P- ISSN 1991-8941 E-ISSN 2706-6703
2025,(19), (01):269 – 278

Journal of University of Anbar for Pure Science (JUAPS)

Open Access

Using Fuzzy Linear Regression Models to Identify Factors That Affect Myocardial Infarction

Aya Mohammed Hussein , Wafaa S. Hasanain *

Department of Mathematics, College of Science, Mustansiriyah University, Baghdad, Iraq
*E-mail: w.s.hasanain@uomustansiriyah.edu.iq ,

A R T I C L E I N F O

Received: 08 / 06 /2025
Accepted: 21/ 07 /2025
Available online: 21/ 06 /2025

DOI: 10.37652/juaps.2024.150719.1274

Keywords:
***FLS, FLAR, PLR, PLRLS, BFRL*.**

A B S T R A C T

This study focuses on the application of numerous fuzzy linear regression models to analyze medical data regarding myocardial infarction, particularly with troponin level, which is essential for identifying heart attacks. Specifically, the physiological indicators that describe the state of a patient, including blood pressure, blood sugar, and creatinine levels, and the relationship between these indicators and heart attack enzyme level, are determined.

To accomplish the objective of this study, the necessary data were obtained from hospitals that treated patients diagnosed with myocardial infarction. Then, the performance of several fuzzy regression methods was compared by employing these data.

This study shows that the fuzzy least-squares method presents the lowest mean squared error values among all the models and exhibits the best accuracy in simulating the effect of physiological factors on the level of the heart attack enzyme. Moreover, this study emphasizes the importance of applying fuzzy regression to medical statistics due to the existence of uncertainty in this field and the applicability of this method to enhancing predictive power and decision-making in healthcare.

Introduction

Regression analysis is a statistical technique used in various scientific domains. Its objective is to study a regression equation that provides options for analyzing and forecasting the relation between a dependent variable with one or more independent variables [1].

In settings wherein a model is ambiguous, the relationships among model parameters are indefinite, sample size is small, or the data are hierarchically structured; therefore, fuzzy regression offers an alternative to regular statistical regression. Fuzzy regression can be used in situations wherein statistical analysis is hindered by data structure [2], [3]. Hence, fuzziness deserves more attention, and fuzzy data analysis has increased in significance since Zadeh [4], [5] introduced fuzzy sets in 1965.

*Corresponding author at : Department of Mathematics, College of Science, Mustansiriyah University, Baghdad, Iraq
ORCID: https:// https://orcid.org/0000-0003-4486-8525 ,
Tel: +964 7712220141
Email: w.s.hasanain@uomustansiriyah.edu.iq

Tanaka [6], [7] presented the concept of fuzzy linear regression (FLR) in 1982 with the intention of solving this limitation and applying fuzzy set theory to the formulation of a regression equation. In 1988, Diamond [8] suggested a method, called fuzzy least squares (FLS), as a process for producing a number of basic least-squares models by fitting fuzzy datasets into the models and derived the analogues of normal equations by using distance measurements to implement FLS regression (FLSR). In 1989, Tanaka et al. [9] considered fuzzy data derived from expert knowledge as a possibility distribution that characterizes possibilistic linear systems by condensing fuzzy data into a single linear programming (LP) problem. They offer three formulations of possibilistic linear regression analysis, making extracting fuzzy parameters from possibilistic linear models easier and enabling the observation of additional constraint conditions due to specialist fuzzy parameter knowledge. In 1999, Lee and Tanaka [10] suggested using nonsymmetric fuzzy coefficients in fuzzy regression analysis. They used the quadratic programming (QP) technique and assumed nonsymmetric triangular fuzzy coefficients.

In addition, they proposed an integrated QP problem in which the centers of the two approximation models are assumed to be the same. In this problem, the higher approximation model always includes the lower approximation model at any threshold level. These researchers also used actual data to conduct weight coefficient sensitivity studies of the suggested QP techniques. Fuzzy regression analysis that used nonsymmetric fuzzy coefficients was proposed by Nasrabadi et al. in 2005 [11]. These authors employed the QP technique and assumed nonsymmetric triangular fuzzy coefficients. In 2008, Arabpour and Tata [12] used mathematical programming techniques to estimate fuzzy coefficients in linear regression models. Their study employed a measure developed via the Diamond technique. This new approach exhibits lower total estimation errors and simple computing. In 2017, Zeng et al. [13] presented a new measure of the distance between triangular fuzzy numbers, combined it with the least absolute deviation technique, and suggested a fuzzy regression model. In addition, they transformed the fuzzy least absolute linear regression model into LP and investigated its characteristics and model algorithm. In 2020, Hasanain [14] used discernment regression to assess teachers' knowledge about tuberculosis at a primary school. In 2021, Škrabánek et al. [15] developed the Boscovich regression method, which was designed for a simple linear regression model. Boscovich's estimate was predicated on two limitations: the positive and negative residuals that are added together (as measured along the y-axis) must be equal and the residuals' best absolute values must be as small as possible when added together. In 2023, Li et al. [16] constructed a fuzzy multiple linear least-squares regression model based on two distance measures between LR-type fuzzy numbers. They also defined a similarity measure between LR-type fuzzy numbers and introduced two criteria: the error index and the similarity index, which use the distance and similarity measures between LR-type fuzzy numbers as measurements, respectively, to assess the efficacy of the proposed model.

Methods and Materials of the Fuzzy Regression Models

FLR was introduced by Tanaka et al. in 1982 [7], [9]. This method was further developed by researchers in the years that followed as an extension of the classical linear regression modeling. Estimating a dataset by using FLR was determined to fit most closely with the notion of fuzziness after using numerous fuzzy methods.

