



A Learn Of Fuzzy Regression Model and Its Applications

B. Anandhavel, T. Edwin Prabakaran

Abstract: Many statistics report shown in fuzzy module into clear problems using the centroid system, consequently we will research the usual linear regression model which is modified from the fuzzy linear regression model. The models enter and generate fuzzy numbers, and the regression coefficients are clear numbers. Hybrid algorithms are considered to fit the fuzzy regression model. So that the validity and quality of the suggested methods can be guaranteed. Therefore, the parameter estimation and have an impact on evaluation situated on knowledge deletion. By way of the gain knowledge of example and evaluation with other model, it may be concluded that the model in this paper is utilized without difficulty and better.

Keyword: Fuzzy Linear Regression Model, Centroid Method, Data Deletion Model, Parameter Estimation.

1. INTRODUCTION:

In traditional relapse assessment, deviations among decided and evaluated qualities are thought to be because of arbitrary slip-ups. In any case, pretty frequently those are a result of inconclusiveness of structure of a framework or loose perceptions. In this manner, vulnerability in this sort of relapse model moves toward becoming "fluffiness" and not irregularity [6]. Studies managing Fuzzy direct relapse (FLR) model can be extensively grouped into two methodologies, viz. (I) Linear programming (LP)- based techniques, and (ii) Fuzzy least squares (FLS) strategies. In this system is generally utilized to more than a few functions including advertising, management and revenue forecasting. In traditional regression tactics, the change among the experimental values and the values likely from the model is thought to be as a result of observational error however in fuzzy regression, the change among the experimental and the predictable values is believed to be because of the anomaly fundamentally skill within the method. In this part, a method for fuzzy linear regression model drawback is awarded. In this prototypical, the outputs are non-fuzzy remarks. Additionally, the efforts are non-fuzzy responses. The improper model is believed to be a fuzzy linear operate are [6]:

$$y = f(x, A) = A_0 + A_1X_1 + A_2X_2 + \dots + A_nX_n$$

Where A_i ($i = 1, 2, \dots, n$) are the fuzzy coefficients in the type of (p_i, c_i) where p_i is the middle and c_i is the feast. The spread value signifies the fuzziness of the function.

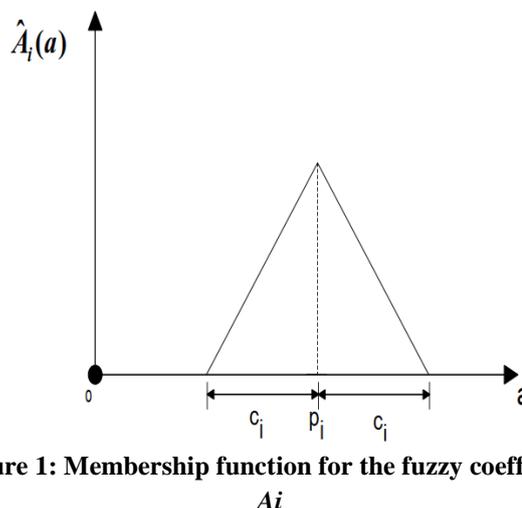


Figure 1: Membership function for the fuzzy coefficient A_i

II - LITERATURE REVIEW:

Dr. Chwan-Chin Song and Dr. Jann-Huei Jinn and Mr. J. C. Chao [2007] Statistical strategies are carried out to perform estimation and derivation in relapse assessment. In any case, the residuals are once in a while due to the woolliness of version shape before vague explanations [2]. The indecision on this kind of deterioration prototypical converts fluffiness, not random. This kind of records is easy to find in herbal language, social technological know-how, psychometric, environments and econometric, and so forth. Fuzzy numbers were used to symbolize fuzzy records. The initial one introduces the focuses of the fluffy records; the other sub-models are worked over the first and yield the spreads. Despite the fact that a remaining examination is valuable in evaluating model fit, takeoffs from the relapse rendition are as often as possible covered up by the best possible framework. For example, there might be "anomalies" in both the response and illustrative factors that may massively affect the exploration [2]. **M. Tata And R. Arabpour [2008]** Fuzzy linear regression models are used to reap the ideal linear relation among-st a based variable and numerous independent variables in a fuzzy environment. Several techniques for evaluating fuzzy coefficients in linear regression models had been proposed [3]. The first tries at estimating the parameters of a fuzzy regression model used Mathematical programming techniques.

