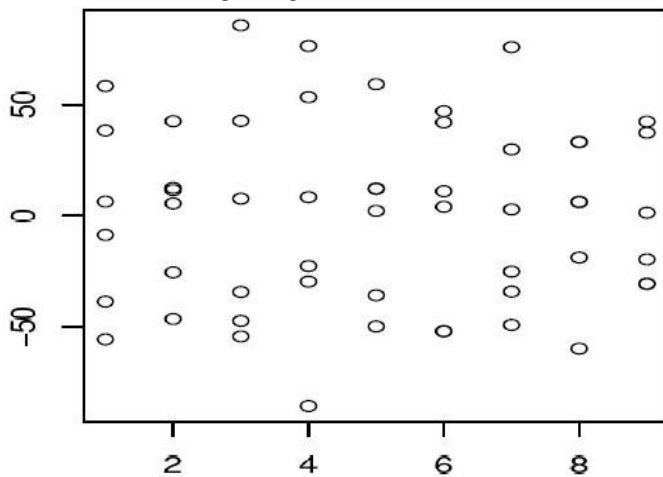


Fig.1: Verification of homocedast

Source: Angels, 2005.

4.3 Normality of the errors

The normal probability plot is a graphical technique for assessing whether a data set is approximately normally distributed and is a special case the probability plot. The data are plotted in relation to a distribution Normal theoretical such that the dots should form an approximate straight line. Matches this straight line indicate departures from normality (Chambers et al., 1983).

The probability graph is formed by the vertical axis the values of requested response and the horizontal axis with the median statistics for ordered the given distribution. According Filiben (1975), the median statistics order They may be approximated according to Equation 6.

$$N_i = G(U_i) \tag{Eq. 6}$$

At where,

U_i is the median uniform statistical order (defined below);

G is the percentage point function to the desired distribution.

The function of a percentage point is the inverse of cumulative distribution function (Probability that x is less than or equal to some value). That is, given a probability, x is the corresponding cumulative distribution function. At medians uniform statistics order are defined as:

$$m_i = 1 - m \text{ for } i = 1$$

$$m_i = (i - 0.3175) / (n + 0.365) \text{ for } i = 2, 3, \dots, n-1$$

$$0.5 m_i = (1 / n) \text{ for } i = n$$

Furthermore, a straight line may be fitted to points, added as a reference line. The more points vary this line, the greater the indicating a departure from the specified distribution. This definition implies that a probability plots can be easily generated for any distribution to which point the percentage can be calculated (ANSCOMBE, 1973).

A disadvantage of this method of calculating probability plots is that estimates of intercept and slope of the fitted line are in fact estimates for the parameters of location and distribution scale. Although this is not very important for the normal distribution, since the location and scale are the estimated mean and standard deviation, respectively, can be useful for many other distributions (WILK et al, 1968).

In addition to the graphical methods we have just considered for assess the residual normality, we can perform a hypothesis test in which the null hypothesis is that the errors have a normal distribution. A large value of p , therefore, fails to reject the null hypothesis is a good result. This means that it is reasonable to assume that the errors have a normal distribution. Normally, assessment of the appropriate residual plots is sufficient to diagnose deviations from normality. However, more rigorous and formal quantification of normality can It is requested (TUFTE, 1983). Therefore, one can apply several test procedures common to normal.

4.3.1 Anderson-Darling

Test The Anderson-Darling test measures the area between line an adjusted (based on chosen distribution) and a non-parametric function (based on points of Plot). The statistical distance is a squared which is heavier tails distribution. (TUKEY et al., 1977) under Anderson-Darling values indicate that the distribution fits the data better. The test statistic is given by Equation 7.

$$AD = -n - \frac{1}{n} \sum_{i=1}^n (2i - 1) \{ \text{Ln} F(X_i) + \text{Ln} [1 - F(X_{n-i+1})] \} \tag{Eq. 7}$$

When the statistical Anderson-Darling test is an associated p -value no We reject the null hypothesis and

conclude that it is reasonable to assume that the errors have a normal distribution.

