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Comparison between Multiple Linear Regression and Fuzzy C-Regression Models towards Scale of Health in ICU

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Abstract The multiple linear regression (MLR) model is well-known in analyzing linear model. Whereas, the new technique in clustering data, the fuzzy c-regression models (FCRM) are being widely used in analyzing the nonlinear model. The FCRM models are tested on simulated data and the FCRM models can approximate the given nonlinear system with a higher accuracy. A case study in scale of health at intensive care unit (ICU) using the two methods of modelling as mentioned above was carried out. The comparison between the MLR and FCRM models were done to find the better model by using the mean square error (MSE). After comparing the two models, it was found that the FCRM models appeared to be the better model, having a lower MSE. The MSE for MLR model is 498.29 whereas the MSE for FCRM models is 97.366.

Keywords Multiple linear regression (MLR) model; fuzzy c-regression models (FCRM); mean square error (MSE).

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1 Introduction

Regression analysis has become one of the standard tools in data analysis. Its popularity comes from different disciplines. The mathematical equation from its analysis could explain the relationship between the dependent and independent variables. It provides much explanatory power, especially due to its multivariate nature. It is widely available in computer packages, easy to interpret, and there is a widespread belief that it remains a reasonable procedure even if some of the assumptions underlying it are not met in the data. It has been widely used in applied sciences, economic, engineering, computer, social sciences and other fields [1].

The new fuzzy modelling has become popular for the past few years because it explains and describes complex systems better. The fuzzy c-mean (FCM) model proposed by Bezdek in 1981 develops hyper-spherical-shaped clusters. In contrast, the fuzzy c-regression models (FCRM) proposed by Hathaway and Bezdek [2] develop hyper-plane-shaped clusters. The FCRM models assume that the input–output data are drawn from c different regression models where c is the number of clusters.

The minimization of the objective function in FCRM models is obtained when the clustering is done simultaneously which yields a fuzzy c-partitioning matrix of the data and the c regression models. Kim et al. [3] successfully applied FCRM to construct fuzzy models into two phases of learning algorithms i.e. coarse learning phase and fine-tuning learning phase. For a known system, the number of clusters (rules), c, is fixed and assigned by the user. For an unknown system, the appropriate number of clusters (rules) is supposed to be unknown and could be estimated by using formula in Chuang et al. [4].

An essential component of acute hospital care is intensive care for the critically ill patients. The intensive care unit (ICU) plays an important role in the medical care sector not only for the critically ill who makes up 5% of inpatients, but also in terms of generating a major contribution of health care funds. The United States health care industry makes up 1% of the GNP and 15-20% total hospital cost, while in the United Kingdom (UK), the National Health Services (NHS) used up £700 annually on critical care. These facts have created the awareness of outcome evaluation and quality assurance by having clear objective on the assessment of performance, effectiveness of therapy and utilization of resources in clinical audits.

In 1968, the first ICU in Malaysia was established. Since then, intensive care has developed rapidly and it is now available in all tertiary care hospitals and selected secondary care hospitals in the Ministry of Health. Rapid expansion of medical and surgical subspecialties in the last decade results in increasing demands for more ICU beds and provides impetus for its development. There is a scarcity of information on its clinical practice, performance and outcome even though intensive care practice is well established in Malaysia. Clinical audits of individual units have been published, however, to date, no clinical audits have been done on a national scale. The situation in the UK in the early 1980s was similar to what we are currently experiencing in Malaysia. More ICU beds were open up and high dependency units mushroomed without proper assessment for their needs.

The Intensive Care National Audit & Research Centre (ICNARC) was established in UK in 1994. It was co-funded by the Intensive Care Society and the Department of Health to conduct a review on intensive care practice. The £142.5 million in year 2000 was used to further improve intensive care unit and established a national database for clinical review and planning purposes. The National Audit on Adult Intensive Care Units in Malaysia is modeled on the UK experience. It is coordinated by a national committee comprising of senior intensive care specialists in the Ministry of Health. This audit develops a national database and to assess three fundamental aspects of intensive care functions within a hospital. The clinical indicators developed by ACHS (The Australian Council on Healthcare Standard) are useful tools for clinicians to flag potential problems and areas for improvement [5].

The fuzzy models are still not a common method used in ICU since many method used in ICU involves logistic regression [6–11]. Only Pilz and Engelmann [12] did a basic fuzzy rule to determine the medical decision in ICU. For example, the five condition of mean arterial pressure (MAP) were determined by 25 fuzzy rules of heart rate (very high, high, normal, low and very low) and blood pressure (very high, high, normal, low and very low) which could give a confusing decision. However they did not use FCM and FCRM models to analyze their data. In addition FCRM models did not give too many rules in medical decision. By inspiring their work in fuzzy model into ICU area could give a challenge to this study.