FLS Linear Regression Method

Regression analysis by using FLS linear regression is a technique used when working with fuzzy data. It was proposed by Phil Diamond [8] in 1988, when the fitted line and data points' squared deviations are minimized when using regular least-squares regression to determine the line. To manage uncertainty and imprecision in data, the FLS linear regression approach combines least-squares linear regression with fuzzy set theory.

The basic summary of the essential steps is provided as follows:

1. The inputted data points are examined, i.e., $(x_i, \widetilde{yf_i})$ for i=1, 2, … n. The input crisp numbers are denoted by x_i, and the output is represented by the fuzzy numbers $\widetilde{yf_i}$.
2. Each fuzzy output $\widetilde{yf_i}$ should be represented by a membership function. Triangular fuzzy numbers (TFNs) and trapezoidal fuzzy numbers are two examples of common formats. Assuming TFNs are as follows:
$$\widetilde{yf_i} = (\widetilde{yf_i}^L, \widetilde{yf_i}^M, \widetilde{yf_i}^U), \tag{1}$$
where $\widetilde{yf_i}^L$ is the lower end, $\widetilde{yf_i}^M$ is the middle, and $\widetilde{yf_i}^U$ is the upper end.
3. The fuzzy linear regression model is set as
$$\widetilde{yf_i} = \widetilde{bf_0} + \widetilde{bf_1} x_i,\ i = 1, 2, \dots, n; \tag{2}$$
where $\widetilde{bf_0}$ and $\widetilde{bf_1}$ are fuzzy coefficients,
$$\widetilde{bf_0} = (\widetilde{bf_0}^L, \widetilde{bf_0}^M, \widetilde{bf_0}^U),$$
and $\widetilde{bf_1} = (\widetilde{bf_1}^L, \widetilde{bf_1}^M, \widetilde{bf_1}^U)$. (3)
4. TFNs are transformed into intervals $\widetilde{cf}$.
For $TFNs\ \widetilde{cf} = (\widetilde{cf}^L, \widetilde{cf}^M, \widetilde{cf}^U)$, the representation of the interval is $(\widetilde{cf} \in (\widetilde{cf}^L, \widetilde{cf}^U))$.
5. After constructing the fuzzy regression coefficients, the criteria for fuzzy least squares is known as the fuzzy objective function, which minimizes the squared

deviation or distance between the expected fuzzy output, as follows:

$$\widetilde{yf_i}^{\wedge} = \widetilde{bf_0} + \widetilde{bf_1} x_i, \quad (4)$$

and the real fuzzy output of $\widetilde{yf_i}$ is an objective function, as follows:

$$OJf = \sum_{i=1}^{n} [\widetilde{yf_i} - (\widetilde{bf_0} + \widetilde{bf_1}\, x_i)]. \quad (5)$$

Then, by dividing it into three components, i.e., managing the intervals' lower and upper limits separately and identifying their midpoints, the objective function is transformed as follows:

$$MIN(OJf) = MIN\left\{\sum_{i=1}^{n}\left[\widetilde{yf_i}^{L} - \left(\widetilde{bf_0}^{L} + \widetilde{bf_1}^{L}\, x_i\right)\right] + \sum_{i=1}^{n}\left[\widetilde{yf_i}^{U} - \left(\widetilde{bf_0}^{U} + \widetilde{bf_1}^{U}\, x_i\right)\right]\right\}. \quad (6)$$

Fuzzy Least Absolute Residual (FLAR) Method

FLAR, introduced by Zeng et al. [13] in 2017, is a method for fitting a linear regression model into data when the dependent variable is fuzzy and the independent variable is crisp. The process minimizes the total absolute residuals between the observed and expected values.

The description formula for FLAR is as follows:

1. The fuzzy numbers of y_i, including triangular fuzzy numbers defined by the mean, lower, and upper spreads, and the membership functions μ_{yf} (y_{fi}) are determined.
2. The coefficient of parameters is initialized.
3. A definition is provided for the residuals' fuzzy membership functions, and then, the residuals for β's estimate (ef = yf – xf) are determined.
4. A measure for fuzzy distance is selected. The signed distance between membership functions is a common choice for FLAR.

$$Distance\,(yf_i\,, f(x_i)) = \int [\mu_{yf}(yf_i) - \mu_f(f(x_i)]\,dyf, \quad (7)$$

where $\mu_{yf}(yf_i)$ represent the membership function of the fuzzy number yf_i, and $\mu_f(f(x_i))$ represents the membership function of the predicted value $f(x_i)$ from the model at a given value yf_i.

5. Fuzzy weights are assigned using the membership function to determine the fuzzy weight (wf_i) for each residual (ef_i).
6. The objective that minimizes the weighted sum of the absolute residuals is determined by applying an iterative optimization approach, such as iteratively reweighted least squares, to solve the weighted least absolute residual problem. For each iteration,

- the current β's residuals (ef_i) is determined.
- the weights (wf_i) are recalculated to the updated residuals to obtain a new estimate of βfs.

$$\underbrace{Min}_{\beta} \sum_{i=1}^{n} wf_i\ |yf_i - x_i'\beta| \quad (8)$$

Possibilistic Linear Regression (PLR) Analysis for the Fuzzy Data Method

An additional strategy for handling ambiguous data in regression analysis is PLR. In 1989, Tanaka, Hayashi, and Watada [17] pointed out that the basis of this strategy was possibility theory, a mathematical theory for handling specific types of imprecision and uncertainty. The objective of PLR is fitting a regression model into fuzzy data points, where the input and the output may be both fuzzy numbers.

