 Approximation Of Randomized Block Design Towards Fuzzy Multiple Linear Regression: A Case Study In Health Sciences

Wan Muhamad Amir W Ahmad, Soban Q. Khan, RabiAlt Adawiyyah Abdul Rohim, Nor Azlida Aleng, Farah Muna Mohamad Ghazali

Abstract: ANOVA also provides a method of data analysis that is motivated by consideration of the experimental design or Design of Experiment (DOE). In this paper, we introduce a new dimension of the methodology by involving fuzzy regression approach to randomized block designs which is involving qualitative predictor variables under consideration on multiple linear regression. The idea from this research will be a useful thread for establishing comprehensive connectivity between randomized block designs and regression. The researchers can conclude that fuzzy MLR can predict much better compared to MLR itself.

Index Terms: Qualitative predictor variables, ANOVA, Design of Experiment, New Dimension, Multiple Linear Regression, Randomized Block Designs and Fuzzy Linear Regression

1. INTRODUCTION

ANOVA was developed by Sir Ronald Fisher in the 1920s [1]. Analysis of variance (ANOVA) is a method of comparing the means of the response variable across different groups specified by the factor variable [2], [3]. On the basis of the statistics, ANOVA also provides a method of data analysis that is motivated by consideration of the experimental design or Design of Experiment (DOE). The design of an experiment should be determined by the scientific question that is being addressed and be balanced by the practical constraints of the experimental system [4]. According to the linear point of view, ANOVA can explain the nature of the statistical relation between the mean response and the level(s) of the predictor variable(s). This paper emphasized the methodology building from ANOVA to multiple linear regression and to fuzzy multiple linear regression. Through this methodology, we are trying to prove and validate the linear model results are equivalent to single-factor ANOVA.

First, let we consider the single-factor ANOVA model which given as follows $Y_{ij} = \mu + \tau_i + \varepsilon_{ij}$, where; $Y_{ij}$ is the value of the response variable in the $j$th trial for $i$th factor level or treatment, $\mu$ = are parameters, $\varepsilon_{ij}$ = are independent N(0, $\sigma^2$) with $i=1, \ldots, t$; $j=1, \ldots, n$. Let us determine the treatment means as $\mu_i$ then it can be assumed that $\mu_i \equiv \mu_i + (\mu_i - \mu)$. The difference can be denoted as $\tau_i = \mu_i - \mu$. The difference $\tau_i = \mu_i - \mu$ is called the $i$th factor level effect. So that, the ANOVA can be expressed as: $Y_{ij} = \mu + \tau_i + \varepsilon_{ij}$, where $\mu$ = is a constant component common to all observations, $\tau_i$ = is the effect of the $i$th factor level are independent [5].

Definition of $\mu$

Let us define $\mu$ be the unweight average of all factor level means $\mu_i$ with $\mu = \sum_{i=1}^{t} \mu_i / t$. This definition implies $\sum_{i=1}^{t} \tau_i = 0$ because by $\tau_i = \mu_i - \mu$. So, we have $\sum_{i=1}^{t} \tau_i = t \mu - \sum_{i=1}^{t} \mu_i = 0$

Then, we also have $\mu = \sum_{i=1}^{t} \mu_i / t$, so, $\sum_{i=1}^{t} \mu_i = t \mu$.

The ANOVA model which is given by $Y_{ij} = \mu + \tau_i + \varepsilon_{ij}$ is called a factor effects model because it is expressed in terms of the factor effects $\tau_i$. To state ANOVA as a linear regression model; we need to signify the parameters $\mu, \tau_1, \ldots, \tau_t$ in the linear regression model. However, constraint $\sum_{i=1}^{t} \tau_i = 0$ implies that one of the $t$ parameters $\tau_i$ is not needed since it can be expressed in term of the other $t-1$ parameters. We shall drop the parameters $\tau_i$ as follows $\tau_i = -\tau_1 - \tau_2 - \tau_3 - \cdots - \tau_{i-1}$. Thus, we shall use only the parameters $\mu, \tau_1, \ldots, \tau_{t-1}$ for the linear model. For example, we now consider a linear regression model developed from single-factor of ANOVA.

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study with $r=5$ factor levels when $n_1=n_2=n_3=4$.