Takrouri [13] made a medical decision in ICU. He organized ICUs that made the care for more seriously sick patients and raised ethical and professional issues related to some patients who had untreatable medical conditions or those who sustained unsalvageable damage to their vital organs. However, he did not use any logistic regression or fuzzy model in his research. The problem exists if there are too many patients who want to be admitted to ICU and there are no available vacancies in the ICU. In fact the calculations of certain method are still needed in ICU's management.

The first research on mortality rates in Malaysia ICU has been done at a general hospital in Ipoh, involving only a logit model [5]. The second research is continued by Mohd Saifullah Rusiman et al. [14] on the analysis of logit, probit and linear probability models. As a comparison among the three models, logit model has been appeared to be the best model with 91.91% accuracy of prediction. These results achieve the conclusion that logit model is one of the famous modelling if the dependent variable is in the categorical form.

This research is an attempt to present a proper methodology and analysis of modelling in ICU. The objectives of this study are to explore the multiple linear regression model (MLR) and fuzzy c-regression models (FCRM) for the scale of health in ICU. The other objectives are to make a comparison between the MLR and FCRM models in order to find a better model and to make recommendation based on the better model in achieving improved services in hospitals.

2 Material

For this research, the data were obtained from the intensive care unit (ICU), general hospital in Johor. The data obtained were classified as a cluster sampling. It involves 1311 patients in ICU within the interval 1$^{\text{st}}$ January, 2001 to 25$^{\text{th}}$ August, 2002. The dependent variable is refers to a patient status with code 0 and 1. Status 0 is coded when patient is still alive in hospital or ICU, whereas 1 is coded when patient died in hospital or ICU. There are seven independent variables considered in this study which are sex, race, organ failure (orgfail), comorbid diseases (comorbid), mechanical ventilator (mecvent), score of SAPS II admit (s2sadm) and score of SAPS II discharge from hospital (s2sdisc).

In this research, we excluded the patient status as dependent variable since the fuzzy clustering for binary data is less suitable. The s2sdisc and s2sadm score are 15 accumulated values for heart rate, blood pressure, age, body temperature, oxygen pressure, urine result, urea serum level, white blood count, potassium serum level, sodium serum level, bicarbonate serum level, bilirubin level, glasgow coma score, chronic illness and type of admittance that have been proposed by Le Gall et al. [15]. The scales of health in hospital are measured by the score of s2sdisc. Then, s2sdisc variable is taken as the dependent variable since the s2sdisc and patient's status are determined at the same time. In fact, the highest correlation among patient's status and independent variables is between the patient's status and s2sdisc with $r = 0.87$.

3 The Basic Theory of Multiple Linear Regression Model

Firstly, the analysis of influential and outlier data should be done to the data in order to discard the data which is not relevant due to human error, machine error or environment error. The analysis used are Pearson standardized residual (outliers in Y) ([1,16]), Leverage (outliers in X) and DFBETA (influential) ([16]). Then, multicollinearity diagnostic should be done to the data to avoid dependency among X variables. The tests used are correlation matrix and Variation Inflation Factor (VIF) as in Neter et al. [17] and Weisberg [18].

The residual analysis was used to ensure that the data are normally distributed. The plot used is residual versus predicted value or X variables as in Draper and Smith [19] and

Montgomery and Peck [20]. The influential variables are selected using backward stepwise method.

For multiple linear regression model, the function of distribution is,

$$\begin{aligned} &Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik} + \varepsilon_i(\beta),\ i = 1, \ldots, N \\ &\text{or } \mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \end{aligned} \tag{1}$$

The function for least squares method is,

$$\begin{aligned} &S(\beta_0, \beta_1, \beta_2, \ldots, \beta_k) = S(\boldsymbol{\beta}) = \sum_{j=1}^{d} \varepsilon_j^2 \\ &\text{or } \boldsymbol{\varepsilon}^T \boldsymbol{\varepsilon}. \end{aligned} \tag{2}$$

From equation (1), $\varepsilon(\boldsymbol{\beta}) = \mathbf{Y} - \mathbf{X}\boldsymbol{\beta}$. Then,

$$S(\boldsymbol{\beta}) = (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^T (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}) = \mathbf{Y}^T\mathbf{Y} - 2\boldsymbol{\beta}^T\mathbf{X}^T\mathbf{Y} + \boldsymbol{\beta}^T\mathbf{X}^T\mathbf{X}\boldsymbol{\beta} \tag{3}$$

To minimize $S(\boldsymbol{\beta})$, we have to differentiate $S(\boldsymbol{\beta})$ with respect to $\boldsymbol{\beta}$ where $\left.\frac{\delta S}{\delta \boldsymbol{\beta}}\right|_{\hat{\beta}}$ is equal to 0, i.e.,

$$\left.\frac{\delta S}{\delta \boldsymbol{\beta}}\right|_{\hat{\boldsymbol{\beta}}} = -2\mathbf{X}^T\mathbf{Y} + 2\mathbf{X}^T\mathbf{X}\boldsymbol{\beta} = 0$$

Hence, the least squares estimator is,

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Y} \tag{4}$$

The detailed explanation of this estimator is shown in Norusis [16], Neter et al. [17], Weisberg [18], Draper and Smith [19], Montgomery and Peck [20] and Seber [21].