Possibilistic regression uses possibility distributions to describe ambiguous data points. These distributions describe the probability (from 0 to 1) that a given data point belongs to a certain value.

From these possibility distributions, crisp information is obtained via α-cuts. An α-cut level (0 ≤ α ≤ 1) establishes a possibility threshold. For each fuzzy number yf_i, all values with a probability larger than or equal to α are included in the α-cut.

An approach for PLR analysis with fuzzy data is described as follows:

1. The fuzzy coefficients are set to their initial values of y_i, as shown in Eq. (3), by using the triangular fuzzy number from a membership function $\mu_y(y_i)$ [17] and then applying the α-cut level to the representation of each y_i.
2. The possibility distribution for the predicted fuzzy output $\widetilde{yf}$ is constructed.
3. The possibilistic error of the fuzzy output that are anticipated and those that are seen is determined. A simple technique for accomplishing this task is to reflect the distance spaced by the fuzzy numbers.
4. An optimization approach, such as the FLS method, is utilized to minimize all the possibilistic errors by adjusting $\widetilde{bf_0}$ and $\widetilde{bf_1}$.

5. The optimization procedure is continuously iterated until the fuzzy coefficient changes fall below a predetermined threshold or until convergence is achieved.
6. An objective function of fuzzy regression is established to minimize the sum of squared errors between the observed and predicted fuzzy output, as shown in Eq. (9).

$$\text{OJf} = \sum_{i=1}^{n}\{[(\text{lower bound of estimated interval}_i) - (\text{lower bound of } \alpha-\text{cut interval\_i}))^2] + [((\text{upper bound of estimated interval}_i) - (\text{upper bound of } \alpha-\text{cut interval\_i}))^2]\}, \quad (9)$$

where

- n is the number of data points.
- The α-cut of a fuzzy number is an interval that contains all values with a membership degree greater than or equal to α. The fuzzy number's endpoints at the α level correspond to the interval's lower and upper limits.
- The lower and upper limits of the PLR model yields the estimated interval.
- The lower and upper limits of the α-cut interval of the observed fuzzy output intervals at a specific α-cut level.

PLR Combined with Least Squares (PLRLS)

Lee et al. [10] introduced fuzzy regression analysis based on a QP approach (1999). In fuzzy regression analysis, a QP strategy produces more varied spread coefficients than an LP strategy.

Moreover, a QP technique can be used to merge the central tendency of least squares with the possibilistic properties of fuzzy regression.

$$\widetilde{yf_i} = \widetilde{bf_0} + \widetilde{bf_1}x_{i1} + \cdots + \widetilde{bf_n}x_{in}, i = 1, 2, \dots, n \quad (10)$$

An optimization problem in Eq. (11) that involves minimizing a quadratic function under linear constraint conditions is known as a QP formulation.

$$\underbrace{Min}_{\text{a,c}} = \sum_{j=1}^{m} c^t\,|x_j|$$
$$subject\ to\quad y_j \epsilon [y(x_j)]_h \quad ,j = 1, \dots, m \quad (11)$$
$$c_i \geq 0, \quad , \quad i = 0, \dots, n,$$

where $c = (c_0, \dots, c_n)^t$ and $|x_j| = (1, |x_{j1}|, \dots, |x_{jn}|)^t$.

The following steps are performed for a fuzzy regression analysis that uses nonsymmetric triangular fuzzy coefficients:

(i) The data for input–output are given as $(x_i, y_i) = (1, x_{i1}, \dots x_{in}; y_i)$, j = 1, …, m.

(ii) The data can be expressed using the fuzzy linear model in Eq. (10).

(iii) When a threshold (h) is specified, the output $\widetilde{yf_i}$ should be part of the h-level set of the estimated fuzzy output yf(xj), fulfilling

$$[yf(x_i)]_h \ni yf_i \leftrightarrow$$
$$\begin{cases} \theta_C(x_j) + (1-h)\theta_R(x_j) \geq yf_j \\ \theta_C(x_j) - (1-h)\theta_L(x_j) \leq yf_j \end{cases}, j = 1, \dots, m. \quad (12)$$

This particular aspect is regarded as a potential property of fuzzy regression.

(iv) The objective function is defined as

$$obj = w_1 \sum_{j=1}^{m}\left(y_j - (a)^t x_j\right)^2 + w_2(1-h)\sum_{j=1}^{m}\left(c^t|x_j| + d^t|x_j|\right), \quad (13)$$

where $c = (c_0, \dots, c_n)^t$ and $d = (d_0, \dots, d_n)^t$ denote the left and right spread coefficient vectors, and $a = (a_0, \dots, a_n)^t$ is the center, where m denotes data size, and w_1 and w_2 are the coefficients of weight.

(v) Fuzzy regression via QP aims to identify the optimal fuzzy coefficients, $\beta_i = (a_i, c_i, d_i)$, which reduce the objective function in Eq. (13) under the constraint conditions imposed by Eq. (12). This scenario can be formulated as a QP problem provided that

(vi) $$\underbrace{Min}_{\text{a,c,d}} = obj = w_1 \sum_{j=1}^{m}\left(y_j - (a)^t x_j\right)^2 + w_2(1-h)\sum_{j=1}^{m}\left(c^t|x_j| + d^t|x_j|\right) + \vartheta(c^t c + d^t d)$$
$$subject\ to \quad \theta_C(x_j) + (1-h)\theta_R(x_j) \geq yf_j$$
$$\theta_C(x_j) - (1-h)\theta_L(x_j) \leq yf_j, \quad j = 1, \dots, m \quad (14)$$
$$c_i \geq 0,\ d_i \geq 0, \quad i = 0, \dots, n.$$

Suppose ϑ is a small positive number where $(w_1, w_2) \gg \partial$. By incorporating the term $\vartheta(c^t c + d^t d)$ into Eq. (13), the objective function outlined in Eq. (14) is modified to form a quadratic function that involves the decision variables a, c, and d. This strategy is a well-established approach for attaining optimal solution by using QP. Through this method, a regression model with a more pronounced central tendency can be derived, in contrast with the models with symmetric triangular fuzzy coefficients in the LP problem in Eq. (11).

