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PREDICTION OF CARBON DIOXIDE EMISSIONS USING FUZZY LINEAR REGRESSION MODEL: A CASE OF DEVELOPED AND DEVELOPING COUNTRIES

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Abstract: Carbon dioxide (CO_2) emissions have been continuously escalating in recent years. The escalating trend is consistent with the current economic activities and other uncertain variables such as demand and supply in businesses and energy needs. Linear model is one of the most commonly used methods to explain the relationship between CO_2 emissions and the related economic variables. However, linear regression model fails to describe the relationship due to the variables' uncertainty and vague information. As to overcome this problem, fuzzy linear regression model has been proposed in explaining the relationship. This paper aims to predict CO_2 emissions using possibilistic fuzzy linear regression model by employing data from two countries. The prediction on the efficiency of CO_2 emissions for the United Kingdom (UK) and Malaysia was measured. The predictive models identified population and Gross Domestic Products as the most effective predictors for the UK and Malaysia respectively. The root mean square errors of the UK and Malaysia predictive models were 2.895 and 1010.117 respectively. It shows that the CO_2 emissions predictors of the UK are more efficient than Malaysia. Instead of crisp deterministic regression coefficients, the fuzzy coefficients with middle and spread values of fuzzy linear regression equations offer new contribution to describe the relationship between CO_2 emissions and the related economic variables.

KEYWORDS: CO_2 emissions, predictive model, error analysis, economic variables.

Introduction

Carbon dioxide (CO_2) emission is an important component in the stability of climate system, and plays a key role in green house effect. In the past few decades, CO_2 emissions have increased exponentially. Goodall (2007), in his book mentioned that almost 30 billion tons of CO_2 enters the atmosphere as a result of various human activities each year. The effect of the higher concentrations of CO_2 to people could not be taken lightly. CO_2 is held responsible for 58.8% of green house effect. The effect may cause major environment pollutions and climate instability. The escalation in CO2 emissions would give disastrous environmental consequences such as droughts, storms, floods and other environmental calamities. As a result of large volume of CO_2 in atmosphere, it is noticeable that global sea level has escalated by 10 -20 cm during the 20th century (Mukhtar *et al.,* 2004). It has been reported that there was not only escalating trend in sea level but also the temperature of the sea. Spence (2005) testified that global CO_2 emissions have escalated by 30% and temperature has risen by 0.3-0.6 degree Celsius. These are among the much feared examples of environmental instability as a result of uncontrolled CO_2 emissions. The risk of environmental catastrophe is therefore considered great enough to justify the awareness and study in CO_2 emissions.

A considerable amount of literature has been published on causal relationship between CO_2 emissions and its contributing factors. Hwang and Yoo (2012) analyzed the short and long-run causality issues between energy consumption, CO_2 emissions, and economic growth in Indonesia using time-series techniques. The relationship between CO_2 emissions with Gross Domestic Product (GDP) and energy consumption were investigated in China (Chang, 2010; Zhang and Cheng, 2009). The similar studies were also conducted in South Africa (Menyah and Wolde-Rufael, 2010), Italy and Switzerland (Ozturk and Acaravci, 2010). Tiwari *et al.,* (2013) studied the association of rainfall and vegetation variability with growth rate of surface observed atmospheric CO_2 concentrations over Cape Rama, west coast of India. The relationship between CO_2 emissions and its related variables have been widely investigated in planning, projections, forecasting and predictions based research. Coutts *et al.,* (2007), for example, investigate CO_2 fluxes in an Australian city, adding to the global database of CO_2 fluxes in a bid to aid in future development of planning policies concerning reductions in CO_2 emissions. Nor Safaai *et al.,* (2010) projected the CO_2 emissions in Malaysia. They used the model of long range energy alternatives planning system to make the CO_2 emissions projection until the year 2020. Electricity generation, transportation, industrial sites and residential areas were exploited as the causal factors. However, this is a projection research where the accuracy or errors of the model were rarely measured. The causal relationships among variables could also be extended to prediction studies.