4 The Basic Theory of Fuzzy C-Regression Models

The analysis of influential and outlier data should be done to the data when using MLR model. However, there are no conditions needed in FCRM models. A switching regression model is specified by

$$Y_i = f_i(X; \theta_i) + \varepsilon_i, \quad 1 \le i \le c \tag{5}$$

The optimal estimate of $\boldsymbol{\theta}$ depends on assumptions made about the distribution of random vectors ε_i. Generally, the $\varepsilon_i$are assumed to be independently generated from some pdf $p(\varepsilon;\, \eta,\, \sigma)$ such as the Gaussian distribution with mean 0 and unknown standard deviation σ_i with pdf given by

$$p(\varepsilon; \eta, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\varepsilon-\eta)^2}{2\sigma^2}} \tag{6}$$

Based on the algorithm in Hathaway and Bezdek [2] and Abonyi and Feil [22] we have to

(a) Fix the number of cluster c, $c \ge 2$. Choose the termination tolerance δ >0. Fix the weight, w, w >1 (a common choice in practice is to set $w = 2$) and initialise the initial value for membership function matrix, $\mathbf{U}^{(0)}$satisfying equation (8)

(b) Estimate $\theta_1, ..., \theta_c$ simultaneously by modifying the fuzzy c means algorithm (FCM). If the regression functions $f_i(x;\theta_i)$ are linear in the parameters θ_i, the parameters can be obtained as a solution of the weighted least squares:

$$\theta_i = [\mathbf{X}_b^T \mathbf{W}_i \mathbf{X}_b]^{-1} \mathbf{X}_b^T \mathbf{W}_i \mathbf{Y} \tag{7}$$

where $\mathbf{X}_b = [\mathbf{X}, 1]$

(c) Calculate the objective function:

$$E_w[\mathrm{U}, \{\theta_i\}] = \sum_{i=1}^{c} \sum_{j=1}^{d} u_{ij}^w E_{ij}[\theta_i] \tag{8}$$

where

(i) $u_{ij}$is membership degree ($i = 1,\ldots, c$; $j = 1,\ldots, N$).

(ii) $E_{ij}[\theta_i]$ is the measure of error with $E_{ij}[\theta_i] = ||Y_j - f_i(X_j;\theta_i)||^2$. The most commonly used is the squared vector Euclidean norm for $Y_j - f_i(X_j;\theta_i)$. y_j is the real data for dependent variable and $f_i(X_j;\theta_i)$ is predicted value for Y_j based on the cluster.

(d) Do iterations in order to minimize the objective function in equation (8). Repeat for $l = 1,2\ldots, \infty$ until $||\mathbf{U}^{(l)} - \mathbf{U}^{(l-1)}|| < \delta$. Next, follow the steps below:

Step 1 : Calculate model parameters $\theta_i^{(l)}$to globally minimize equation (8).

Step 2 **:** Update $\mathbf{U}$ with $E_{ij} = E_{ij}[\theta_i^{(l-1)}]$, to satisfy:

$$u_{ij}^{(l)} = \begin{cases} \dfrac{1}{\sum_{k=1}^{c} \left(\dfrac{E_{ij}}{E_{kj}}\right)^{2/(w-1)}}, & \text{for } I_j = \phi \\ 0, & \text{for } I_j \neq \phi \text{ and } i \notin I_j \end{cases} \tag{9}$$

where

$$I_j = \{\, i |\, 1 \leq i \leq c \text{ and } E_{ij} = 0\}$$

until $||\mathbf{U}^{(l)} - \mathbf{U}^{(l-1)}|| < \delta$

In the FCRM clustering algorithm, the number of clusters, c is assigned by the user. In practice, the appropriate number of clusters is usually decided with the aid of the cluster validity criterion like the proposed new cluster validity criterion or the compactness-to-separation ratio defined as follows,

$$F_{NEW} \equiv \frac{f_{com}}{f_{sep}} = \frac{\sum_{k=1}^{N} \sum_{i=1}^{c} (\mu_{ik})^w |[X_k^{\mathrm{T}}\ 1]\theta_i - Y_k|^2}{N \left(\min_{\substack{i \neq j \\ i=1,...,c \\ j=1,...,c}} \dfrac{b_{ij} + k_2}{|\langle v_i, v_j \rangle| + k_1} \right)} \tag{10}$$

where

N is the number of observations

c is the number of clusters

μ_{ik} is the membership function

X_k is the independent variable

θ_i is the estimated parameter

Y_k is the dependent variable

$b_{ij} = \dfrac{|b_0^i - b_0^j|}{\Delta b_{\max}}$ for $i, j = 1, ..., c \quad i \neq j$ and $\Delta b_{\max} = \max\limits_{\substack{i=1,...,c \\ j=1,...,c}} |b_0^i - b_0^j|$

v_i is the center of the i^{th} cluster

v_j is the center of the j^{th} cluster

$|\langle v_i, v_j \rangle|$ is the absolute value of the standard inner-product of their unit normal vectors for i and j where $u_i = \dfrac{n_i}{\|n_i\|}$ and $\|.\|$ denotes the Euclidean norm

$k_1,\ k_2$ are small real positive constants that prevents the function from being zero or being divided by zero

The numerator reflects the compactness of hyper-plane-shaped clusters, and the denominator indicates the separation of hyper-plane-shaped clusters. The optimal number c is chosen when F_{NEW} reaches its minimum [23–25].