P- ISSN 1991-8941 E-ISSN 2706-6703 Journal of University of Anbar for Pure Science (JUAPS) Open Access
2025,(19), (01):269 – 278

Boscovich Fuzzy Regression Line (BFRL) Method

BFRL is a technique developed by Škrabánek [15] in 2021 for fitting a fuzzy linear relationship between the real number of independent variables and the fuzzy number of dependent variables. It combines the principles of fuzzy logic with Boscovich's classical method. The method is described as follows:

1. Fuzzy intervals for the data points (x_i, y_i) are defined. Every data point y_i is substituted with a fuzzy number $\widetilde{yf_i}$, which is typically represented by $\widetilde{yf_i} = (bf_i^L, bf_i^M, bf_i^U)$, where bf_i^L and bf_i^U are the lower and upper bounds, respectively, and bf_i^M is the peak (possible value) or the middle.
2. The proper fuzzy distance measurement is chosen, such as the sum of absolute deviations (L1 norm):
$$d(\widetilde{yf_i}, \widetilde{yf_j}) = \frac{1}{3}\left(\left|bf_i^L - bf_j^L\right| + \left|bf_i^M - bf_j^M\right| + \left|bf_i^U - bf_j^U\right|\right). \quad (15)$$
3. The situation is inputted into an LP problem, and the simplex approach is used to solve it to determine the best regression coefficients. Then, the final regression formula and objective function are determined:
$$OJf = \sum_{i=1}^{n}\left[\widetilde{yf_i} - \left(\widetilde{bf_0} + \widetilde{bf_1}\, x_i\right)\right]. \quad (16)$$

Troponin Factor

The enzyme troponin is a part of a group of proteins that operate directly to control calcium levels before heart and skeletal muscles can contract. The testing of troponin enzyme levels is used to detect cardiac muscle failure. The protein groups of troponin are dispersed throughout muscle fibers. This test is called cardiac troponin test or cardiac enzyme examination.

In addition to the troponin test, the following test may be necessary: blood troponin level typical for creatine kinase.

The normal troponin level in blood, as determined by a normal troponin test, is as follows:

- Cardiac troponin T: The level of cardiac troponin T is less than 0.1 ng/mL of blood.
- Cardiac troponin I: Less than 0.03 ng/mL of cardiac troponin I are present in blood.
- A slight increase in blood troponin levels to 0.04–0.39 ng/mL indicates the existence of a cardiac disease, while a minor increase in blood troponin levels indicates a heart attack, particularly if levels vary between high and low over several hours [government website that belongs to an official government organization in the United States].

Statistical Analysis

A linear regression model was fitted and developed, where R statistical program and MATLAB R22 were used for the analysis. The data being studied were fitted using fuzzy regression techniques, and parameter estimates were computed to illustrate the roles and influences of each predictor on troponin enzyme levels.

The analysis of clinical data related to myocardial infarction has focused on the potential effects of physiological factors on the enzyme troponin, which is the primary significant indicator of a heart attack. The variables include a dataset of blood pressure measurements, blood sugar measurements, creatinine levels, and troponin levels approved by medical facilities, namely, Al-Furat Hospital and Ibn Al-Bitar Cardiac Surgery Hospital.

This model allows for the independent assessment of the effect of each factor or the cumulative effect of all the variables on troponin level, and thus, it assists in understanding the physiological relationships that occur in instances of myocardial infarction.

Applications and Results

This section uses a set of medical data from patients with myocardial infarction.

1. Description of data and sources: The present dataset was obtained from Al-Furat Hospital and the statistics department of Ibn Al-Bitar Cardiac Surgery Hospital with sample size n = 75. Experts from the internal medicine and cardiac surgery departments organized this dataset. A simple random sampling was utilized to gather information regarding areas associated with changes in troponin enzyme levels.
2. Defined variables:
   - Dependent variable (Y_i): A change in the percentage
   - of troponin enzyme in response to the heart's enzyme reaction to other external stimuli
   - Independent variable (X_i): Three independent variables are included, as follows:

X_{i1}: Blood pressure as a function of change in cardiac enzyme.