The $Y$, $X$, $\beta$, and $\varepsilon$ matrices for this case are as follows:

$$Y = \begin{bmatrix} Y_{ij} \\ Y_{i2} \\ Y_{i3} \\ Y_{i4} \\ Y_{i5} \\ \vdots \\ Y_{i6} \end{bmatrix}$$

$$X = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & \vdots \\ 1 & 1 & 0 & 0 & 0 & \vdots \\ 1 & 1 & 0 & 0 & 0 & \vdots \\ 1 & 0 & 1 & 0 & 0 & \vdots \\ 1 & 0 & 1 & 0 & 0 & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & -1 & -1 & -1 & -1 & \vdots \end{bmatrix}$$

$$\beta = \begin{bmatrix} \mu \equiv \beta_0 \\ \tau_1 \equiv \beta_1 \\ \tau_2 \equiv \beta_2 \\ \tau_3 \equiv \beta_3 \\ \tau_4 \equiv \beta_4 \\ \tau_5 \equiv \beta_5 \end{bmatrix}$$

$$\varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix}$$

(1)

Note that the vector of expected values, $E\{Y\} = X\beta$, yields the following equation:

$$E\{Y\} = X\beta -$$

From the calculation above, we can see that the above equation we can see that $E\{Y_{ij}\} = \mu + \tau_i$ it is equivalent as $E\{Y_{ij}\} = \beta_0 + \beta_1$ and the same process goes to all cells. The expected function for the last cell is given by $E\{Y_{i6}\} = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5$, it is equivalent as $E\{Y_{i6}\} = \mu - \tau_1 - \tau_2 - \tau_3 - \tau_4 - \tau_5$.

The next step is we calculate the estimated parameter of $\beta$ by using the method of least squares as stated below. In, the matrix terms are $X'X\beta = X'Y$. To obtain the estimated regression coefficients from the normal equation, $X'X\beta = X'Y$ by matrix methods, we premultiply both sides by the inverse of $X'X$. It can be shown as $(X'X)^{-1}X'X\beta = (X'X)^{-1}X'Y$ with $(X'X)^{-1}X'X = I$.

Solving that, we obtained the equation as $\hat{\beta} = (X'X)^{-1}X'Y$.

The illustration in (1) points out the general of multiple regression models so that it is equivalent of the single-factor ANOVA model. $Y_{ij} = \mu + \tau_i + \varepsilon_{ij}$. The utmost important part of performing the regression approach to the single-factor analysis of variance is the coding requirement. In this stage, we require indicator variables that take on values 0, 1, or -1. The coding process should be done very carefully because it leads to the regression coefficient in the $\beta$ vector that are the parameters in the factor effects ANOVA model, i.e., $\mu$, $\tau_1$, $\ldots$, $\tau_{r-1}$. Let $X_{ij}$ denote the value of indicator variable $X_1$. For the $i$th case from the $j$th factor level, $X_{ij}$, the value of indicator variable $X_2$ for this same case, and so on, using altogether $t-1$ indicator in the model. The multiple regression model then is as follows:

$$Y_{ij} = \mu + \tau_iX_{ij} + \tau_2X_{j2} + \tau_3X_{j3} + \ldots + \tau_{r-1}X_{ijr-1} + \varepsilon_{ij}$$

(2)

where

$$X_{ij} = -1 \quad \text{if case from factor level 1}$$

$$X_{ij} = 0 \quad \text{otherwise}$$

$$X_{ijr-1} = -1 \quad \text{if case from factor level } t-1$$

$$X_{ijr-1} = 0 \quad \text{otherwise}$$

In this case, the function parameters in (2) are linear in term of regression point of view; the intercept term is $\mu$ and the regression coefficient is denoted as $\tau_1, \ldots, \tau_{r-1}$. To test the equality of the treatment means $\mu_i$ by means of the regression approach, we state the null hypothesis as $H_0: \tau_1 = \tau_2 = \cdots = \tau_{r-1}$ and $H_1$: not all $\tau_i$ are equal zero.

Thus, we can employ the usual test statistic $F = \frac{MSR}{MSE}$ for testing whether or not there is a regression relation.