In describing a large class of nonlinear system, Takagi and Sugeno [26] and Sugeno and Kang [27] has introduced a fuzzy rule-based model. This affine T-S fuzzy model with IF-THEN rules is developed systematically and describes the unknown systems with given input-output data. This model is also called an affine T-S fuzzy models [23], described as follows,

$$\begin{aligned} R^i\text{: IF } X_1 \text{ is } A_1^i \text{ and } \cdots\ X_n \text{ is } A_n^i \\ \text{THEN } Y^i = a_1^i X_1 + \cdots + a_n^i X_n + a_0^i \end{aligned} \tag{11}$$

where R^i denotes the ith IF-THEN rule

$i = 1, 2, \ldots, c$

c is the numbers of rules based on the number of clusters

$X_q,\ q = 1, ..., n$, are individual input variables

A_q^i are individual antecedent fuzzy sets

$a_k^i,\ k = 1, ..., n$ are consequent parameters

a_0^i denotes a constant

$Y^i \in \Re$ is the output of each rule

This linear functions in the consequent part are hyper-planes (n-dimensional linear subspaces) in $\Re^{n+1}$.

For any input vector, $\mathbf{X} = [X_1, ..., X_n]^{\mathrm{T}}$, if the singleton fuzzifier, the product fuzzy inference and the centre average defuzzifier are applied, the output of the fuzzy model $\hat{Y}$ is deduced as follows [25, 28, 29];

$$\hat{Y} = \frac{\sum_{i=1}^{c} w^i(X)\ Y^i}{\sum_{i=1}^{c} w^i(X)} \tag{12}$$

where

$$w^i(X) = A_1^i(X_1) \times A_2^i(X_2) \times ...A_n^i(X_n) = \prod_{q=1}^{n} A_q^i(X_q) \tag{13}$$

denotes the degree of fulfillment of the antecedent, that is, the level of firing of the ith rule.

The consequent parameters can be found directly from the FCRM program output. However, some additional manipulations are needed for the antecedent fuzzy sets A_q^i. The antecedent fuzzy sets are usually achieved by projecting the membership degrees in the fuzzy partitions matrix $\mathbf{U}$ onto the axes of individual antecedent variable $x_q$to obtain a point-wise defined antecedent fuzzy set A_q^i and then approximate it by a normal bell-shaped membership function [23, 29].

Hence, each antecedent fuzzy set A_q^i is calculated from the sampled input data $x_h = [x_{1h}, ..., x_{nh}]^{\mathrm{T}}$ and the fuzzy partition matrix $\mathbf{U} = [\mu_{ih}]$ as follows [3, 30],

$$A_q^i(z) = \exp\left\{-\frac{1}{2}\left(\frac{z - v_q^i}{\sigma_q^i}\right)^2\right\} \tag{14}$$

where

mean,$v_q^i = \frac{\sum_{h=1}^{N} \mu_{ih} X_{qh}}{\sum_{h=1}^{N} \mu_{ih}}$ and standard deviation, $\sigma_q^i = \sqrt{\frac{\sum_{h=1}^{N} \mu_{ih}(X_{qh} - \alpha_q^i)^2}{\sum_{h=1}^{N} \mu_{ih}}}$.

In finding the better model, mean square error (MSE) is used as follows;

(a) For Multiple Linear Regression Model

$$MSE = \frac{1}{N-p}\sum\left(Y_i - \hat{Y}_1\right)^2$$

(b) For FCRM models

$$MSE = \frac{1}{N}\sum\left(Y_i - \hat{Y}_i\right)^2$$

where Y_i denotes the real data,

$\hat{Y}$ represents the predicted value of Y_i,

N is the number of data and

p is the number of parameters.

5 Results and Discussions

5.1 Simulation Data

Consider simulation data which are generated using S-Plus program. The number of suitable data chosen is 1000 since the data are normally distributed and the data are more stable against outliers. The data are generated with a certain limit interval where $Y \in [0, 1008]$. There are 4 independent variables, X_1, X_2, X_3 and $X_4 \in [0, 10]$. We restricted the data within a certain limit to avoid any outliers and influential data that can affect the results. By applying equation (10), the plot of cluster criterion F_{NEW} against number of clusters c is depicted in Figure 1. It can be observed that the proposed cluster criterion F_{NEW} indicates the correct number of clusters $c = 2$.