4.3.2 Shapiro-Wilk test

The Shapiro-Wilk test uses the test statistic. First it is necessary reorganize the data in ascending order so that $x_1 \leq \dots \leq x_n$. Then calculate SS according to equation 8.

$$SS = \sum_{i=1}^n (x_i - \bar{x})^2 \quad (\text{Eq. 8})$$

If n is even, allowed to $m = n / 2$, while if n is odd, left to $m = (n - 1) / 2$. If n is odd, the median data value b is not used in the calculation (Equation 9). To calculate the test statistic used-if $W = \pm 2$

$$b = \sum_{i=1}^m a_i (x_{n+1-i} - x_i) \quad (\text{Eq. 9})$$

These values a_i are calculated using the means, variances and covariance's of (i) . W is compared with tabulated values of distribution of this statistic. Smaller values of W will lead to rejection of the null hypothesis (Shapiro, 1965).

4.3.3 Kolmogorov-Smirnov test

The Kolmogorov-Smirnov test (also known as Lilliefors Test) compares the empirical cumulative distribution function of the sample data with the expected distribution if data were normal. If this difference is observed sufficiently large, the test will reject the null hypothesis of normality of the population (CALLEGARI-JACQUES, 2003). The test statistic is given by equation 10.

$$D_{\max} = (D^+, D^-) \quad (\text{Eq. 10})$$

Where

D^+ It is the $\max_i \{ i/n - Z(i) \}$;

D^- It is the $\max_i \{ Z(i) - (i-1)/n \}$.

Being that,

Z it's the same as $F(X(i))$;

$F(x)$ is the probability distribution function of the normal distribution;

$X(i)$ it's the same as i The order statistics of a random sample, $1 \leq i \leq n$;

n it's the sample size.

The test statistic is compared with the critical values of a distribution Normal to determine the p value.

4.3.4 Chi-square test

The chi-square test is used to test whether a data sample came from a population with a specific distribution.

An attractive feature of the chi-square adequacy test is that it can be applied to any univariate distribution for which you can calculate the cumulative distribution function. The suitability of the chi-square test is applied the binary data (ie, data placed into classes). In fact, this is not a restriction because you can simply calculate the histogram or table often before generating the chi-square test. However, the statistic value Chi-square depends on

how the data are categorized. another disadvantage Chi-square test is that it requires sufficient sample size for the approximation of chi-square is valid (Snedecor and Cochran, 1989).

The chi-square test is an alternative to test suitability Anderson-Darling and Kolmogorov-Smirnov. The chi-square test adjustment can be applied to discrete distributions as the binomial and Poisson. tests of Kolmogorov-Smirnov and Anderson-Darling are restricted to continuous distributions. O chi-square test is set for the event:

H_0 : The data follow a specified distribution.

H_a : The data do not follow the specified distribution.

Test statistic: For the computation of chi-square adjustment, the data They are divided into k (Equation 11).

$$\chi^2 = \sum_{i=1}^k \frac{(O_i - \Sigma_i)^2}{\Sigma_i} \quad (\text{Eq. 11})$$

At where,

O_i is observed for the frequency bin i ;

Σ_i It is the expected frequency for i .

In which Σ_i it is calculated by:

$$\Sigma_i = C [F(Y_u) - F(Y_l)]$$

Being,

F cumulative distribution function for distributing being tested;

Y_u it is the upper limit for class i ;

Y_l is the lower limit for class i ;

N is the sample size.

V. TECHNICAL ANOVA

ANOVA is a statistical technique to analyze the variation in one variable response (continuous random variable) measured under conditions defined by factors discrete (classification variables, often with nominal levels). Often used ANOVA to test the equality of several means, comparing the variance between groups regarding the variance within groups (Random error). Sir Ronald Fisher pioneered the development of ANOVA analyze the results of agricultural experiments (Fisher, 1925).

Today, the ANOVA It is included in almost all statistical packages, which makes it accessible to researchers in all experimental sciences. It is easy to insert a set of data and perform a simple ANOVA, but it is challenging to choose the ANOVA suitable for different experimental designs, examine whether the data adhere to modeling assumptions and interpret the results correctly (STEEL et al., 1980).