X_{i2}: Blood glucose fluctuations and their effect on

Table 1. Estimated parameters with ($\widetilde{bf}$'s: L, M, U) and MSE(f) for the lower dependent variable ($\widetilde{yf}^{L}$) using the models of (FSLR)

Method	$\widetilde{bf}_0{}^{L}$	$\widetilde{bf}_0{}^{M}$	$\widetilde{bf}_0{}^{U}$	$\widetilde{bf}_1{}^{L}$	$\widetilde{bf}_1{}^{M}$	$\widetilde{bf}_1{}^{U}$	MSE(f)
FLS	-2.38103	-2.40467	-2.43005	0.25390	0.25640	0.25905	0.28921
FLAR	-3.27730	-3.30708	-3.34016	0.32774	0.33072	0.33403	0.30088
PLR	-0.00188	-0.00190	-0.00194	0.10752	0.10870	0.10978	0.72050
PLRLS	-0.36706	-0.37620	-0.40043	0.10047	0.10187	0.10444	0.45138
BFRL	-3.13690	-3.16689	-3.19800	0.31370	0.31670	0.31981	0.28927

Table 2. Estimated parameters with ($\widetilde{\beta f}$'s: L, M, U) and MSE(f) for the middle dependent variable ($\widetilde{yf}^{M}$) using the models of (FSLR)

Method	$\widetilde{bf}_0{}^{L}$	$\widetilde{bf}_0{}^{M}$	$\widetilde{bf}_0{}^{U}$	$\widetilde{bf}_1{}^{L}$	$\widetilde{bf}_1{}^{M}$	$\widetilde{bf}_1{}^{U}$	MSE(f)
FLS	0.34580	0.34004	0.35525	0.00155	0.00161	0.00157	0.70152
FLAR	0.00000	-0.05710	0.00000	0.00144	0.00180	0.00178	0.74335
PLR	1.23387	1.25220	1.25981	0.00080	0.00080	0.00082	1.03488
PLRLS	0.75223	0.75860	0.76707	0.00048	0.00049	0.00049	0.70203
BFRL	0.51559	0.52333	0.52425	0.00153	0.00154	0.00157	0.71434

Table 3. Estimated parameters with ($\widetilde{\beta f}$'s: L, M, U) and MSE(f) for the upper dependent variable ($\widetilde{yf}^{U}$) using the models of (FSLR)

Method	$\widetilde{bf}_0{}^{L}$	$\widetilde{bf}_0{}^{M}$	$\widetilde{bf}_0{}^{U}$	$\widetilde{bf}_1{}^{L}$	$\widetilde{bf}_1{}^{M}$	$\widetilde{bf}_1{}^{U}$	MSE(f)
FLS	0.42275	0.42691	0.43368	0.33001	0.33307	0.33424	0.65340
FLAR	-0.15770	-0.15861	-0.15929	0.59257	0.59614	0.59904	0.75416
PLR	1.50305	1.51943	1.53464	0.00000	0.00000	0.00000	1.17024
PLRLS	0.63569	0.63985	0.64662	0.15672	0.15978	0.16095	0.66716
BFRL	0.28419	0.29088	0.29933	0.44277	0.44377	0.44357	0.65904

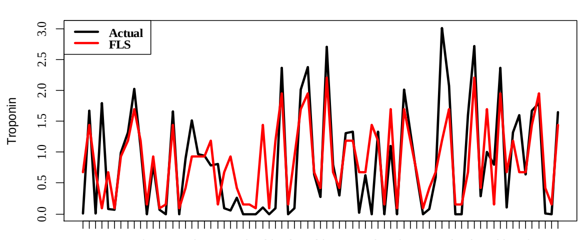

Figure 1. Plots of the actual and fuzzy values of $(\widehat{yf_i}),(\widetilde{\widetilde{yf_i}})$ of Blood Pressure for FLS.

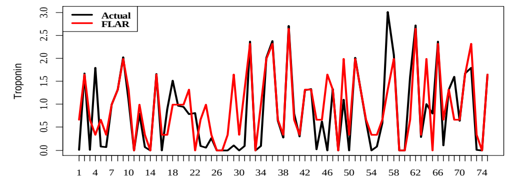

Figure 2. Plots of the actual and fuzzy values of $(\widehat{yf_i}),(\widetilde{\widetilde{yf_i}})$ of Blood Pressure for FLAR.

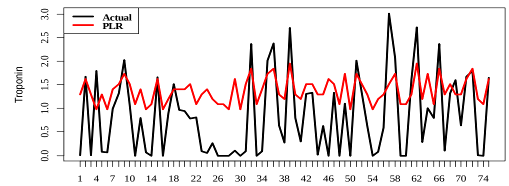

Figure 3. Plots of the actual and fuzzy values of $(\widehat{yf_i}),(\widetilde{\widetilde{yf_i}})$ of Blood Pressure for PLR.

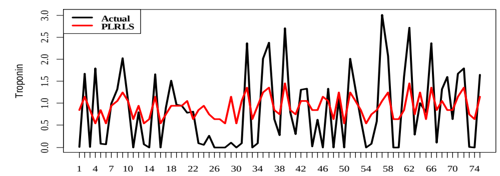

Figure 4. Plots of the actual and fuzzy values of $(\widehat{yf_i}),(\widetilde{\widetilde{yf_i}})$ of Blood Pressure for PLRLS.

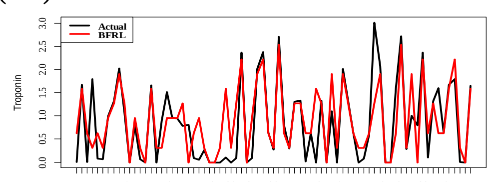

Figure 5. Plots of the actual and fuzzy values of $(\widehat{yf_i}),(\widetilde{\widetilde{yf_i}})$ of Blood Pressure for BFRL.

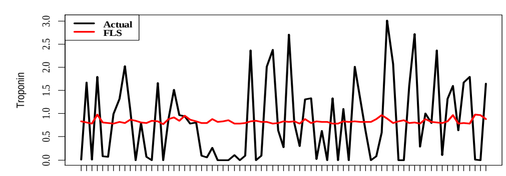

Figure 6. Plots of the actual and fuzzy values of $(\widehat{yf_i}),(\widetilde{\widetilde{yf_i}})$ of Blood Glucose for FLS.