One of the common methods in describing the causal relationship between variables is linear regression. Linear regression analysis is a powerful and comprehensive method for analyzing linear relationships between a response variable or popularly known as dependent variable and one or more explanatory variables, or termed as independent variables. Inferential problems associated with regression model include the estimation of the model parameters and prediction of the response variable from knowledge of the explanatory variables. The linear regression method has been used in many experiments of daily related activities including CO_2 emission related research. Brondfield *et al.,* (2012), for example, applied a linear model of the linear regression downscaling to model on-road CO_2 emissions at Boston, Massachusetts and tested the approach with surface-level CO_2 observations. The accuracy of the estimated model was measured using coefficient of determination (R^2). Nwachukwu1 and Anonye (2012) used linear regression analysis to determine the strength of the correlation between CH_4 and CO_2 concentrations and barometric pressure. R^2 was computed to measure the effect of atmospheric pressure on methane and CO_2 emission from a landfill site. Ming and Niu (2011), used non linear logistic regressions to improve the goodness of fit of the CO_2 emissions prediction model. Mean absolute percentage errors (MAPE) were measured to check the efficiency of estimated values. In spite of the widespread use of the liner regression methods in many real life applications, there exists uncertainty in variables used in the linear regression method. As to handle the uncertainty, fuzzy linear regression was introduced. Conventional linear regression cannot handle visual inspection results that are inherently non-crisp or linguistic. On the other hand, fuzzy linear regression provides an effective means for coping with such fuzzy data or linguistic variables. It was stemmed from the fuzzy sets theory that was able to deal with vague predicates (Zadeh, 1965). The fuzzy linear regression analysis was introduced more than thirty years ago by Tanaka *et al.,* (1980, 1982). Fuzzy linear regression is used in estimating the relationships among variables where the available data are very limited and imprecise and variables are interacting in an uncertain, qualitative and fuzzy way.

The goal of fuzzy linear regression analysis is to find a regression model that fits all observed fuzzy data within a specified fitting criterion. Different fuzzy linear regression models are obtained depending on the fitting criterion used. In order to fulfill the criterion, two main approaches were proposed. The first approach is based on the possibilistic concept (see , for instance, Tanaka *et al.,* 1980,1982; Chang and Lee, 1996; Tanaka and Lee, 1998; Chen, 2001; Lee and Chen, 2001). The approach often referred as possibilistic linear regression since fuzzy data can be regarded as distribution of possibility (Tanaka, 1987). They explain fuzzy uncertainty of dependent variables with the fuzziness of response functions or regression coefficients in the linear regression model. The uniqueness of Tanaka fuzzy linear regression is the spread of fuzzy numbers of dependent variables. In order to minimize the spread, Tanaka *et al.,* (1982) introduced linear programming problems. The possibilistic fuzzy linear regression model is quite popular due to its major breakthrough in minimizing the spread of fuzzy numbers. Furthermore, the Tanaka fuzzy linear regression used symmetrical triangular fuzzy numbers which relatively easier compared to other types of fuzzy numbers. Due to these advantages, the possibilistic fuzzy linear regression is one of the successful predictive models and has been applied to numerous real life applications specifically in predicting and forecasting. Dereli and Durmusoglu (2010), for example, used possibilistic linear fuzzy regression in alert triggering mechanism of pattern alerts system. Wen and Lee (1997) developed a cost function for waste water treatment systems in Taiwan using possibilistic fuzzy linear regression. The second approach in fuzzy linear regression is the least-squares regression approach and is not intended to describe in this paper.

