INTRODUCTION

1.1 EXPERIMENTAL DESIGN

In 1935 Sir Ronald A. Fisher laid the foundation for the Experimental Design. Experimentation provides what is called experimental data in contrast to observational data with which we have been mainly concerned up to this point. Observational data are represented by observations on the elementary units of population or of a sample and are not changed or modified by any attempt on the part of an investigator during the course of the observation. It is often difficult to assign cause and effect by studying observational data. If one is interested in establishing causal relationship, he should work with experimental data, data arising from observations on a universe or a segment thereof which have been ‘controlled’ or modified by varying certain factors in order to determine what effect, if any, the factors have on the data. In other words, experimental data are the results from logically designed experiments which provide evidence for or against theories of cause and effect. Further described about the experimental design Gupta & Kapoor [32].

The subject-matter of the experimental design includes:

- Planning of the experiment.
- Obtaining relevant information from it regarding the statistical hypothesis under study.
- Making a statistical analysis of the data.

Experience has shown that proper consideration of the statistical analysis before the experiment is conducted, forces the experimenter to plan more
carefully the design of the experiment. The observations obtained from a carefully planned and well-designed experiment in advance give entirely valid inferences.

However, the certainty of the conclusion so drawn, regarding the acceptance or rejection of the null hypothesis, is given only in terms of probability. Accordingly, the Experimental Design may be defined as “the logical construction of the experiment in which the degree of uncertainty with which the inference is drawn may be well defined.” The experimenter may easily recognize three important phases of every project.

**Experimental or Planning Phase.**

- Statement of problem.
- Choice of response or dependent variable.
- Selection of factors or treatment to be varied.
- Choice of levels of these factors: Quantitative or qualitative & Fixed or random.
- How factor levels are to be combined?

**Design Phase**

- Number of observation to be taken.
- Order of experimentation.
- Method of randomization to be used.
- Mathematical model to describe the experiment.
- Hypothesis is to be tested.
Analysis Phase

- Data collection and processing.
- Computation of test statistics.
- Interpretation of results for the experimenter.

Experiments are performed by investigators in virtually all field of inquiry, usually to discover something about a particular process or system. An experiment is a test. An experiment as a series of tests in which purposeful changes are made to the input variables of a process or system so that we may observe and identify the reasons for changes that may be observed in the output response Montegomery [67].

Rangaswamy [78] described that, the choice of treatments, the method of assigning treatments to experimental units and arrangement of experimental units in various patterns to suit the requirement of particular problem, are combined known as experimental design. On the basis of experimentation to study the effect of changes in one variable (such as application of fertilizer or machine) on another variable (such as grain yield of a crop or machine production). The variable whose change we wish to study may be termed as a dependent or response variable. The variable whose effect on the response variable we wish to study may be termed as an independent variable or a factor. Thus, fertilizer, spacing, irrigation schedule, pesticide, drugs, machine etc., are known as factors. The crop yield, mortality of pests, etc., are known as responses.

The definitions of basic terminology described by Gupta & Kapoor [32] are given below for understanding of the experimental design,
1.1.1 Terminology in Experimental Designs

- **Experiment**: An experiment is a device or a means of getting an answer to the problem under consideration. Experiment can be classified into two categories:
  
  - **Absolute Experiment**: Absolute experiments consist in determining the absolute value of some characteristics e.g. obtaining the average intelligence quotient (I.Q.) of a group of people.
  
  - **Comparative Experiment**: Comparative experiment are designed to compare the effect of two or more objects on some population characteristic e.g. comparison of different manures or fertilizers, different kinds of varieties of a crop, different cultivation processes, different pieces of land in a field experiment.

- **Treatments**: Various objects of comparison in a comparative experiment are termed as treatments, e.g. in field experimentation different fertilizers or different varieties of crop or different methods of cultivation are the treatments.

- **Experimental Unit**: The smallest division of the experimental material to which we apply the treatments and on which we make observations on the variable under study, is termed as experimental unit, e.g., in field experiments the plot of ‘land’ is the experimental unit. In other experiments, unit may be a patient in a hospital, a lump of dough or a batch of seeds.
- **Blocks**: In agricultural experiments, most of the times we divide the whole experimental unit into relatively homogeneous sub-groups or strata. These strata, which are more uniform amongst themselves than the field as a whole, are known as blocks.

- **Yield**: The measurement of the variable under study on different experimental units are termed as yields.

- **Experimental Error**: Variation from plot to plot, which is due to random (or chance or random assignable) factors beyond human control, is known as experimental error.

1.1.2 **Principles of Experimental Design**

It is worth to describe the basic principles of experimental design which have been described and used by many researchers.

- **Replication**: Replication serves to reduce experimental error and thus enables us to obtain more precise estimates of the treatment effects. From statistical theory we know that the standard error (S.E.) of the mean of sample of size $n$ is $\frac{\sigma}{\sqrt{n}}$, where $\sigma$ is the standard deviation of the population. Thus if a treatment is replicated $r$ times, then the S.E. of
its mean effect is $\sigma/\sqrt{n}$, where $\sigma^2$, the variance of the individual plot is estimated from the ‘error variance’. Thus, the precision of the experiment is inversely proportional to the square root of the replications. Consequently replication has an important but limited role in increasing the efficiency of the design.