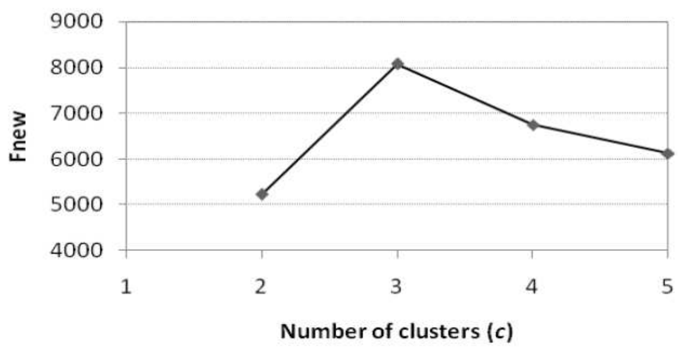

Figure 1: Plot for F_{NEW} versus the Number of Clusters (c)

The affine T-S fuzzy models with the optimal of two clusters are described as follows. The antecedent parameters are described in detail in Table 1 involving their mean and standard deviation for each cluster.

Cluster 1

$$R^1\text{: IF } X_1 \text{ is } A_1^1 \text{ and } X_2 \text{ is } A_2^1 \text{ and } X_3 \text{ is } A_3^1 \text{ and } X_4 \text{ is } A_4^1$$
$$\text{THEN } Y^1 = 5.8558X_1 + 2.7853X_2 + 4.4376X_3 - 5.3082X_4 + 694.2758$$

Cluster 2

$$R^2\text{: IF } X_1 \text{ is } A_1^2 \text{ and } X_2 \text{ is } A_2^2 \text{ and } X_3 \text{ is } A_3^2 \text{ and } X_4 \text{ is } A_4^2$$
$$\text{THEN } Y^2 = 13.3936X_1 + 1.094X_2 + 0.2287X_3 - 3.1357X_4 + 134.0393$$

The mean square error (MSE) for the MLR model is 64,565.9, whereas the MSE for FCRM models is 5794.25. It means that the FCRM models can approximate the given nonlinear system with a higher accuracy than the MLR model can. This simulation data shows the potential of the proposed FCRM models.

Table 1: Details of the Antecedent Parameters

R^i		$i = 1$	$i = 2$
A_1^i in X_1	: μ : σ	1.6070 2.0916	1.3115 1.9576
A_2^i in X_2	: μ : σ	4.9598 4.1139	4.5568 3.7143
A_3^i in X_3	: μ : σ	5.0712 3.8915	4.7834 3.7047
A_4^i in X_4	: μ : σ	6.2185 6.0795	5.9534 6.1004

5.2 Multiple Linear Regression Model

From the analysis of influential and outlier data, it was found that eight data should be discarded due to the human error (s2sdisc value is not recorded) and insufficiency of ventilation machine. Before estimating the parameters, multicollinearity diagnostic should be done to the data. From the correlation analysis, no value of correlation exceeds 0.99 among X_i's variable. The largest value of *VIF* is 1.604 which is less than 10. This indicates that multicollinearity does not exist among the X variables.

The assumption that the residual is normally distributed must also be checked. From Figure 2, the normal quantile-quantile (Q-Q) plot for unstandardized residual has shown that the points in the Q-Q plot lie approximately in a straight line. Hence, the data is approximately normal distributed.

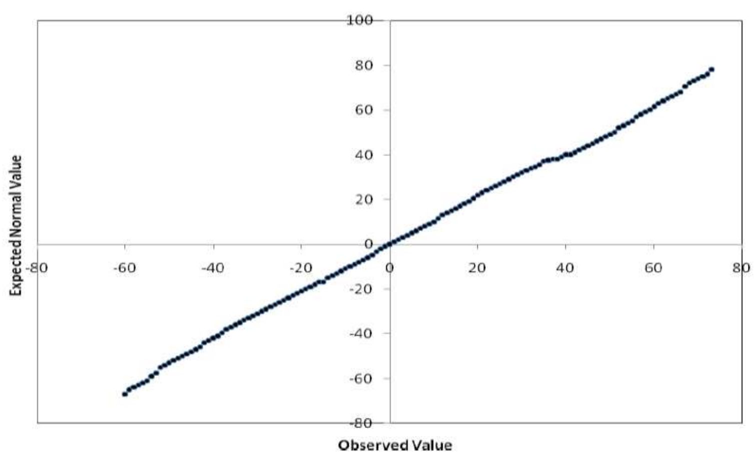

Figure 2: Normal Q-Q Plot for Unstandardized Residual

The analysis of data in Table 2 has shown that five variables of X are significant which are sex, orgfail, comorbid, mecvent and s2sadm. The backward stepwise is used in choosing the influential variable with r^2 =0.515. The multiple linear model can be stated as,

$$\begin{aligned} Y = & - 20.762 + 3.159 \text{ sex} + 8.157 \text{ orgfail} + 4.542 \text{ comorbid} \\ & - 4.333 \text{ mecvent} + 0.987V \text{ s2sadm} \end{aligned}$$