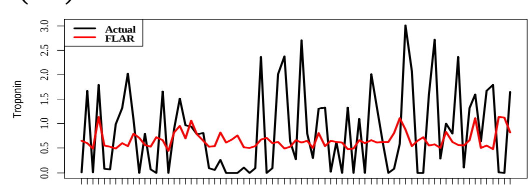

Figure 7. Plots of the actual and fuzzy values of $(\widehat{yf_i}),(\widetilde{\widetilde{yf_i}})$ of Blood Glucose for FLAR.

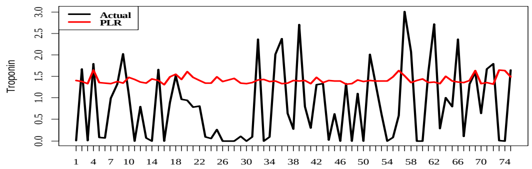

Figure 8. Plots of the actual and fuzzy values of $\left(\widehat{yf_i}\right), \left(\widetilde{\widehat{yf_i}}\right)$ of Blood Glucose for PLR.

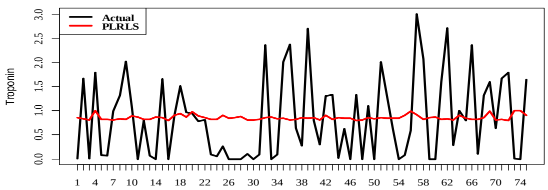

Figure 9. Plots of the actual and fuzzy values of $\left(\widehat{yf_i}\right), \left(\widetilde{\widehat{yf_i}}\right)$ of Blood Glucose for PLRLS.

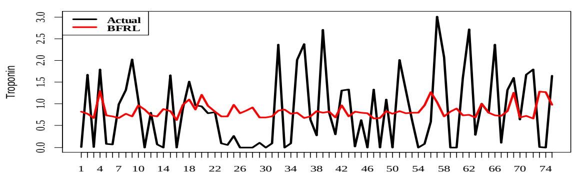

Figure 10. Plots of the actual and fuzzy values of $\left(\widehat{yf_i}\right), \left(\widetilde{\widehat{yf_i}}\right)$ of Blood Glucose for BFRL.

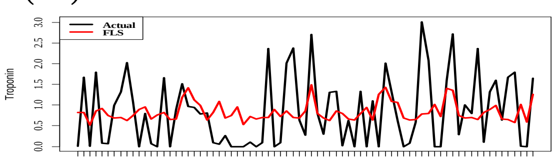

Figure 11. Plots of the actual and fuzzy values of $\left(\widehat{yf_i}\right), \left(\widetilde{\widehat{yf_i}}\right)$ of Creatine for FLS.

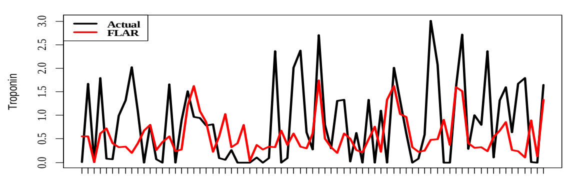

Figure 12. Plots of the actual and fuzzy values of $\left(\widehat{yf_i}\right), \left(\widetilde{\widehat{yf_i}}\right)$ of Creatine for FLAR.

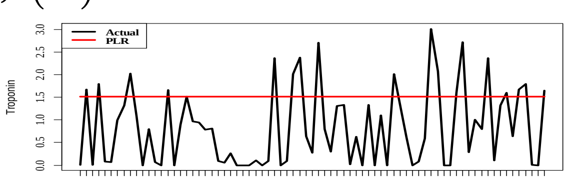

Figure 13. Plots of the actual and fuzzy values of $\left(\widehat{yf_i}\right), \left(\widetilde{\widehat{yf_i}}\right)$ of Creatine for PLR.

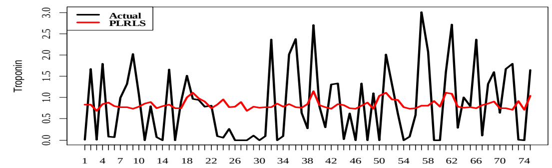

Figure 14. Plots of the actual and fuzzy values of $\left(\widehat{yf_i}\right), \left(\widetilde{\widehat{yf_i}}\right)$ of Creatine for PLRLS.

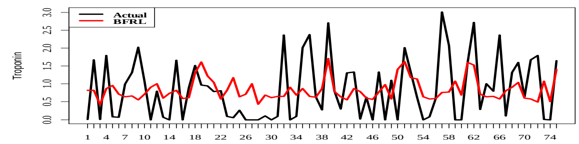

Figure 15. Plots of the actual and fuzzy values of $\left(\widehat{yf_i}\right), \left(\widetilde{\widehat{yf_i}}\right)$ of Creatine for BFRL.

Fuzzy multiple linear regression (FMLR) is a development of traditional multiple linear regression [2], [18]. It uses a fuzzy logic to deal with an improvement on classical multiple linear regression imprecision and uncertainty in the data. This is especially helpful in cases where there are ambiguous relationships between the variables which are common in real-world issues particularly in medical.

For the purpose to assess the simultaneous effect of the three independent variables on the dependent variable, fuzzy multiple regression was employed and applied it to the data set utilizing the two approaches (FLR, PLFLR) and the results are shown in table (4).