- **Randomization**: In the absence of the prior knowledge of the variability of the experimental material, this objective is achieved through ‘randomization’, a process of assigning the treatments to various experimental units in a purely chance manner. Randomization provides a logical basis for that and makes it possible to draw rigorous inductive inferences by the use of statistical theories based on probability theory. This assumption of randomness is necessary since S.E. ($x$) = $\sigma/\sqrt{n}$ for random sampling only. Randomizing the treatments over the experimental units is an essential safeguard against distortion of experimental results by un-anticipated influences such as rise in ambient temperature, drift in calibration of instruments and equipment, fertility of the soil or other systematic changes.

  The purpose of randomness if to assure that the sources of variation, not controlled in the experiment, operate randomly so that the average effect on any group of units is zero.

- **Local Control**: The process of reducing the experimental error by dividing the relatively heterogeneous experimental area into homogeneous blocks is known as local control. In local control some known causes of variation in the experimental material can be controlled. If these principles are used are the experimental error can be controlled.
1.2 Parametric Methods in Experimental Design

1.2.1. Analysis of Variance (ANOVA)

The analysis of variance (ANOVA) is a powerful statistical tool for tests of significance. The test of significance based on t-distribution is an adequate procedure only for testing the significance of the difference between two sample means. In a situation when we have three or more samples to consider at a time an alternative procedure is needed for testing the hypothesis that all the samples are drawn from the same population means they have the same mean. The basic purpose of the analysis of variance is to test the homogeneity of several means.

The term ‘Analysis of Variance’ was introduced by Prof. R.A. Fisher in 1920’s to deal with problem in the analysis of agronomical data. variation is inherent in nature. The total variation in any set of numerical data is due to a number of causes which may be classified as: Assignable causes and chance causes. The variation due to assignable causes can be detected and measured whereas the variation due to chance causes is beyond the control of human hand and cannot be traced separately.

Assumption for Analysis of Variance (ANOVA) Test

ANOVA test is based on the test statistics F (or Variance Ratio). For the validity of the F-test in ANOVA, the following assumptions are made:

- The observation are independent.
- Parent population from which observation are taken is normal.
- Various treatment and environmental effects are additive in nature.

Basically there are two type of classification or layout of ANOVA,
- One-way classification or layout of ANOVA: Completely Randomized Design is analogous to this one-way layout of ANOVA.
- Two-way classification or layout of ANOVA: Randomized Block Design (one observation per cell) is analogous to this Two-way layout of ANOVA.

The details of one-way and two-way layout ANOVA is given below,

### 1.2.2. One-Way Analysis of Variance (ANOVA) or Completely Randomized Design

A One-Way Analysis of Variance (ANOVA) or Completely Randomized Design (CRD) is basic experimental design where the treatments are assigned at random so that each experimental unit has the same chance of receiving any one of the treatment. For the one-way ANOVA, any difference among experimental units receiving the same treatment is considered as experimental error. Hence, the one-way Analysis of Variance is only appropriate for experiments such as laboratory experiments, field experiment and some clinical trial experiment which have homogeneous experimental units. Kwanchai et.al [51].

**Mathematical Model of One-Way ANOVA for Completely Randomized Design**

Let \( j^{th} \) individual unit in the \( i^{th} \) treatment may be represented by the equation

\[
y_{ij} = \mu_i + t_i + e_{ij}
\]

Where, \( \mu_i \) = Overall mean  

\( t_i = i^{th} \) treatment effect.  

\( e_{ij} = \) error term.
This means that any $y_{ij}$ is made up of overall mean + treatment effect + an error term. Since the effects are added in this model, it is known as a linear additive model. It is commonly known as linear additive model and also known as analysis of variance model. The statistical analysis of one-way ANOVA or Completely Randomized Design as follows,

\[
\text{Correction Factor} = \frac{(GT)^2}{rt}
\]

\[
\text{Total S.S.} = \sum Y_{ij}^2 - \text{CF}
\]

\[
\text{Treatment S.S. (Treat. S.S.)} = \frac{1}{n} \sum T_i^2 - \text{CF}
\]

\[
\text{Error S.S.} = \text{Total S.S} - \text{Treat. S.S.}
\]

With these results the One-way ANOVA table is completed and as follows,

Table 1.1 General ANOVA (One-Way Classification) Layout or CRD

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>D.F.</th>
<th>S.S.</th>
<th>M.S.S.</th>
<th>F ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
<td>$t-1$</td>
<td>Treatment SS</td>
<td>TMS</td>
<td>TMS / EMS</td>
</tr>
<tr>
<td>Error</td>
<td>$(n-t)$</td>
<td>ESS</td>
<td>EMS</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>$n-1$</td>
<td>Total S.S.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

If by $F$-test we find significant difference between treatment, then we can use critical difference (CD) for comparing pairs of treatments. The CD is given by,

\[
CD = t \cdot SE (d)
\]
Where, $t =$ table value of $t$ for a specified level of significance and error degrees of freedom & $SE (d)$ is the S.E. of difference between two means Rangaswamy [ ].