The fuzzy linear regression method has been used for many years in developing predictive models for various applications including marketing, management and sales forecasting (Heshmaty and Kandel, 1985; Chang, *et al.,* 1996; Abdullah and Zakaria, 2012). Kahraman (2002), for example, forecasts sale levels of computer equipment in using fuzzy linear regressions. Wu *et al.,* (2009) describes an application of the fuzzy linear regression analysis for land-cover classification of Landsat TM data in remote sensing field. In energy forecasting, Al-Kandari *et al.,* (2004) have developed a fuzzy linear regression model for forecasting summer and winter seasons' related to electrical load. Srivastava and Nema (2008) used fuzzy linear regression for forecasting the solid waste composition of Delhi, India over a period from 2007 to 2024. In 2009, Taghizadeh *et al.,* have formulated a forecasting multi-level fuzzy linear regression model to predict the transport energy demand of Iran up to 2020 using socio-economic and transport related indicators. Motivated by the superiority of fuzzy linear regression and silent attempt to perform the method in modelling of the atmospheric pollutions and economic parameters, this paper intends to extend the applications of this approach in predicting CO_2 emissions. However, it was also hypothesized that CO_2 emissions from developed countries are more efficient than developing countries. Rosa and Tolmasquim (1993), for example, proposed an analytical model to compare energy efficiency indices and CO2 emissions in developed and developing countries. The index of CO_2 emissions was about ten times higher in Brazil than in the USA, Japan and Germany. This analysis shows that efficiency of CO_2 emissions between developed and developing countries seem to differ significantly. Therefore, predicting efficiency of CO_2 emissions using the linear relationship between developed and developing countries is an interesting investigation. To add another contribution to this paper, a predictive performance between two countries from a developed country and developing countries is made. Specifically, the aim of this paper is to identify effective predictor of CO_2 emissions using fuzzy linear regression. Data of CO_2 emissions and its related economic variables from Malaysia and the United Kingdom (UK) are employed to test the efficiency of the possibilistic fuzzy linear regression model.

Possibilistic Fuzzy Linear Regression Model

In this section, formulations for fuzzy linear regression estimation are presented. The inputs and outputs of the model are non-fuzzy observations. The base model is assumed to be a fuzzy linear function as presented below:

$$\tilde{y} = f(x,\tilde{A}) = \tilde{A}_0 + \tilde{A}_1 x_1 + \tilde{A}_2 x_2 + \ldots + \tilde{A}_n x_n \quad (1)$$

where A_i ($i = 1,2,\ldots,n$) are the fuzzy coefficients in the form of (p, c_i, c_i) where p_i is the middle and c_i is the spread. The spread value denotes the fuzziness of the function.

The membership functions for each type of A_i are assumed a triangular membership. So it can be expressed as:

$$\tilde{A}_i(a) = \begin{cases} 1 - \dfrac{|a - p_i|}{c_i}, & p_i - c_i \le a \le p_i + c_i \\ 0, & otherwise \end{cases} \quad (2)$$

Equation (1) can be written as:

$$\tilde{y} = (p_0, c_0) + (p_1, c_1)x_1 + (p_2, c_2)x_2 + \ldots + (p_n, c_n)x_n \quad (3)$$

By applying the Extension Principle (Zadeh, 1975), it implies that the membership function of fuzzy number is given by:

$$\tilde{y}(y) = \begin{cases} \max(\min_i \{\tilde{A}_i(a_i)\} & \{a_i | y = f(x, a_i) \ne \varphi\} \\ 0, & otherwise \end{cases} \quad (4)$$

From equation (3) and equation (4), we get:

$$\tilde{y}(y) = \begin{cases} 1 - \dfrac{\left| y - \sum_{i=1}^{n} p_i x_i \right|}{\sum_{i=1}^{n} c_i |x_i|}, & x_i \ne 0 \\ 1, & x_i = 0, y_i = 0 \\ 0, & x_i = 0, y_i \ne 0 \end{cases} \quad (5)$$

The spread of $\tilde{y}$ is $\sum_{i=1}^{n} c_i |x_i|$ and the middle of $\tilde{y}$ is $\sum_{i=1}^{n} p_i x_i$.

Equation (1) can be written as:

$$\tilde{y}_j = (p_0, c_0) + (p_1, c_1)x_{1j} + (p_2, c_2)x_{2j} + \ldots + (p_n, c_n)x_{nj} \quad (6)$$

$j = 1,2,3,\ldots,m$

where m is the number of observation.