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In this thesis, we generalize the metric described through manner of Diamond and use it as a criterion to estimate the ones parameters. Let $F(R)$ denote the set of normalized fuzzy numbers: that is, the set of upper semi non-stop convex capabilities $X^* : R \rightarrow [0, 1]$ such that $x \in R : X^*(x) = 1$ is nonempty [3].

Jian Zhou, Fangning Chen, Yizeng Chen and Yuanyuan Liu [2013] The parameter h in a fuzzy linear regression version is important as it influences the degree of the great of the predicted fuzzy linear dating to the given statistics directly. However, it's also subjectively pres-elected by way of a selection-maker as an input to the version in practice. The value of parameter h determines the range of the opportunity distributions of the bushy parameters, so it's far crucial to pick a appropriate price for h in fuzzy regression analysis. The most advantageous h value for a given set of sample information pairs is proposed with the aid of combining the criterion of minimizing the gadget fuzziness with that of maximizing the device credibility of an FLR version with uneven TFNs. The technique proposed in this paper may also offer appropriate answers for the unsure members of the family inside the sensible troubles [6].

Jana Nowakov´a and Miroslav Pokorn´y [2013] the theoretical historical past for summary formalization of indistinct wonder of the muddled structures is fluffy set rule. In the paper vague realities as particular fluffy sets - fluffy numbers are characterized and its miles depicted a fluffy straight relapse form as a fluffy trademark with fluffy numbers as obscure parameters. Interim and fluffy relapse advances are referenced, the straight fluffy relapse adaptation is proposed [7]. Direct relapse form of examined machine Shapiro (2006) is given by method for a straight total of estimations of it enter factors, The two-dimensional numerical precedent is introduced and the likelihood zone of unclear model is graphically shown. Next research will be centered around improvement of fluffy non-direct relapse model with fluffy yield esteem Pokorn'y (1993) to have probability to examine and display obscure non-straight framework [7].

Pavel Skrab´anek and Nat´alia Mart´inkov´a [2019] Beginning with Fitting Fuzzy Linear Regression Models in R. Fluffy relapse introduces an option in contrast to measurable relapse while the model is uncertain, the connections among model parameters are ambiguous, and test size is low or when the data are progressively based. The fuzzy regression is for that reason applicable in instances, in which the information shape prevents statistical examination. The package Fuzzy Numbers [12] provides a first-rate creation into fuzzy numbers and offers a first rate flexibility in designing the fuzzy numbers. Here, we enforce a unique case of fuzzy numbers, the triangular fuzzy numbers. Methods implemented in fuzzyreg 0.4.0 suit fuzzy linear models. The TFN definition utilized in fuzzyreg allows a clean setup of the regression version the usage of the well-installed syntax for regression examines in R. To cite fuzzyreg, encompass the connection with the software and the used technique [12].

III - EXISTING METHODOLOGY:

PREDICTING THE TRANSPORT CLAIM: THE DIFFERENT-STAGE FLR APPLICATION & MODEL DESIGN:

The transport power request is forecasted utilizing a different-stage FLR model involving to socio-financial and vehicle related warning signs from .2006 to. 2020. Three principal variables had been identified to have foremost special effects on transport power claim: 1) The quantity of cars, 2) population and 3) GDP. Prior experiences regarded descriptive variables comparable to gross country wide product (CWP), populace and the complete yearly natural auto distance, gross home product (GHP), development price, traveller-income and consignment-income and oil fee for predicting transport drive demand [6]. Transport vigor demand has swiftly been increasing seeing that of developments within the industrial, agricultural, transportation and business sectors. The population development is the other purpose for growing of transport energy demand. The speedy growth on the GDP results in develop within the quantity of automobile owners and consequently to increase in energy demand in transportation sector.