For equal & unequal replications, $SE (d) = \sqrt{EMS \left( \frac{1}{r_i} + \frac{1}{r_j} \right)}$

The treatments are ranked on the basis of CD value and the significance of the treatments is decided on this value.

**Conditions under which CRD is used or important points to be noted for CRD**:

- It allows complete flexibility as any number of treatments and replicates may be used. The number of replicates, if desired, can be varied from treatment to treatment.
- The statistical analysis is easy even if the number of replicates are not the same for all treatments or if the experimental errors differ from treatment to treatment.
- The relative loss of information due to missing data is smaller in comparison with any other design and they do not pose any problem in carrying out the standard analysis of data.
- It provides the maximum number of degrees of freedom for the estimation of the error variance, which increases the sensitivity or the precision of the experiment for small experiments, i.e., for experiments with small number of treatments.
- In CRD, experimental material is homogeneous i.e. experiments used in Lab, Polyhouse, green house. Also CRD be used in field when experimental material is homogenous.
1.2.3. Two–Way Analysis of Variance (ANOVA) or Randomized Block Design

If the treatments are applied at random to relatively homogeneous units within each strata or block and replicated over all the blocks, the design is a Randomized Block Design (R.B.D.). Gupta and Kapoor [32]. The RBD is special case of Two-way ANOVA Layout. The entire experimental material is divided into number of homogeneous blocks. If there are t treatments each block is divided into t units. The units in each block are numbered from 1 to t. The treatments are also numbered conveniently.

By using random number tables, we select t distinct random numbers from 1 to t. These random numbers correspond to the treatment numbers. The first selected treatment is allotted to the first unit of a block, the second selected treatment to the second units, and so on. The randomization is done for each block in the same way Rangaswamy [78].

Mathematical Model of Two-Way ANOVA or Randomized Block Design

Let the individual unit in the ith treatment may be represented by the equation

\[ y_{ij} = \mu + t_i + r_j + e_{ij} \]

Where, \( \mu \) = Overall mean

\( t_i \) = ith treatment effect.

\( r_j \) = jth replication effect

\( e_{ij} \) = error term.
This means that any \( y_{ij} \) is made up of overall mean + replication effect + treatment effect + an error term. Since the effects are added in this model, it is known as a linear additive model. It is commonly known as linear additive model and also known as analysis of variance model Rangaswamy [78].

\[
\text{Correction Factor} = \frac{(GT)^2}{rt}
\]

\[
\text{Total S.S.} = \sum Y_{ij}^2 - \text{CF}
\]

\[
\text{Block or Replication S.S. (R.S.S.)} = \frac{1}{t} \sum R_j^2 - \text{CF}
\]

\[
\text{Treatment S.S. (T.S.S.)} = \frac{1}{rt} \sum T_i^2 - \text{CF}
\]

\[
\text{Error S.S.} = \text{Total S.S.} - \text{Replication S.S.} - \text{Treatment S.S.}
\]

With these results the analysis of variance table is completed. The form of ANOVA table for RBD with \( t \) treatments and \( r \) replications each is given in Table 1.2.

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>D.F.</th>
<th>S.S.</th>
<th>M.S.S.</th>
<th>F ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Replication</td>
<td>( r-1 )</td>
<td>RSS</td>
<td>RMS</td>
<td>RMS / EMS</td>
</tr>
<tr>
<td>Treatment</td>
<td>( t-1 )</td>
<td>TSS</td>
<td>TMS</td>
<td>TMS / EMS</td>
</tr>
<tr>
<td>Error</td>
<td>((t-1)(r-1))</td>
<td>ESS</td>
<td>EMS</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>( rt-1 )</td>
<td>Total S.S.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
If by $F$– test we find significant difference between treatment, then we can use critical difference (CD) for comparing pairs of treatments. The CD is given by,

$$CD = t \cdot SE (d)$$

Where, $t$ = table value of $t$ for a specified level of significance and error degrees of freedom.

$$SE. (d) = \sqrt{\frac{2EMS}{r}}$$

If the absolute difference $|T_i - T_j|$ for treatments $i$ and $j$ is greater than the critical difference, the treatments are considered to be significantly different otherwise non-significant.

**Conditions and important advantages to be noted for RBD:**

- **Accuracy**: R.B.D. has been shown to be more accurate than C.R.D. for most of the experimental works. The elimination of between sum of square from residual sum of square, usually results in a decrease of Error mean sum of square.

- **Flexibility**: In two-way layout or R.B.D no restrictions for the number of treatments or replications. Generally, at least two replicates shows the test of significance. Control or some other treatments may be included in the analysis.

- **Ease of analysis**: Statistical Analysis is easy and simply solved. The error in any treatment can be isolated and any number of treatment may be omitted from the statistical analysis without any complication.
1.3 Non-Parametric Methods used in Basic Experimental Design

Analysis of experimental data is based on the assumptions like normality, independence and homoscedasticity of the observations. However, there may arise experimental situations where these assumptions, particularly the assumption of normality, may not be satisfied. In such situations non-parametric test procedures may become quite useful. A lot of attention is being made to develop non-parametric tests for analysis of experimental data. Most of these non-parametric test procedures are based on rank statistic or rank analysis. The rank statistic has been used in development of these tests as the statistic based on ranks is,

- Distribution free.
- Easy to simplified.
- Simple to explain and understand.