Fuzzy linear regression was introduced in 1980 by Tanaka, Uejima & Asai [6]. It is showed that the problem of fuzzy regression can be formulated as a mathematical programming problem [7]. It is a fuzzy type of classical regression analysis in which some element of the model is represented by fuzzy numbers. It is used in evaluating the functional relationship between the dependent and independent variables in a fuzzy environment. However, ways to estimate the parameters under fuzzy environment is a challenge to the classical regression analysis [8]. The basic model assumes a fuzzy linear function as where is a vector of independent variables; is a vector of fuzzy coefficients presented in the form of symmetric triangular numbers. According to Kumar et al., fuzzy regression methodology is more efficient than the linear regression technique [9]. A fuzzy regression method is based on minimizing fuzziness was used for model development for forecasting agriculture system. It has been found that the average widths for fuzzy linear regression models much lower compared to linear regression models for all values of fitness criterion. Thus, Fuzzy regression methodology is more efficient than the linear regression technique which indicated that fuzzy regression models possess considerable potential as an alternative to regression models for forecasting agriculture system [9]. In linear regression, one drawback of the linear methodology is that the underlying relationship is assumed to be precise, as it gives a precise value of response for a set of values of explanatory variables. However, in a realistic situation, the underlying relationship is not a crisp function of a given form; it contains some vagueness or impreciseness. So, by assuming a crisp relationship, some vital information may be lost [10]. A fuzzy regression model corresponding to this case can be written as:
\[ \text{BMI} = A_0 + A_1(X_1) + A_0(X_2) \]

All independent variables need to be significant before we proceed with the fuzzy regression analysis. Variable caries is not crisp but is instead fuzzy in nature. This implies that the parameter is also fuzzy in nature. Our aim is to estimate this parameter. \( A_1 = < a_{1c}, a_{1w} > \) and \( A_2 = < a_{2c}, a_{2w} > \), where \( a_{1c}, a_{2c} \) is the center and \( a_{1w}, a_{2w} \) is radius or vagueness associated. The above fuzzy set describes the belief of regression coefficient around \( a_{nc} \) in terms of the symmetric triangular membership function. It is also to be noted that the methodology is applied when the underlying phenomenon is fuzzy which means that the response variable is fuzzy and the relationship is also considered to be fuzzy. In fuzzy regression methodology, parameters are estimated by minimizing total vagueness in the model. From equation (3), we can rewrite the equation as follows:

\[ \text{BMI}_j = a_{0c} + a_{1c}X_{ij} + a_{2c}X_{2j} \]

\[ \text{BMI}_j = a_{0w} + a_{1w}|X_{ij}| + a_{2w}|X_{2j}| \]

\[ \text{BMI}_w \] represent radius and cannot be a negative value. The linear programming of the methodology can be expressed as follows:

\[ \text{Minimize } \sum_{j=1}^{m} \left( a_{0w} + a_{1w}|X_{ij}| + a_{2w}|X_{2j}| \right) \]

Subject to

\[ \left( a_{0c} + a_{1c}X_{ij} + a_{2c}X_{2j} \right) \leq \text{BMI}_j \]

(4a)

\[ \left( a_{0w} + a_{1w}|X_{ij}| + a_{2w}|X_{2j}| \right) \geq \text{BMI}_j \]  

(4b)

\[ a_{1w} \geq 0. \]

2 NUMERICAL EXAMPLES

For example, we now consider a linear regression model developed from single-factor of ANOVA. Table 1 gives the full dataset of the case study.

<table>
<thead>
<tr>
<th>Num</th>
<th>deft</th>
<th>BMI</th>
<th>Num</th>
<th>deft</th>
<th>BMI</th>
<th>Num</th>
<th>deft</th>
<th>BMI</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1</td>
<td>14.64</td>
<td>1</td>
<td>2</td>
<td>11.78</td>
<td>1</td>
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<td>11.63</td>
</tr>
<tr>
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<td>15.00</td>
<td>2</td>
<td>2</td>
<td>12.02</td>
<td>2</td>
<td>3</td>
<td>11.63</td>
</tr>
<tr>
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<td>1</td>
<td>13.42</td>
<td>3</td>
<td>2</td>
<td>12.63</td>
<td>3</td>
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<td>11.98</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>14.11</td>
<td>4</td>
<td>2</td>
<td>12.35</td>
<td>4</td>
<td>3</td>
<td>12.10</td>
</tr>
<tr>
<td>5</td>
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<td>2</td>
<td>12.32</td>
<td>5</td>
<td>3</td>
<td>12.10</td>
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<tr>
<td>6</td>
<td>1</td>
<td>12.33</td>
<td>6</td>
<td>2</td>
<td>12.41</td>
<td>6</td>
<td>3</td>
<td>12.25</td>
</tr>
</tbody>
</table>

Code: BMI= Body Mass Index
Code: deft = Caries Status : 1 = No caries; 2 : Low Caries , 3 : Moderate

Consider a single study with \( r=3 \) factor levels when \( n_1 = n_2 = n_3 = 6 \).