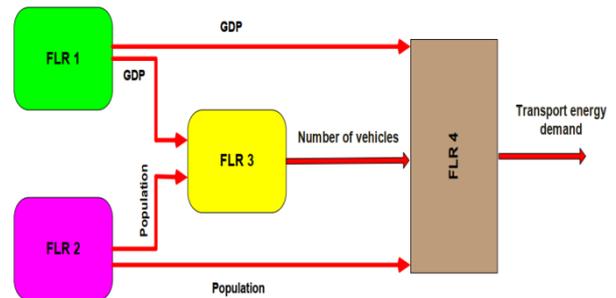


Figure 2. Structure of the designed multi-level FLR.

Table 1. FLRs inputs and outputs:

Inputs	Output
GDP in the last year GDP in the last two years	GDP
Population in the last years Population in the last two years	Population
Number of vehicles in the last year Number of vehicles in the last two years Population Ratio of GDP over population	Number of Vehicles
Transport energy demand in the last year Transport energy demand in the last two years Number of vehicles Population Ratio of GDP over population	Transport energy demand

In these studies, delivery energy calls for is statistics based totally on gross domestic product (GDP), populace and the range of vehicles. To estimate the electricity call for version, its miles needed to forecast the number of cars, populace and GDP from 2006 to 2020. In this have a look at, vehicle regressive fashions are used for this motive. The shape of the designed multi-degree FLR is given in Figure 3. For finding the pleasant specification, distinct fashions have been taken into consideration. Then, the communal complete error proportion (CAEP) values of these fuzzy techniques are considered and the models with minimal mistake are decided on. The CAEP is designed from the subsequent calculation:

$$AAEP = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{x}(i) - x(i)}{x(i)} \right| \times 100$$

Everywhere $\hat{x}(i)$ is the expected value and $x(i)$ is the real cost of established variables. Table 1 suggests the FLRs source and outcome. The major FLR (FLR 4) shows the population, the ratio of GHP above population, the variety of motors and the delivery power demand within the remaining 12 months and in the remaining 2 years as efforts and produces the transport drive demand. The populace, the GHP and the quantity of cars are foretasted using FLRs. Data related to delivery strength modelling is accrued from different sources.

Table 2: The population, GDP, the number of vehicles and transport energy demand (Iran Ministry of Energy, 2005).

Years	GD (10 R)	Population	No of Vehicles	Emergency Demand (MBOE)
1993	258601.4	57767560	3091340	122.1
1994	259876.3	58657180	3162697	144.6
1995	267534.2	59531172	3253854	141.9
1996	283806.6	60412234	3379396	147.9
1997	291768.7	61309355	3555776	153.2
1998	300139.6	62222865	3760960	161.2
1999	304941.2	63159319	3975413	170.3
2000	320068.9	64125656	4341927	183.4
2001	330565	65126017	4747493	194.2
2002	355554	66168033	5300463	208.9
2003	379838	67256497	6084973	220.8
2004	398234.6	68399857	7027124	233.4
2005	419705	69670535	8033737	252.3

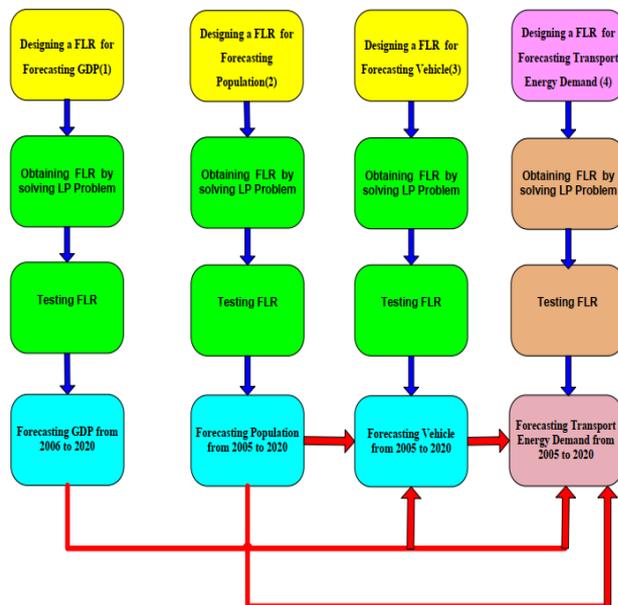


Figure 3. The Framework Of The Forecasting.