The another reason of use of the rank statistic is due to the well known result that the average rank approaches normality quickly as (number of observations) increases, under the rather general conditions, while the same might not be true for the original data. Some non-parametric test are available for randomized block design as follow Rajender [ 79 ]. The Non-Parametric test procedure for Analysis of one-way and two-way ANOVA classified data. Some of these procedures are:

- Kruskal-Wallis Test
- Friedman Test
- Quade Test
- Durbin Test
- Skillings and Mack Test
- Gore test for Multiple Observations per Plot
For research study purpose, we use Non-parametric test such as Kruskal-Wallis Test, Quade Test and Friedman Test (For one observation per cell). The analytical procedure of this test as below,

1.3.1 Kruskal-Wallis Test:

In situations where the normality assumption is unjustified, the experimenter may wish to use an alternative procedure to the One-Way Analysis of Variance or Completely Randomized Design that does not depend on this assumption. Such procedure has developed by Kruskal and Wallis (1952). A One-Way Analysis of Variance (ANOVA) or Completely Randomized Design is basic experimental design where the treatments are assigned at random so that each experimental unit has the same chance of receiving any one of the treatment Gupta and Kapoor [32]. For the one-way ANOVA, any difference among experimental units receiving the same treatment is considered as experimental error. Hence, the one-way Analysis of Variance is only appropriate for experiments such as laboratory experiments, field experiment and some clinical trial experiment which have homogeneous experimental units Kwanchai et.al [51]. The objective of analysis of variance (ANOVA), refer Montgomery and Runger [68] is to analyse statistics about treatment mean, treatment effect, random error so as to take out conclusions about such statistics.

Maxwell & Delaney [60] stated that the Kruskal-Wallis test is the non-parametric alternative to the ANOVA F test of Complete Randomized Design (CRD).

The Kruskal-Wallis [47] proposed test is a rank-based approach for three or more unpaired or independent samples. Generally, ranked-based test convert samples values to respective ranks based on their magnitude- since the data are
only determined positionally (by rank order), rank-based tests are actually based on the median rather than the mean. Rank based tests are more robust than parametric tests because the median is less influenced by outliers, skew and non-normality than the sample mean Allison et.al [7].

The K-W Statistic is based on the assessment of the differences among the average ranks. This may be described procedure as follows by Rajendra [79],

Let \( R_{ij} \) be the rank of \( y_{ij} \), \( i = 1, 2, \ldots, \nu; \ j = 1, 2, \ldots, \ ri \) and \( R_i = \sum_{j=1}^{\nu} R_{ij} \) (the sum of the ranks of the observations pertaining to the \( i^{th} \) treatment) and \( \overline{R_i} = \frac{R_i}{ri} \) (the average of the ranks of the observations pertaining to the \( i^{th} \) treatment). Let \( \overline{R_i} \) is the mean of the all \( \overline{R_i} \). The K-W statistic is, then given by

\[
T = \frac{12}{N(N+1)} \sum_{i=1}^{\nu} ri \ (\overline{R_i} - \overline{R})^2
\]

\[
\Rightarrow T = \frac{12}{N(N+1)} \sum_{i=1}^{\nu} ri \left( \frac{R_i}{ri} \cdot \frac{N+1}{2} \right)^2
\]

\[
T = \frac{12}{N(N+1)} \sum_{i=1}^{\nu} \frac{R_i^2}{ri} - 3(N+1)
\]

\( T \) may be approximate by the \( \chi^2 \) with (\( \nu-1 \)) degree of freedom

When ties occur between two or more observations, each observation is given the mean of ranks for which it is tied. The T-statistic after correcting the effect of ties is computed by using following formula
Pair-Wise Comparisons :

If the KWt rejects the null hypothesis of equality of \( v \) treatment effects, it indicates that at least two of the treatment effects are unequal. It does not tell the researcher which one are different from each other. Therefore, a test procedure for making pair wise comparisons is needed. For this, null hypothesis \( H_0 : \tau_i = \tau_i^* \) against \( H_1 : \tau_i \neq \tau_i^* \) for all \( i \neq i^* = 1, 2, \ldots, v \) can be tested at \( \alpha \% \) l.o.s. by using the inequality

\[
| \bar{R}_i - \bar{R}_{i^*} | \geq Z_p \sqrt{\frac{N(N+1)}{12} \left( \frac{1}{r_i} + \frac{1}{r_i^*} \right)} \quad \forall i, i', i \neq i' = 1, 2, \ldots, v
\]

Where \( p = \alpha / v(v-1) \) and \( Z_p \) is the quantile of order \( 1-p \) under the standard normal distribution. From the above, we can say that the least significant difference between the treatments \( i \) and \( i' \) is

\[
C_{ii'} = Z_p \sqrt{\left( \frac{1}{r_i} + \frac{1}{r_i'} \right)}
\]