Table 2: Analysis of Variance (ANOVA) and Coefficients for MLR Model

ANOVA

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	685,265.639	5	137,053.128	275.047	0.000
Residual	646,281.720	1,297	498.290		
Total	1,331,547.359	1,302			

Predictors: (Constant), s2sadm, sex, comorbid, mecvent, orgfail
Dependent Variable: s2sdisc

Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	−20.762	4.142		−5.012	0.000
Sex (X_1)	3.159	1.264	0.049	2.499	0.013
Orgfail (X_2)	8.157	1.589	0.126	5.133	0.000
Comorbid (X_3)	4.542	1.269	0.071	3.578	0.000
Mecvent (X_4)	−4.333	1.723	−0.057	−2.515	0.012
S2sadm (X_5)	0.987	0.037	0.650	26.676	0.000

5.3 FCRM Models

The FCRM clustering for the data were analysed using Matlab program. Figure 3 shows the FCRM clustering for s2sdisc (Y) versus sex (X_1), s2sdisc (Y) versus orgfail (X_2), s2sdisc (Y) versus comorbid (X_3), s2sdisc (Y) versus mecvent (X_4) and s2sdisc (Y) versus s2sadm (X_5) where the number of clusters is 2. Two linear straight line graphs show two different MLR equations for the two clusters where the below line is for cluster 1 and the above line represents the cluster 2. Though, a thicker straight line graph shows the MLR equation for all data.

Next, the FCRM clustering involving s2sdisc with the significant of independent variables such as sex, orgfail, comorbid, mecvent and s2sadm should be done as described in MLR model. By using formula F_{NEW} in equation (10), the number of clusters chosen is two since the F_{NEW} reaches minimum value as summarized in Table 3.

An affine T-S fuzzy model with the optimal of two clusters described as follows. The antecedent parameters are described in detail in Table 4 involving their mean and standard

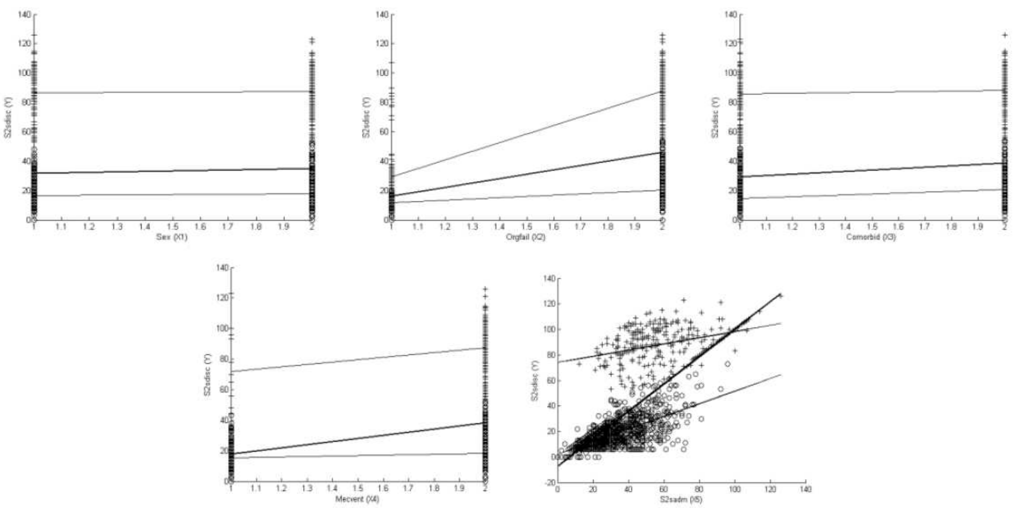

Figure 3: Plot for Individual Clusterin

Table 3: The Value of c and F_{NEW}

Number of Clusters, c	2	3	4	5
F_{NEW}	43.73	133.92	2755.03	11355.43

deviation for each cluster. For instance, the antecedent A_1^i in X has a mean of 1.6247 and standard deviation of 0.4842 for cluster 1. In fact, the antecedent A_1^i in X for cluster 2 has a mean of 1.5805 and standard deviation of 0.4935.

Cluster 1

$$R^1\text{: IF } X_1 \text{ is } A_1^1 \text{ and } X_2 \text{ is } A_2^1 \text{ and } X_3 \text{ is } A_3^1 \text{ and } X_4 \text{ is } A_4^1 \text{ and } X_5 \text{ is } A_5^1$$
$$\text{THEN } Y^1 = 3.82X_1 + 32.239X_2 + 4.289X_3 + 32.839X_4 + 0.293X_5 - 71.268$$

Cluster 2

$$R^2\text{: IF } X_1 \text{ is } A_1^2 \text{ and } X_2 \text{ is } A_2^2 \text{ and } X_3 \text{ is } A_3^2 \text{ and } X_4 \text{ is } A_4^2 \text{ and } X_5 \text{ is } A_5^2$$
$$\text{THEN } Y^2 = 1.558X_1 - 1.509X_2 + 3.381X_3 - 7.236X_4 + 0.561X_5 + 8.12$$