Table 4. Estimated parameters of FMLR with $(\widetilde{\beta f}$'s: L, M, U) and MSE(f) of the dependent variable $(\widetilde{yf})$ using (FLS, PLRLS)

<table>
<tr><th>Method</th><th>$\widetilde{\beta f}_0^L$</th><th>$\widetilde{\beta f}_0^M$</th><th>$\widetilde{\beta f}_0^U$</th><th>MSE(f) FLS</th><th>MSE(f) PLRLS</th></tr>
<tr><td>FLS</td><td>-2.82748</td><td>-2.85652</td><td>-2.88427</td><td rowspan="8">0.26893</td><td rowspan="8">0.27444</td></tr>
<tr><td>PLRLS</td><td>-2.98380</td><td>-3.00386</td><td>-3.04483</td></tr>
<tr><td>FLS</td><td>$\widetilde{\beta f}_1^L$</td><td>$\widetilde{\beta f}_1^M$</td><td>$\widetilde{\beta f}_1^U$</td></tr>
<tr><td>PLRLS</td><td>0.25502</td><td>0.25757</td><td>0.26033</td></tr>
<tr><td>FLS</td><td>$\widetilde{\beta f}_2^L$</td><td>$\widetilde{\beta f}_2^M$</td><td>$\widetilde{\beta f}_2^U$</td></tr>
<tr><td>PLRLS</td><td>0.00125</td><td>0.00127</td><td>0.00128</td></tr>
<tr><td>FLS</td><td>$\widetilde{\beta f}_3^L$</td><td>$\widetilde{\beta f}_3^M$</td><td>$\widetilde{\beta f}_3^U$</td></tr>
<tr><td>PLRLS</td><td>0.14390</td><td>0.14501</td><td>0.14424</td></tr>
</table>

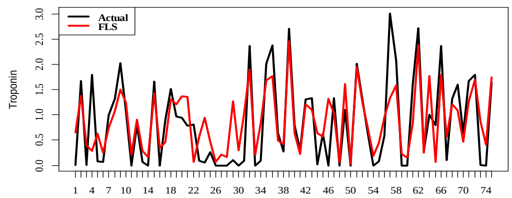

Figure16. Plots of the actual and fuzzy values of $(\widehat{yf_i})$, $(\widetilde{\widehat{yf_i}})$ for FLS

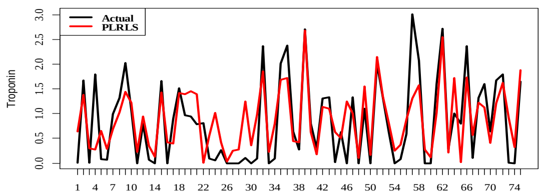

Figure 17. Plots of the actual and fuzzy values of $(\widehat{yf_i})$, $(\widetilde{\widehat{yf_i}})$ for PLRLS method

Conclusion

The sample that comprised myocardial infarction patients and troponin enzyme levels was used as a model in this study's extensive exploration of FLR models to study uncertainty in medical data. The effectiveness of these methods in understanding the effects of the model on one another and on troponin was assessed. The data were analyzed using several fuzzy regression methods (FLS, FLAR, PLR, PLRLS, and BFRL). Finally, the following significant results were obtained:

1. From the results presented in Tables 1, 2, and 3, the MSE(f) of FLS exhibited the smallest value (0.28921 at $\widetilde{yf_i}^{L}$, 0.70152 at $\widetilde{yf_i}^{M}$, and 0.65340 at $\widetilde{yf_i}^{U}$) compared with the values of the other methods, followed by these methods (in this order): FLAR, PLR, PLRLS, and BFRL.
2. The results presented in Table 4 show that after utilizing and studying the two fuzzy multiple regression methods (i.e., FLS are PLRLS), the MSE(f) results are extremely close. However, the FLS method appears to be slightly preferred, as indicated in the value of MSE(f) = 0.26893.
3. Troponin enzyme was demonstrated to exhibit an exact relationship with blood pressure and blood sugar levels, in accordance with the regression model used in this study. These factors definitely exert an effect on heart enzyme level. By contrast, the heart enzyme is unaffected or barely affected by the change in creatinine enzyme levels.

Beneficial development and potential for more precise medical data analysis beyond several dimensions are provided. Medical research and clinical practice will be significantly affected by the alternatives offered and more thoughtful reliance on the model's comparative explanatory skill, where physicians can obtain a more in-depth grasp of the elements that govern life-saving signals by employing fuzzy regression approaches. Consequently, physicians may be assured that patients are receiving the most accurate diagnosis possible.

Acknowledgment

We are grateful for the support of our research team from the Mathematics Department, College of Science, Mustansiriyah University, and your prominent journal for supporting this research.

Conflict of Interest

The authors declare no conflict of interest in the conduct of this research.

References

[1] Vittinghoff, E., Shiboski S., Glidden D., & McCulloch C. (2005). Regression Methods in Biostatistics, Springer.

[2] Klir, G. J., & Wierman, M. J. (1999). Uncertainty Based Information, 2nd ed. ser. Studies in Fuzziness and Soft Computing,15., Heidelberg, Germany: Physica, Verlag.

[3] Cao, B. Y. (2010). Optimal Models and Methods with Fuzzy Quantities: Springer, Verlag Berlin Heidelberg.

[4] zadeh, L. A. (1965). fuzzy set, information and control. 338-353.

[5] zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning, Part 1. Information Science, 199-249.

[6] Tanaka, H. (1982). A linear regression model with fuzzy function. *Journal of the Operations Research Society of Japan*, 25, 162-173.

[7] Tanaka, H., Uejima, S., & Asai, K. (1982). Linear regression analysis with fuzzy model. *IEEE*

Transactions on Systems, Man and Cybernetics, 12(6) no, 903–907.