Therefore, if \( | \bar{R}_i - \bar{R}_{i^*} | > C_{ii'} \) then the difference between \( i \) and \( i^* \) treatment effect is considered significant at \( \alpha \% \) l.o.s. The above procedure is illustrated with the help of following example.
1.3.2 Quade Test

Quade [76,77] proposed non-parametric alternative test for Two-way ANOVA or Randomized Block Design with one observation per cell. In this non-parametric test, the treatments within block are ranked in the usual manner. The rank of the treatment \( j \) of block \( i \) is denoted by \( r_{ij} \). Then the ranks are assigned to the blocks themselves according to the size of the range in each block. The range within a block is the difference between the largest and the smallest observations within that block. Thus, there will be \( b \) ranges. The procedure described as follows by Rangaswamy[78],

The ranks of these ranges may be denoted by \( Q_1, Q_2, \ldots , Q_b \). Then for each treatment we compute:

\[
R_{ij} = Q_i \left( r_{ij} - \frac{n+1}{2} \right)
\]

For each treatment we have:

\[
F_j = \sum \sum R_{ij} \quad \text{for } j = 1,2,\ldots ,b
\]

Using these values we can compute the Total Sum of Square (T.S.S.)

\[
A = \sum R_{ij}^2 \quad \text{for all } i \text{ and } j
\]

Treatment Sum of Square computed a (S.S.T.)

\[
B = \frac{1}{b} \sum R_j^2
\]

Error Sum of Square (E.S.S.) \( E = T.S.S. - S.S.T. \)
The test statistic is
\[ F_1 = (b-1) \cdot \frac{B}{E} \]

The distribution of \( F_1 \) is approximated by F distribution with \( n-1 \) and \( (b-1)(n-1) \) d.f. If the computed value \( F_1 \) is greater than the critical value the null hypothesis is rejected i.e. statistically significant; otherwise it is accepted i.e. statistically Non-Significant.

If the null hypothesis is rejected all pairs of treatments are compared using the quantity,

\[ \text{C.D.} = t \sqrt{\frac{2bE}{(b-1)(n-1)}} \]

Which is the critical difference. The value of \( t \) is obtained from t-tables against \( (b-1)(n-1) \) degrees of freedom and the specified level of significance. If the absolute difference \( |R_i - R_j| \) is greater than the critical difference, the treatments \( i \) and \( j \) are significantly different from each other.

1.3.3 Friedman Test

The K-W test is alternative Non-Parametric test for Parametric CRD. A CRD is used when experimental units are homogeneous in a blocks. However, there do occur experimental situations where one can find a factor, which, though not of interest to the experimenter, does contribute significantly to the variability in the experimental material Rajendra [79]. He further explained that various levels of this factor are used for blocking. For the experimental situations where there is only one nuisance factor, the block designs are being used. The simplest and most commonly used block design by the agricultural research or any industrial
experimental workers is Randomized Block Design (RBD). The problem of non-normality of data may also occur in RCB design as well.

Friedman test is useful for non-normality data in case of Two-way ANOVA or RBD situations Friedman [25]. Let there are \( v \) treatments that are arranged in \( N = vb \) experimental units arranged in \( b \) blocks of size \( v \) each. Each treatment appears exactly once in each block.

The data generated though a RCB design can analyzed by the following linear model

\[
Y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij} \quad i = 1, 2, \ldots, v; \quad j = 1, 2, \ldots, b
\]

Where \( Y_{ij} \) is yield (response) of the \( i \)th experimental unit receiving the treatment in \( j \)th block. \( \tau_i \) is the effect due to \( i \)th treatment. \( \beta_j \) is the effect of \( j \)th block. \( \varepsilon_{ij} \) is random error in response. Now we are interested to test the equality of treatment effect. In other words, we want to test the null hypothesis \( H_0 : \tau_1 = \tau_2 = \ldots = \tau_v = \tau \) (say) against the alternative \( H_1 : \) at least two of the \( \tau_i \)'s are different. Friedman test statistic is expressed in following two different forms as follow, which described by Rajender [79].

- **Approximately distributed F distribution** :

  The data arrangement is similar to that for Qade test. The treatments within a block are ranked from 1 to \( n \) in the usual manner. Then the ranks \( r_{ij} \) for each treatment is summed to obtain \( R_j \). To test the null hypothesis that the treatments have identical effects, we use the test statistic,

  \[
  F_2 = \frac{(b-1)\left[ B - \frac{bn(n+1)^2}{4} \right]^2}{E}
  \]
Where,
\[ E = A - B, \quad A = \sum R_{ij}^2, \quad B = \frac{1}{b} \sum R_{ij}^2, \quad R_j = \sum r_{ij} \text{ for treatment } j \]

b = number of block, \quad n = number of treatments.

The test statistic, \( F_2 \) is approximately distributed as \( F \) with \( n - 1 \) and \( (b-1)(n-1) \) degrees of freedom.