To determine the appropriate ANOVA model, we must know the relationships between factors and experimental units. Statistical distinguish two types of factors in experimental design and ANOVA: "fixed factors" and "random factors". a "Fixed factor" is one for

which specific levels are of interest. a researcher could repeat the experiment using identical factor levels in twice. (SCHEFFE, 1959).

Conceptually, each level of a fixed factor is a distinct population with a single response average. When one researcher deliberately organizes or modifies the levels of a fixed factor, called these levels treatments. The primary objective of the ANOVA is to test whether the means response are identical between the levels of the factors. In contrast to a fixed factor, levels of a "random factor" represent a random sample of a number potentially infinite levels. Different levels of factors would be chosen randomly if the experiment was redone. With random factors, the objective of ANOVA is to make an inference about random variation within a population. When a factor level is applied to two or more experimental units independent, he is "replicated". If replicates are equal in number to each factor level, the experimental design is "balanced" (LEVENE, 1960).

The ANOVA concept provides details for two common models. The first model, one-way ANOVA fixed end, is an extension test t Student- Independent 2 that allows you to simultaneously compare averages of several samples independent. The second model, fixed effects ANOVA 2-way has two factors, A and B, and each level of factor A appears in combination with each factor level B. This model allows us to compare the means of the factor A levels and between levels B. factor Moreover, we examined whether the combined factors induce effects interaction (synergic or antagonistic) in response (SCHLOTZHAUER et al., 1987).

VI COEFFICIENTS DETERMINATION AND CHANGE OF AN EXPERIMENT

In addition to hypothesis testing and confidence intervals, otherwise analyze whether the model adopted in a given experiment is efficient or not treated if the coefficient of determination or explanation and the coefficient of variation.

The coefficient of determination or explanation is represented by the symbol R^2 . This indicator determines what percentage of the variance explained by Regression is the total variation (VIALI, 2018).

It is given by the ratio between SQ_{Treat} (sum of squares of treatment) and SQ_{Tot} (total sum of squares of the values found), indicating the proportion of the total variance explained by the variation due to treatment ($0 \leq R^2 \leq 1$) (PADOVANI, 2014).

The coefficient of variation of an experiment, represented by (CV) estimates the accuracy of experiments representing the standard deviation expressed as average percentage (MOHALLEM et al., 2008).

According to Snedecor (1980), the distribution coefficient of variation allows the establishment of tracks values that guide researchers on the validity and veracity of their experiments.

It is given by the ratio between the standard deviation (ANOVA, is the square root a positive QMR_{es}) and the overall mean data, inferring how data comportam-in relation to the general average. The magnitude of the reverse precision CV refers to the idea the experimental data (PADOVANI, 2014).

VII MULTIPLE COMPARISONS

Multiple comparisons are used when the variance analysis detects that there is a significant effect on certain treatment of an experiment, the certain level of significance, where it rejects the null hypothesis (SOUSA et al., 2012). They have his theory based on the normality of the model residues linear used to fit the data (and BORGES FERREIRA, 2003).

The test multiple comparisons of means are of great importance in applied research (CONAGIN et al., 2008) when trying to compare the Qualitative treatments.

In this sense, several tests are used for this purpose, and the same usually take the name of its author, the main ones being: Tukey, Student-Newman Keuls (SNK), Student's t test (LSD), Duncan, among others (BORGES & FERREIRA, 2003).

The choice of test to be used should be based on statistics qualities the study aims, considering it is always for the non-violation of the assumptions Basic to their application, such as normality and homoscedasticity errors of independence (EAX. et al., 2005).

7.1 Tukey test

Tukey's test is based on the amplitude of estudentizada distribution, and can It is used to compare any and all contrast between two averages treatment, with accuracy when the number of repetitions is equal in all treatments. When there is a different number of repetitions Test Tukey can still be used, however, the result will approximate (GOMES, 2000).