Table 4: Details of the Antecedent Parameters

R^i		$i = 1$	$i = 2$
A_1^i in X_1	: μ : σ	1.6247 0.4842	1.5805 0.4935
A_2^i in X_2	: μ : σ	1.6724 0.4693	1.5399 0.4984
A_3^i in X_3	: μ : σ	1.5468 0.4978	1.4541 0.4979
A_4^i in X_4	: μ : σ	1.9577 0.2013	1.7184 0.4498
A_5^i in X_5	: μ : σ	60.3827 21.9781	31.5439 15.6459

Figure 4 represents the membership function graph for Y versus X_1, X_2, X_3, X_4 and X_5 with the optimal two clusters.

5.4 Comparison between MLR and FCRM Models

In order to find the better model, mean square error (MSE) is used. The comparison between these two models can be summarized in Table 5 below;

According to Table 5, the comparison between FCRM models and MLR model indicates that the FCRM models appeared to be a better model in analyzing continuous data since the MSE is 1/5 of the MSE for the MLR model. The MSE for MLR model is 498.29 whereas the MSE for FCRM models is 97.366. Hence, the FCRM approach is implemented and performs satisfactorily if compared to the MLR model.

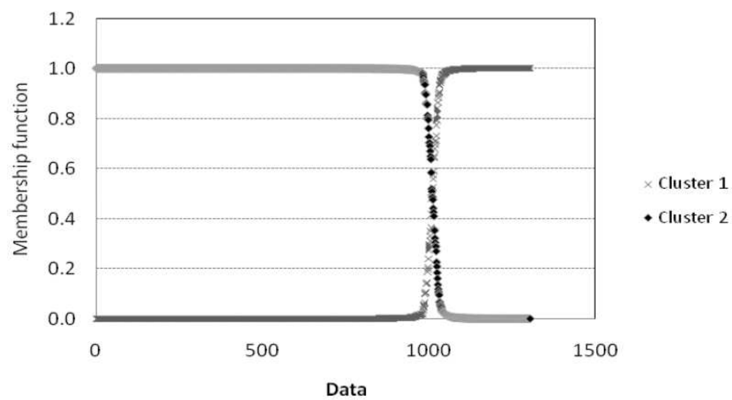

Figure 4: Plot for Membership for Y vs X_1, X_2, X_3, X_4 and X_5 Versus Data

Table 5: The Comparisons between Two Models

Method	MLR Model	FCRM models
Assumption	Multicollinearity and normality test should be fulfilled	Not needed
Model	$Y = 3.159X_1 + 8.157X_2 + 4.542X_3 - 4.333X_4 + 0.987X_5 - 20.762$	R^1 : IF X_1 is A_1^1 and X_2 is A_2^1 and X_3 is A_3^1 and X_4 is A_4^1 and X_5 is A_5^1 THEN $Y_1 = 3.82X_1 + 32.239X_2 + 4.289X_3 + 32.839X_4 + 0.293X_5 - 71.268$ R^1 : IF X_1 is A_1^1 and X_2 is A_2^1 and X_3 is A_3^1 and X_4 is A_4^1 and X_5 is A_5^1 THEN $Y_2 = 1.558X_1 - 1.509X_2 + 3.381X_3 - 7.2336X_4 + 0.561X_5 + 8.12$
Pattern of model	Linear function	Nonlinear function
MSE	498.29	97.366

6 Conclusion

The FCRM models introduced by Harthway and Bezdek are one of the great methods in analyzing a continuous and categorical data. In addition, there are no assumptions needed in this analysis. This model is effective especially for a given nonlinear system from its input-output data. The FCRM models are tested on the simulated data. It shows that the FCRM models can approximate the given simulated data with a higher accuracy than the MLR model. The comparison between FCRM models and MLR model indicates that the FCRM models appeared to be a better model in analyzing continuous data. This new modelling technique could be proposed as one of the best models in analyzing a complex system. Hence, the scale of health or s2sdisc at ICU could be predicted based on the independent variables which are sex, orgfail, comorbid, mecvent and s2sadm. The scales of health in ICU hospital could be monitored by managing the independent variables and also the other qualities in the hospital management.

References

[1] Agresti, A. *An Introduction to Categorical Data Analysis*. New York: John Wiley and Sons. 1996.

[2] Hathaway, R. J. and Bezdek, J. C. Switching regression models and fuzzy clustering. *IEEE Transactions on Fuzzy Systems*. 1993. 1: 195–204.

[3] Kim, E., Park, M., Ji, S. and Park, M. A new approach to fuzzy modeling. *IEEE Transactions on Fuzzy Systems*. 1997. 5: 328–337.

[4] Chuang, C. C., Su, S. F. and Chen, S. S. Robust TSK fuzzy modeling for function approximation with outliers. *IEEE Transactions on Fuzzy Systems*. 2001. 9: 810–821.