**Pair-wise Comparisons**

If the Friedman test results in rejection of the null hypothesis then multiple comparisons are made. For this we compute the critical difference.

\[
C.D. = t \sqrt{\frac{2bE}{(b-1)(n-1)}}
\]

Here \( t \) is the critical value of \( t \) for \( (b-1)(n-1) \) degrees of freedom and the specified level of significance. If the absolute difference \( |R_i - R_j| \) for treatments \( i \) and \( j \) is greater than the critical difference, the treatments are considered to be significantly different.

- **Approximately distributed \( \chi^2 \) distribution:**

This test statistic are classified in following two ways,

- **Without tie observations in block:**

    Arrange the observations in \( v \) rows (treatments) and \( b \) columns (blocks). The observations in the different rows are independent and those in different columns are dependent. Rank all the observations in a column (block) i.e. ranks are assigned separately for each block. Let \( R_{ij} \) be the rank of the observations pertaining to \( i^{th} \) treatment in the \( j^{th} \) block. Then \( 1 \leq R_{ij} \leq v \). As the ranking has been done within blocks from 1 to \( v \), therefore sum of ranks in \( j^{th} \) block is \[ R_j = \sum R_{ij} = \frac{v(v+1)}{2} \]
and $\overline{R_j} = \frac{v+1}{2}$ and the variance is $\frac{v^2-1}{12}$. Sum of ranks for each treatment is $R_i = \sum_{j=1}^{b} R_{ij}$. If the treatment effects are all the same then we expect each $R_i$ to be equal $b(v+1)/2$, that is, under $H_0$,

$$E(R_i) = \frac{1}{v} \frac{bv(v+1)}{2} = \frac{b(v+1)}{2}$$

The sum of squared deviations of $R_i$’s from $E(R_i)$ is, therefore, a measure of the differences in the treatment effects.

Let $$S = \sum_{i=1}^{v} \left( R_i - \frac{b(v+1)}{2} \right)^2$$

The Friedman test statistic is then defined as

$$T = \frac{12S}{bv(v+1)} = \frac{12}{bv(v+1)} \sum_{i=1}^{v} \left( R_i - \frac{b(v+1)}{2} \right)^2$$

$$= \frac{12}{bv(v+1)} \sum_{i=1}^{v} R_i^2 - 3b(v+1) \chi^2_{(v-1)}$$

The method of determining the probability of occurrence when $H_0$ is true of an observed values of $T$ depends upon the sizes of $v$ and $b$. For large $b$ and $v$, the associated probability may be approximated by the $\chi^2$ distribution with $v-1$ d.f. Rajender [79]

**With tie observations in block:**

When there are ties among the ranks for any given block, the statistics $T$ must be corrected to account for changes in the sampling distribution. So if ties occur then we use following statistic
Where gj is the number of sets of tied ranks in the jth block and tj is the size of the jth set of tied ranks in the ith block.

**Pair-wise Comparisons**

When the Friedman test rejects the null hypothesis that the all treatment effects are not the same, it is of interest to identify significant difference between the paired treatments, therefore, a test procedure for making pair wise comparisons is needed. The null hypothesis $H_0: \tau_i = \tau^{'}$ against $H_1: \tau_i \neq \tau^{'}$ for all $i \neq i' = 1, 2, \ldots, v$ can be tested at $\alpha \%$ l.o.s. using the inequality.

$$|R_i - R_{i'}| \geq Z_p \sqrt{\frac{b(v+1)}{6}} \quad \forall i, i' = 1, 2, \ldots, v, i \neq i'$$

Where $p = \alpha / v(v-1)$ and $Z_p$ is the quantile of order 1-p under the standard normal distribution. From the above, we can say that the least significant difference between the treatments i and i’ is, $c = Z_p \sqrt{\frac{b(v+1)}{6}}$

If $|R_i - R_{i'}| > c$ then the difference between treatment i and i’ are considered as significantly different at $\alpha \%$ l.o.s.

**1.4 Intercropping Experiment**

In Agricultural field experiments, simultaneous growing of two or more crops on the same piece of land in separate rows is known as intercropping. The experiments are conducted on sole crop (only one crop) and intercropping
crops like combination of Cotton with Tur or Cotton with other crops. In such a case we get data of not the sole crop but the data of intercrop. The data are not absolute values, it is in the proportions. Intercropping experiment is very beneficial small scale formers, through experiment they get maximum income.

We studied the advantages of intercropping experiments however the advantages of intercropping stated by Aloke [8] are the adequate which are described below.

- Increasing cropping intensity
- Diversification of crops
- Mitigating risks due whether aberrations.
- Optimal use basis resources i.e. moisture, light and nutrients.
- Insect, pest and weed control.

**Intercropping studies has following aspects.**

- Identify the appropriate crop combination so that the yield of the base crops is not sacrificed.
- Identify the appropriate crop combination so that the total production and revenue is maximized.
- Identify the proper geometry of planting component crops.
- Evaluate the effect of singly or in combinations of several factors, such as fertilizers, geometry, plant population, germ-plasm.