The GHP, population and shipping power demand are accrued from Iran Organization of Energy. The range of automobiles is accumulated from Iranian Petroleum Preservation Organization (IPPCO). Data is shown in Table 1. Figure 2 shows the structure of the predicting. Fuzzy linear regression is castoff to build estimating models for GHP, populace, the number of cars and Transport Energy Demand. The take a look at spans the time period from 1993 to 2005. This period is used to educate and test the FLR models. For predicting delivery strength demand from 2006 to 2020, GHP, population and the form of cars are expected. The fuzzy linear regression is complete to find fuzzy parameters [9].

Table 3: Estimated Transport energy demand.

Years	Transport energy demand (MBOE)
2006	257.75
2007	269.21
2008	284.96
2009	302.57
2010	321.94
2011	342.79
2012	365.03
2013	388.59
2014	413.47
2015	439.7
2016	467.29
2017	496.29
2018	526.82
2019	558.87
2020	592.55

Result:

Fuzzy models designated as appropriate model for estimating the transfer energy demand. Then, the predictable fuzzy parameters are used to forecast the transport energy demand till the year 2020. The result can be seen in Table 3. The appraised values are given in Figure 3. Transport energy demand will extend to a level of 592 MBOE in 2020.

IV - PROPOSED SYSTEM:

Techniques for suitable fuzzy regression technique:

Techniques implemented in fuzzyreg 0.4 fit fuzzy linear models (Table 1). Table 1: Methods for becoming fuzzy regression with fuzzyreg. *m* - wide variety of allowed impartial variables *x*; *x*, *y*, \hat{y} - Type of anticipated number for independent, dependent variables and predictions; *s* - symmetric; *ns* - non-symmetric [11].

Method	<i>m</i>	<i>x</i>	<i>y</i>	\hat{y}
PLRLS	∞	crisp	crisp	nsTFN
PLR	∞	crisp	sTFN	sTFN
OPLR	∞	crisp	sTFN	sTFN
FLS	1	crisp	nsTFN	nsTFN
MOFLR	∞	sTFN	sTFN	sTFN

Methods that require symmetric TFNs handle input specifying one spread, but in methods expecting non-symmetric TFN input, both spreads must be defined even in cases when the data contain symmetric TFNs.

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The possibility linear regression combined with the least squares (PLRLS) method [5] fits the model prediction spreads and the central tendency with the possibility and the least squares approach, respectively. The input data represent crisp numbers and the model predicts the response in form of a non symmetrical TFN. Local outliers in the data strongly influence the spreads, so a good practice is to remove them prior to the analysis.

The method by Hung and Yang [3] expands PLR [8] by adding an omission approach for detecting outliers (OPLR). We implemented a version that identifies a single outlier in the data located outside of the Tukey's fences. The input data include crisp explanatory variables and the response variable in form of a symmetric TFN.

Fuzzy least squares (FLS) method [1] supports a simple FLR for a nonsymmetric TFN explanatory as well as a response variable. This probabilistic based method (FLS calculates the fuzzy regression coefficients using least squares) is relatively robust against outliers compared to the possibility-based methods.

A multi-objective fluffy straight relapse (MOFLR) technique assesses the fluffy relapse coefficients with a plausibility come closer from symmetric TFN input information [6]. Given a particular weight, the strategy decides an exchange off between exception punishment and information fitting that empowers the client to adjust anomaly taking care of in the exploration.