[5] The Committee for National Audit on Adult Intensive Care Units. Protocol: National audit on adult intensive care unit. 2002.

[6] Colpan, A., andA. Erbay, E. A., Balaban, N. and Bodur, H. Evaluation of risk factors for mortality in intensive care units: A prospective study from a referral hospital in Turkey. *American Journal of Infection Control*. 2005. 33: 42–47.

[7] Fan, J. S., Kao, W. F., Yen, D. H. T., Wang, L. M., Huang, C. I. and Lee, C. H. Risk factors and prognostic predictors of unexpected intensive care unit admission within 3 days after ED discharge. *The American Journal of Emergency Medicine*. 2007. 25: 1009–1014.

[8] Garland, A. Improving the ICU, part 1. *American College of Chest Physicians*. 2005. 127: 2151–2164.

[9] Knaus, W. A., Wagner, D. P., Loirat, P., Cullen, D. J., Glaser, P., Mercier, P., Nikki, P., Snyder, J. V., Gall, J. R. L., Draper, E. A., Campos, R. A., Kohles, M. K., Granthil, C., Nicolas, F., Shin, B., Wattel, F. and Zimmerman, J. E. A comparison of intensive care in the U.S.A. and France. *The LANCET Journal*. 1982. 320: 642–646.

[10] Noortgate, N. V. D., Vogelaers, D., Afschrift, M. and Colardyn, F. Intensive care for very elderly patients: outcome and risk factors for in-hospital mortality. *British Geriatrics Society*. 1999. 28: 253–256.

[11] Ruiswyk, J. V., Hartz, A., Kuhn, E. and Rimm, A. Linking process and outcome in quality of care assessment. *IEEE Journal*. 1991. 8: 2117–2120.

[12] Pilz, U. and Engelmann, L. Integration of medical knowledge in an expert system for use in intensive care medicine. *Fuzzy and Neuro-fuzzy systems in medicine*. 1998. 2: 290–315.

[13] Takrouri, M. S. M. Intensive care unit. *The Internet Journal of Health*. 2004. 3: 1528–8315.

[14] Rusiman, M. S., Daud, Z. M. and Mohamad, I. The comparison between logit, probit and linear probability model toward mortality rate at ICU General Hospital. *Jurnal Statistika Universitas Islam Bandung*. 2004. 4: 129–138.

[15] Gall, J. R. L., Lemeshow, S. and Saulnier, F. A new simplified acute physiology score (SAPS II) based on a European/North American multicenter study. *The Journal of the American Medical Association*. 1993. 24: 2957–2963.

[16] Norusis, M. J. *SPSS for Windows Advanced Statistics Release 6.0*. USA: SPSS Inc. 1993.

[17] Neter, J., Wasserman, W. and Kutner, M. H. *Applied Linear Regression Models*. New York: Richard D. Irwin Inc. 1983.

[18] Weisberg, S. *Applied Linear Regression (2nd edition)*. New York: John Wiley and Sons. 1985.

[19] Draper, N. R. and Smith, H. *Applied Regression Analysis (2nd edition)*. New York: John Wiley. 1981.

[20] Montgomery, D. C. and Peck, E. A. *Introduction to Linear Regression Analysis (2nd edition)*. New York: John Wiley and Sons. 1992.

[21] Seber, G. A. F. *Linear Regression Analysis*. New York: John Wiley. 1977.

[22] Abonyi, J. and Feil, B. *Cluster Analysis for Data Mining and System Identification*. USA: Springer. 2007.

[23] Babuska, R. *Fuzzy Modeling for Control*. Boston: Kluwer Academic Publishers. 1988.

[24] Xie, X. L. and Beni, G. A. A validity measure for fuzzy clustering. *IEEE Transaction Pattern Anal. Machine Intell*. 1991. 3: 841–846.

[25] Kung, C. C. and Su, J. Y. Affine takagi-sugeno fuzzy modelling algorithm by fuzzy c-regression models clustering with a novel cluster validity criterion. *IET Control Theory Application*. 2007. 1: 1255–1265.

[26] Takagi, T. and Sugeno, M. Fuzzy identification of systems and its applications to modeling and control. *IEEE Trans. Syst., Man Cybernatic*. 1985. 15: 116–132.

[27] Sugeno, M. and Kang, G. T. Structure identification of fuzzy model. *Fuzzy Sets System*. 1988. 28: 15–33.

[28] Wang, L. X. *Adaptive Fuzzy Systems and Control: Design and Stability Analysis*. New Jersey: Prentice-Hall. 1994.

[29] Wang, L. X. *A Course in Fuzzy Systems and Control*. New Jersey: Prentice-Hall. 1997.

[30] Hoppner, F., Klawonn, F., Kruse, R. and Runkler, T. *Fuzzy Cluster Analysis, Methods for Classification, Data Analysis and Image Recognition*. New Jersey: John Wiley and Sons. 1999.