[8] Diamond, PH. (1988). Fuzzy least squares. *Information Sciences,* 46(3), 141-157.

[9] Tanaka, H., Hayashi, I., & Watada, J. (1989). Possibilistic linear regression analysis for fuzzy data. *European Journal of Operational Research,* 40(3), 389-396.

[10] Lee, H., & Tanaka, H. (1999). Fuzzy Approximation with Non-Symmetric Fuzzy Parameters in Fuzzy Regression Analysis. *Journal of the Operations Research Society of Japan,* 24(1), 98-112.

[11] Nasrabadi, M., Nasrabadi, E., & Nasrabady, A. (2005). Fuzzy linear regression analysis: a multi-objective programming approach. *Applied Mathematics and Computation,* 163(1), 245-251.

[12] Arabpour, A. R., & Tata, M. (2008). Estimating the parameters of A fuzzy linear regression model, *Iranian Journal of Fuzzy Systems*, 5(2) , 1-19.

[13] Zeng, W., Feng, Q., & Li, J. (2017). Fuzzy least absolute linear regression. *Applied Soft Computing*, 52(5), 1009-1019.

[14] Hasanain, W. S. (2020). Assessment of Teachers' Knowledge about Tuberculosis at Primary School in Balad City. *Journal of Physics: Conference Series,* 159(1).

[15] Škrabánek, P., Marek, J., & Pozdílková, A. (2021). Fuzzy Regression Line. *Mathematics*, 9(6).

[16] Yingfang, Li, Xingxing, He., &Xueqin, Liu. (2023). Fuzzy multiple linear least squares regression analysis. *Fuzzy Sets and Systems*, 459, 118-143.

[17] Tanaka, H., Hayashi, I., & Watada, J. (1989). Possibilistic linear regression analysis for fuzzy data. *European Journal of Operational Research,* 40(3), 389-396.

[18] Chachi, J., & Taheri, M. (2016). Multiple fuzzy regression model for fuzzy input-output data. *Iranian Journal of Fuzzy Systems*, 13(4), 63-78.

[19] Yingfang, L., Xingxing, H., & Xueqin, L. (2003). Fuzzy multiple linear least squares regression analysis. *Fuzzy Sets and Systems*, 459, 118-143.

[20] Khan, M., Kumar, R., Aledaily, A. N., Kariri E., Viriyasitavat, W., Yadav, K., Dhiman, G., Kaur, A., Sharma, A., & Vimal, S. (2024). A systematic survey on implementation of fuzzy regression models for real life applications. *Archives of Computational Methods in Engine,* 31(1).

[21] Yen, K. K., Ghoshrya, S., & Roig, G. (1999). A linear regression model using triangular fuzzy number coefficient. *Fuzzy Sets and Systems*, 106, 167-177.

[22] Elaibi, W. M., Hasanain W.S., & Taha, A. R. (2022). Optimality criterion for three proposed methods to unbalansed transportation models. *Italian Journal of Pure and Applied Mathematics*, 48, 67–79.

[23] Hameed, A. S., Chachan, H. A., & Ali, H. J. (2023). Optimizing multi-objective problem with setup times. *AIP Conference Proceedings*, 2414(1).

P- ISSN 1991-8941 E-ISSN 2706-6703 *Journal of University of Anbar for Pure Science (JUAPS)* Open Access
2025,(19), (01):269 – 278

استخدام نماذج الانحدار الخطي الضبابي لتحديد العوامل المؤثرة على احتشاء عضلة القلب

آية محمد حسين[1] ، وفاء سيد حسنين[1*]

قسم علوم الرياضيات ، كلية العلوم ، جامعة المستنصرية ، بغداد ، العراق

الخلاصة:

تركز هذه الدراسة على تطبيق العديد من نماذج الانحدار الخطي الضبابي لتحليل البيانات الطبية المتعلقة بأحتشاء عضلة القلب، وخاصة فيما يتعلق بمستوى التروبونين، وهو دليل وعلامة حيوية على تحديد النوبات القلبية. وبشكل أكثر تحديدًا، المؤشرات الفسيولوجية التي تصف حالة المريض بما في ذلك ضغط الدم، وسكر الدم، والكرياتينين، والعلاقة بين هذه المؤشرات ومستوى إنزيم النوبة القلبية.

ولإنجاز هدف الدراسة، تم الحصول على البيانات اللازمة من المستشفيات التي عالجت المرضى الذين تم تشخيصهم باحتشاء عضلة القلب. تم بعد ذلك مقارنة أداء أساليب الانحدار الضبابي باستخدام بيانات التي تم الحصول عليها من المستشفيات.

وتبين الدراسة ان اسلوب المربعات الصغرى الضبابية يتمتع بأقل قيمة من قيم متوسط مربعات الخطأ مقارنة بالنماذج الاخرى، وأفضل دقة في محاكاة تأثير العوامل الفسيولوجية على مستوى إنزيم النوبة القلبية. بالإضافة إلى ذلك، تؤكد هذه الدراسة على أهمية تطبيق الانحدار الضبابي في الإحصاء الطبي نظرًا لوجود عوامل الضبابية وعدم اليقين في المجال وقابلية تطبيق هذه الطريقة لتعزيز القوة التنبؤية واتخاذ القرار في الرعاية الصحية.

الكلمات المفتاحية: المربعات الصغرى الضبابية، البواقي المطلقة للمربعات الضبابية، الانحدار الخطي الاحتمالي، الانحدار الخطي الاحتمالي المقترن بالمربعات الصغرى، الانحدار الخطي الضبابي لبوسكوفيتش.