In intercropping experiment two or more crops are studied and in this study serious problem arises such as appropriate statistical analysis. In the past, a good number of attempts have been made by various research workers to identify appropriate statistical experiment for various types of intercropping.
experiment and their method of analysis. As regards, the problem of design, it will not be out of place to mention that they are not very different from those of sole cropping Mead & Riley [ 64 ]. The problem of designing of experiments has to be viewed more variability in intercropping experiment than in sole cropping experiment. It is generally accepted that more than one analysis should be applied to Intercropping experiment. Mead & Stern [ 65 ].

In various types of methodological problems for analysis of intercropping data are concerned, considerable interest has recently been generated by advocating different approaches. When the two-way intercropping experimental data does not meet the assumption of normality, in such situation we convert the intercropping data in Land equivalent ratio (LER). On the LER data, we test and compare the effect of Parametric Test Two-way ANOVA or Randomized Block Design and Non-Parametric Test such as Friedman [ 25 ].

1.4.1 Land Equivalent Ratio (LER)

In case of intercropping experiment, the form of underlying distribution of the data is not known, arises while handling the data from intercropping experiments. In such experiments the physical yields of both the crops are converted into univariate variable and this variable known as Land Equivalent Ratio (LER) N.S Gandhi Prasad [ 71 ]

This LER variable is use for further analysis purpose.
The computational Procedure of LER

\[ LER = \left( \frac{Y_{AI}}{Y_A} \right) + \left( \frac{Y_{BI}}{Y_B} \right) \]

Where, \( Y_A \) = The yield of base crop grown singly
\( Y_B \) = The yield of companion crop grown singly
\( Y_{AI} \) = The yield of base crop grown in intercropping
\( Y_{BI} \) = The yield of companion crop grown in intercropping

Partial LER(base crop) = \( \left( \frac{Y_{AI}}{Y_A} \right) \) & Partial LER (Companion crop) = \( \left( \frac{Y_{BI}}{Y_B} \right) \)

\[ LER = \text{PLER(base crop)} + \text{PLER (Companion crop)} \]

According to Wiley [96], the most generally useful single index for expressing the yield advantage is probable the Land Equivalent ratio (LER), defined as the relative land area required as sole crops to produce the same yields as intercropping. The advantages of LER (Mead & Wiley [66]) are that it provides standardized basis so that crops can be added to form combine yield.

1.4.2 Income Equivalent Ratio (IER)

Income Equivalent Ratio (IER) is similar in concept of LER, except that yield is measured in terms of net income, rather than plant product productivity. Because income is a function of both yield and crop price, even if the agronomic response is consistent, IER for intercrops may vary in different years as crop prices fluctuate.
IER (or LER) can be determined for systems involving more than two crops by summing the intercrop to sole crop yield (or net income) ratios of each crop included in the intercropping system.

The computational Procedure of IER

\[
IER = \left( \frac{I_{AI}}{I_A} \right) + \left( \frac{I_{BI}}{I_B} \right)
\]

Where,
- \( I_A \) = The income of base crop grown singly
- \( I_B \) = The income of companion crop grown singly
- \( I_{AI} \) = The income of base crop gown in intercropping
- \( I_{BI} \) = The income of companion crop gown in intercropping

Partial IER(base crop) = \( \left( \frac{I_{AI}}{I_A} \right) \)
Partial IER (Companion crop) = \( \left( \frac{Y_{RI}}{Y_B} \right) \)

\[ IER = PIER(base \ crop) + PIER(Companion \ crop) \]

1.5 Test of Normality

Mostly researchers do not considered the ANOVA assumption of normality, they directly use regular Parametric test such as One-way ANOVA or CRD and Two-way ANOVA or RBD for non-normal data. So before use this parametric test, data pass through test of normality such as Anderson-Darling Test. This test is used to check the data follow normal distribution or does not follow. Anderson-Darling Test compares the data nature with normal distribution i.e. this test is based on normal distribution. In this test, if \( p < 0.05 \) then data is significant (Reject Null Hypothesis) i.e. data does not follow normal distribution and if \( p > 0.05 \) then non-significant (Accept Null Hypothesis) i.e. data follow normal distribution. The graph of normal and non-normal distribution as below,
1.6 Data Transformation Techniques

When data do not follow normality assumptions in ANOVA, following data transformation may help to meet normality. Data transformations are often a very effective way to deal with the problem of non-normal response and the associated inequality of variance Montgomery [67].
1.6.1 Logarithmic Transformation

The logarithmic transformation is mostly appropriate for data where the standard deviation is proportional to the mean. To transform a data set into the logarithmic scale, simply take the logarithm of each and every value of the data set.

If the data set involves small values (e.g., < 10), log(X+1) should be used instead of log X, where X is the original data value, Kwanachai et.al [51]. Further some authors have empirically suggested using the logarithmic transformation as a means of making the data at hand conform more nearly to the three assumptions of ANOVA.

1.6.2 Square–Root Transformation

Square-root transformation is applicable for data consisting of small whole numbers. The square-root transformation is also appropriate for percentage data where the range is between 0 and 30% or between 70 and 100%. If most of the values in the data set are small (e.g., < 10), especially with zeros present, (X + 0.5)^{1/2} should be used instead of X^{1/2}, where X is the original data value, Kwanachai et.al [51]. Square-root transformation appears to have been used in the early 1930s.