The learning calculation of FWLS strategy.

This calculation is like FWLP's aside from that the resulting parameters are distinguished by fluffy least squares issue Eq are cry, we use MATLAB programming apparatus for coding.

Fuzzy least squares problem in the prediction of the consequence parameters. By using fuzzy least squares problem, we can obtain the consequence parameters estimation for the fuzzy regression model as follows [11]:

$$(\hat{b}_i^k)^T = (X^T X)^{-1} X^T A_Y,$$

$$(\hat{\alpha}_i^k)^T = (X^T X)^{-1} X^T \alpha_Y,$$

where,

$$X = \begin{pmatrix} \bar{\omega}_{11} & \bar{\omega}_{12} & \dots & \bar{\omega}_{1m} & \bar{\omega}_{11}x_{11} & \dots & \bar{\omega}_{1m}x_{11} & \dots & \bar{\omega}_{11}x_{1p} & \dots & \bar{\omega}_{1m}x_{1p} \\ \bar{\omega}_{21} & \bar{\omega}_{22} & \dots & \bar{\omega}_{2m} & \bar{\omega}_{21}x_{21} & \dots & \bar{\omega}_{2m}x_{21} & \dots & \bar{\omega}_{21}x_{2p} & \dots & \bar{\omega}_{2m}x_{2p} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{\omega}_{n1} & \bar{\omega}_{n2} & \dots & \bar{\omega}_{nm} & \bar{\omega}_{n1}x_{n1} & \dots & \bar{\omega}_{nm}x_{n1} & \dots & \bar{\omega}_{n1}x_{np} & \dots & \bar{\omega}_{nm}x_{np} \end{pmatrix}$$

$$A_Y = \begin{pmatrix} a_{y1} \\ a_{y2} \\ \vdots \\ a_{yn} \end{pmatrix}, \alpha_Y = \begin{pmatrix} \alpha_{y1} \\ \alpha_{y2} \\ \vdots \\ \alpha_{yn} \end{pmatrix}, (\hat{b}_i^k)^T = \begin{pmatrix} \hat{b}_0^k \\ \vdots \\ \hat{b}_p^k \\ \vdots \\ \hat{b}_m^k \end{pmatrix}, (\hat{\alpha}_i^k)^T = \begin{pmatrix} \hat{\alpha}_0^k \\ \vdots \\ \hat{\alpha}_p^k \\ \vdots \\ \hat{\alpha}_m^k \end{pmatrix}$$

V - PROPOSED ARCHITECTURE:

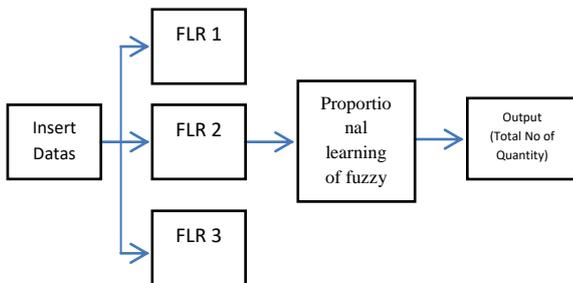


Figure 4: Proposed architecture

By using this architecture tool changed fuzzy linear regression model and proportional learning get exact output when using Matlab and R-studio and some other platform. In this examination we are utilizing ongoing informational indexes, by utilizing this current information's we discover which items are for the most part like by individuals, organization offer esteem count, discover issue, step by step insights report and so forth., at long last reports are demonstrated by utilizing ROC curve.

Step 1: Insert Dataset

Step 2: 3 dissimilar fuzzy linear regression model.

Step 3: Proportional learning of fuzzy linear regression model.

Step 4: Output

IV – CONCLUSION:

By changing fuzzy records into clear information, the bushy linear regression model is modified into previous linear regression version. We take a look at the parameter assessment and manipulate examination of the case-elimination fuzzy linear regression model. By evaluating with extra strategies via a realistic version we can determine that the proposed device in this session can be used simply and feature a worthy becoming act.

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