<table>
<thead>
<tr>
<th>i</th>
<th>j</th>
<th>deft</th>
<th>Y \text{ij}</th>
<th>X \text{ij1}</th>
<th>X \text{ij2}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>14.64</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>15.00</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>1</td>
<td>13.42</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>(3a)</td>
<td>4</td>
<td>14.11</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>1</td>
<td>12.51</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>6</td>
<td>1</td>
<td>12.33</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>(3b)</td>
<td>1</td>
<td>11.78</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>2</td>
<td>11.82</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>2</td>
<td>12.03</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>2</td>
<td>12.25</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>2</td>
<td>12.32</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>2</td>
<td>12.41</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>3</td>
<td>11.63</td>
<td>-1.00</td>
<td>-1.00</td>
</tr>
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<td>3</td>
<td>2</td>
<td>3</td>
<td>11.63</td>
<td>-1.00</td>
<td>-1.00</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>3</td>
<td>11.98</td>
<td>-1.00</td>
<td>-1.00</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>3</td>
<td>12.10</td>
<td>-1.00</td>
<td>-1.00</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
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<td>12.10</td>
<td>-1.00</td>
<td>-1.00</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>3</td>
<td>12.26</td>
<td>-1.00</td>
<td>-1.00</td>
</tr>
</tbody>
</table>

The \( Y, X, \beta \), and \( \epsilon \) matrices for this case are as follows:

\[
Y = \begin{bmatrix} Y_{11} \\ Y_{12} \\ Y_{13} \\ Y_{14} \\ Y_{15} \\ Y_{16} \\ \vdots \\ Y_{36} \end{bmatrix}, \quad X = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ \vdots \\ 1 & -1 & -1 \end{bmatrix}, \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix}, \quad \epsilon = \begin{bmatrix} \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{13} \\ \epsilon_{14} \\ \epsilon_{15} \\ \epsilon_{16} \\ \vdots \\ \epsilon_{36} \end{bmatrix}
\]
The regression equation can be written as
\[ BMI = 12.596 + 1.106X_1 + 0.460X_2 \]
\[ BMI < 12.596, \text{ Std error} > + < 1.106, \text{ Std error} > X_1 + < 0.460, \text{ Std error} > X_2 \]
For the upper limit
\[ BMI = 12.596 + 0.152 > + < 1.106 + 0.214 > X_1 + < 0.460 + 0.214 > X_2 \]
\[ = 12.748 + 1.32X_1 + 0.674X_2 \]
For the lower limit
\[ BMI = 12.596 - 0.152 > + < 1.106 - 0.214 > X_1 + < 0.460 - 0.214 > X_2 \]
\[ = 12.444 + 0.892X_1 + 0.246X_2 \]
run;
ods rtf file="result_ex1.rtf";
Proc optmodel;
set j= 1..18;
number BMI [j], x1[j], x2[j];
read Data ANOVA into[n]BMI x1 x2;
Print BMI x1 x2;
number n int 18;
var aw[1..3] = 0;
var ac[1..3];
min z1 = aw[1] * n + sum{i in j} x1[i] * aw[2] + sum{i in j} x2[i] * aw[3];
con c{i in 1..n}: ac[1] + x1[i] * ac[2] + x2[i] * ac[3]
con c{i in 1..n}: ac[1] + x1[i] * ac[2] + x2[i] * ac[3] +
expand;
solve;
print ac aw;
quit;
ods rtf close;

Output

The fitted model for fuzzy regression is

\[ \text{BMI} = 12.75333 - 0.780 + + \times 0.00167, 0.465 + + \times < -0.19333 \times 0.000 \times X_1 \]

For the fuzzy regression model, the prediction equations for the computing upper and lower limits, obtained are as follows.