For the minimum significant difference in the Tukey test, is used to formula described in equation 12:

$$d.m.d = q \sqrt{QMR/r} \text{ (Eq. 12)}$$

At where:

q: refers to the value of the table Tukey significance level;
QMR: refers to the mean square of ANOVA;

A: refers to the number of repetitions of each treatment (Oliveira, 2008).

Again using the example proposed by Angels (2005), after identifying the existence of significant differences between treatments using the F test can evaluate the magnitude of these differences through

multiple comparisons test. O Tukey Test, which is based on the least significant difference (LSD) is a means of obtaining this magnitude.

Applying we test:

$$\Delta(5\%)=4,64\sqrt{1937,8/6}=83,39$$

$$q=4,64$$

$$\alpha=0,05$$

If the contrast is greater than the value of Δ , then the average level differ α of significância.

In addition to the Tukey test, it is also possible to carry out comparison tests multiple of that example by Duncan test, SNK, among others.

7.2 Student-Newman-Keuls test (SNK)

The SNK test is performed the same way as the Tukey test, however, exception is that the critical value in SNK is not the number of treatments, but the number average amplitude included in the medium being tested (CALLEGARI-JACQUES, 2003).

One of the advantages of using SNK test is that it allows separating means in discrete groups, without overlap between the groups (CANTERI et. al., 2001).

In terms of accuracy, it is intermediate between the Tukey test and Duncan, using Duncan's method with Tukey table. When the average treatment have the same number of repetitions, the following formula is used (Equation 13):

$$\text{SNK (5\%)} = q \frac{s}{\sqrt{r}} \quad (\text{Eq. 13})$$

At where,

q: refers to the value of the total amplitude estudentizada 5% probability;

s: refers to the square root of QMR (error mean square), which corresponds the estimate of the standard deviation of the experimental error;

A: refers to the number of repetitions of the experiment and / or average (FERREIRA, 2011).

According to Sampaio (2002), when average compared feature different numbers of repetitions, the formula will be shown below (Equation 14):

$$Q = \text{SNK} \sqrt{\frac{s^2}{2} \left(\frac{1}{R_a} + \frac{1}{R_b} \right)} \quad (\text{Eq. 14})$$

At where,

Ra: refers to the number of repetitions of treatment experiment "A";

Rbb: refers to the number of repetitions of the experiment Treatment "B".

7.3 t test Student

The Student t test, t test or simply seeks to reject or not a hypothesis null when the test statistic (t) follows a Student's t distribution. Can be conducted to compare a sample of a population, comparing two samples compare two parallel and independent samples (Lopes et. al., 2015), two means A and B obtained in experimental

groups can be compared in the following relationship by t test (Equation 15).

$$t = \frac{x-\mu}{\frac{s}{\sqrt{n}}} \quad (\text{Eq. 15})$$

At where,

X: refers to the median of the sample;

μ : refers to the average population (or reference);

S: refers to standard deviation; n: refers to the number of subjects (JUNIOR, 2012).

7.4 Duncan test

Duncan test is taken to a new method for the comparison of averages, with a more difficult application of the Tukey test, however, much more efficient with regard to the breakdown of the results and breakdown of treatments. It requires that all treatments have the same number of repetitions so that their results show accuracy (OLIVEIRA, 2008).

Typically, it is applied at 5% probability, and despite being more work is less rigorous than the Tukey test (VIANA, 2012). it should be point out that when using three or more averages, Duncan's theory is wrong, because the global significance level is not maintained (BANZATTO & KRONKA, 2006).

According to Gomes (2000), when the number of averages is very large (greater than 10, for example), the application of this test becomes very cumbersome.

According Vieira and Hoffmann (1989) to obtain DMS is the following formula applied (Equation 16):

$$d.m.s = z \sqrt{\text{QMR} / r} \quad (\text{Eq. 16})$$

At where,

Z: refers to a standard value at significance level and the number means covered by the range delimited by the medium in comparison;

QMR: refers to the mean square of ANOVA;

A: refers to the number of repetitions.

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