1.6.3 Arc Sine Transformation or Angular Transformation

The arc sin transformation was first suggested by Fisher (1922) and again in Fisher (1930), to stabilize the variance of a binomial variate. An arc sine or angular transformation is application of data such as proportions, count, and data expressed as decimal fractions or percentages. Almost the percentage data that are derived from count data. The mechanics of data transformation are greatly
facilitated by using a table of the arc sine transformation. The value of 0% should be substituted by \((1/4n)\) and the value of 100% by \((100 - 1/4n)\), where n is the number of units upon which the percentage data was based (i.e., the denominator for used in computing the percentage).

1.7 Objectives of the Thesis

The main aim of the present research work is to study the various Non-Parametric test contribution in basic experimental design and their consequences. Further to suggest the appropriate test for the analysis of experimental data. The objective of the present study are:

- To study and review the alternative non parametric methods for analysis of One way, Two Way ANOVA and Intercropping Experiments.
- To propose analytical procedure for non-statistician, agricultural, biological sciences, medical and industrial researchers. Also to use test of normality before use of Parametric Test and Non-Parametric test in experimental design.
- To Propose appropriate data transformation technique for non-normal data in experimental design.
- To test the consequences of Parametric Test and Non-Parametric Test used in basic experimental design. Mainly One-way Analysis of Variance. Further to propose appropriate non parametric alternative test for one way ANOVA.
• To study the consequences of Parametric and Non-Parametric Test used in basic experimental design with special reference to Two-way Analysis of Variance. Further to propose appropriate non-parametric alternative test for two way ANOVA.

• To propose analytical procedure using non-parametric method for intercropping experiment in case of Two-Way ANOVA with special reference to Land Equivalent Ratio (LER) and Income Equivalent Ratio (IER).

1.8 Organization of the Thesis

In this proposed study, Parametric ANOVA methods and Non-Parametric methods have been compared on experimental data. Result of this comparative study shows crucial role of Non-Parametric tests instead of Parametric ANOVA in certain situations. Other main objective of this study is to give proposed analytical procedure to the researchers in the field of biological sciences, medical and industrial research regarding consequences of non-normality of data and how it effects on significance of treatments.

Chapter-I :Introduction

This chapter gives information of Some basic Parametric ANOVA methods of CRD & RBD. Further the necessity of Non-Parametric methods when experimental data that do not follows normality assumption, have been critically examined. Also briefly information of Non-Parametric Tests such as Kruskal-Wallis test, Quade Test, Friedman Test, rank analysis in case of RBD intercropping experiments have been described and critical revived.
Chapter-II : Research Trend : Non-Parametric tests used in Experimental Design

This chapter focus on trend of research related to Alternative Nonparametric Tests for various basic experimental design such as One-way Analysis of Variance or Completely Randomized Design, Two-way Analysis of Variance or Randomized Block Design, Two-way ANOVA in interaction and higher way layout and RBD Intercropping experiment. This review will not only help to statisticians but also to the Bio-Statisticians and Industrial statisticians working in the field of non-normal data experimental design.

Chapter-III : On Analysis of Two-way ANOVA using Data Transformation Techniques

In this chapter an attempt has been made to compare different type of data transformation for non-normal data in experimental design and test consequences in result between analysis of Two-way ANOVA with various data transformation. How significance of the treatment affects have been critically examined and consequences have been reported. In this chapter, we proposed analytical procedure for use appropriate data transformation and further analysis. The results are supported by numerical data. Here we proposed proper transformation for percentage data in Two-way ANOVA or RBD & some recommendations are given on this basis.

Chapter-IV: Analysis of One-way ANOVA using Parametric and Non-parametric Approach

This chapter describe the non-parametric tests like Kruskal-wallis test applied to the non-normal data. The effect and consequences of parametric and non-parametric test for non-normal data has been studied and discussed. Also proposed analytical procedure for use of proper parametric and non-parametric analysis. The results obtained are useful to the researcher.
Chapter-V : Alternative Non-Parametric approach for Analysis of Two-way ANOVA

This chapter emphasizes on distinguishing the precise criteria of the result between Two-way Analysis of Variance (ANOVA) or RBD parametric test and Quade, Friedman Non-Parametric test applied to analyze the experiment with non-normal data. Further in this chapter both these non-parametric Quade and Friedman tests are applied to the non-normal two-way data and compared with the parametric ANOVA. In this chapter we proposed analytical procedure for use of proper parametric and non-parametric analysis for two-way data. The different tests are compared and recommendations based on the analysis of data are given for two-way analysis of data.

Chapter-VI: Rank Analysis in Two-way ANOVA Intercropping Experiment

This chapter describe, when the experiments are conducted on sole crop (only one crop) and intercropping crops like combination of Cotton with Tur or Cotton with other crops. In such a case we get data of not the sole crop but the data of intercrop. For analysis of the data of intercrop Land Equivalent Ratio (LER) and Income Equivalent Ratio (IER) are used and then use Friedman Non-Parametric Test is applied for non-normal intercrop data have been explained. Here we proposed method of rank analysis based on Friedman Test (Non-Parametric Test) for Two-way ANOVA or RBD Intercropping Experiment.