For the upper limit

\[ \text{BMI} = 12.75333 + 0.780 + + \times 0.00167, 0.465 + + \times X_1 + + \times < -0.19333 + 0.000 + \times X_2 \]

For the lower limit

\[ \text{BMI} = 12.75333 - 0.780 + + \times 0.00167 - 0.465 + + \times X_1 + -0.19333 - 0.000 - \times X_2 \]

\[ -13.333 + 1.46667 X_1 - 0.19333 X_2 \]

\[ -11.9733 + 0.53667 X_1 - 0.19333 X_2 \]

\[ \text{TABLE 4}

COMPARISON THE ORIGINAL AND PREDICTED VALUE
(95% CI) THROUGH THE MLR AND FUZZY MLR

<table>
<thead>
<tr>
<th>Original value BMI</th>
<th>Predicted Value MLR</th>
<th>Predicted Value Fuzzy MLR</th>
<th>Absolute Residual</th>
<th>Absolute Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.64</td>
<td>13.70</td>
<td>13.76</td>
<td>0.94</td>
<td>0.88</td>
</tr>
<tr>
<td>15.00</td>
<td>13.70</td>
<td>13.76</td>
<td>1.30</td>
<td>1.24</td>
</tr>
<tr>
<td>13.42</td>
<td>13.70</td>
<td>13.76</td>
<td>0.28</td>
<td>0.34</td>
</tr>
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<td>14.11</td>
<td>13.70</td>
<td>13.76</td>
<td>0.41</td>
<td>0.36</td>
</tr>
<tr>
<td>12.51</td>
<td>13.70</td>
<td>13.76</td>
<td>1.19</td>
<td>1.24</td>
</tr>
<tr>
<td>12.53</td>
<td>13.70</td>
<td>13.76</td>
<td>1.17</td>
<td>1.22</td>
</tr>
<tr>
<td>11.78</td>
<td>13.06</td>
<td>12.56</td>
<td>1.27</td>
<td>0.78</td>
</tr>
<tr>
<td>12.02</td>
<td>13.06</td>
<td>12.56</td>
<td>1.04</td>
<td>0.54</td>
</tr>
<tr>
<td>12.03</td>
<td>13.06</td>
<td>12.56</td>
<td>1.02</td>
<td>0.53</td>
</tr>
<tr>
<td>12.25</td>
<td>13.06</td>
<td>12.56</td>
<td>0.80</td>
<td>0.31</td>
</tr>
<tr>
<td>12.32</td>
<td>13.06</td>
<td>12.56</td>
<td>0.74</td>
<td>0.24</td>
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<tr>
<td>12.41</td>
<td>13.06</td>
<td>12.56</td>
<td>0.65</td>
<td>0.15</td>
</tr>
<tr>
<td>11.63</td>
<td>11.03</td>
<td>11.94</td>
<td>0.60</td>
<td>0.31</td>
</tr>
<tr>
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<td>11.94</td>
<td>0.60</td>
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</tr>
<tr>
<td>11.98</td>
<td>11.03</td>
<td>11.94</td>
<td>0.95</td>
<td>0.04</td>
</tr>
<tr>
<td>12.10</td>
<td>11.03</td>
<td>11.94</td>
<td>1.07</td>
<td>0.15</td>
</tr>
</tbody>
</table>

The efficiency of the proposed method can be measured through absolute mean that obtained from the residual. The smallest mean value of residual indicates the better prediction of the results. Table 4 indicates the residual that obtained from our calculation. To determine which of proposed method the best is, the independent samples t-test was used to determine either the residual from MLR or fuzzy MLR is the smallest.

\[ c = y - \hat{y}_{\text{MLR}} \]

\[ e = y - \hat{y}_{\text{FuzzyMLR}} \]

\[ \text{TABLE 5}

SUMMARY OF THE RESIDUAL FROM MLR AND FUZZY MLR

<table>
<thead>
<tr>
<th>Variables</th>
<th>MLR</th>
<th>Fuzzy MLR</th>
<th>T statistic (df)</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residual</td>
<td>0.8891 (0.3322)</td>
<td>0.5726 (0.4175)</td>
<td>2.84 (44)</td>
<td>&lt; 0.05</td>
</tr>
</tbody>
</table>

Since \( p = 0.007 < 0.05 \), the null hypothesis is rejected and the mean of residual can be concluded to be significantly different between MLR and fuzzy MLR. Therefore, we can say that the residual mean of fuzzy MLR 0.5726 (0.4175) is lower compared to MLR 0.8891 (0.3322). Therefore, this indicates that the fuzzy methodology of MLR is much better in giving the prediction compared to MLR.

3 CONCLUSION

The objective of this research is to build a methodology which can be used to predict the observation from randomized block design. Besides that, this methodology can be used as a tool for assessing the significant level of factor determination. According to the result that gained from section numerical example, we can conclude that fuzzy MLR can predict much better compared to MLR itself.

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