We seek to find the coefficient $\tilde{A} = (p_i, c_i)$ that minimize the spread of the fuzzy output for all data sets. From Montgomery and Peck, (1982), the objective function is given as:

$$Min \sum_{j=1}^{m} \sum_{i=1}^{n} (c_0 + \sum_{i=1}^{n} c_i |x_{ij}|) \quad (7)$$

According to Redden and Woodall (1996) the constraints require that each observation y_j has at least h degree of belonging to $\tilde{y}(y)$, that is:

$$\tilde{y}(y_j) \ge h, j = 1,2,\ldots,m \quad (8)$$

The degree h is specified by the user.

By substituting equation (2) into equation (5), we obtain:

$$\begin{aligned} y_j &\ge p_0 + \sum_{i=1}^{n} p_i x_{ij} - (1-h)(c_0 + \sum_{i=1}^{n} c_i |x_{ij}|, \quad j = 1,2,\ldots,m \\ y_j &\le p_0 + \sum_{i=1}^{n} p_i x_{ij} + (1-h)(c_0 + \sum_{i=1}^{n} c_i |x_{ij}|, \quad j = 1,2,\ldots,m \end{aligned} \quad (9)$$

The aforementioned analysis leads to the following linear programming problem (Tanaka *et al.,* 1982):

$$\begin{aligned} & Min \sum_{j=1}^{m} \sum_{i=1}^{n} (c_0 + \sum_{i=1}^{n} c_i |x_{ij}|) \\ & subject\, to \\ & y_j \ge p_0 + \sum_{i=1}^{n} p_i x_{ij} - (1-h)(c_0 + \sum_{i=1}^{n} c_i |x_{ij}|, \quad j = 1,2,\ldots,m \\ & y_j \le p_0 + \sum_{i=1}^{n} p_i x_{ij} + (1-h)(c_0 + \sum_{i=1}^{n} c_i |x_{ij}|, \quad j = 1,2,\ldots,m \\ & c_i \ge 0, \quad p_i \ge 0 \end{aligned} \quad (10)$$

Solutions of the linear programming problem (equation (10)) will provide the fuzzy coefficients of possibilistic fuzzy linear regression. The model is tested to the case of CO_2 emissions data of two countries.

CO_2 Emission Predictions: Examples of the UK and Malaysia

In general, one may presume that the efficiencies of CO_2 emission between developed and developing countries differs due to environmental, economics and energy sustainability awareness and also governments respective policy. To confirm this premise, data of CO_2 emissions and its associated variables from Malaysia and the UK were employed to be tested using the possibilistic fuzzy linear regression. This study collects data on CO_2 emissions for the period between 1990 to 2010 and 1981 to 2005 for the UK and Malaysia respectively. CO_2 emissions per year were in kiloton. Different period of data were considered due to limitation in retrieving secondary data. Data of the response variable and predictors were retrieved from the official websites of World Bank (2012).

Predictors of the UK data are Energy supply, Business, Transportation, Population, Agriculture, Industrial process and Waste management and labeled as x_1, x_2, x_3, x_4, x_5, x_6, *and* x_7 respectively. Predictors of Malaysian data are Fuel mix, Transportation, Gross Domestic Product (GDP), and Population. It is labeled as x_1, x_2, x_3 and x_4. CO_2 emission is the response variables and denoted as $\tilde{y}$. The response variables and the predictors for the two countries are summarised in Table 1.

Table 1: Variables Used in Modelling.

Variables of the UK Model		Variables of Malaysia Model	
x_1	Energy supply	x_1	Fuel mix
x_2	Business	x_2	Transportation
x_3	Transportation	x_3	Gross Domestic Product
x_4	Population	x_4	Population
x_5	Agriculture		
x_6	Industrial process		
x_7	Waste management		

The implementation of the forecasting model was executed using the optimization software LINGO. Equations (10) with h = 0.5 is used to obtain the possibilistic fuzzy linear regression models.

The optimization software successfully yielded the fuzzy coefficients of the model. Spreads and centre values of fuzzy coefficients of the UK and Malaysia are shown in Table 2 and Table 3 respectively.

Table 2. Fuzzy Coefficients of possibilistic fuzzy linear regression of the UK data.

Table 2: Fuzzy Coefficients of Possibilitic Fuzzy Linear Regression of the UK Data.

n	p	c
0	0	0
1	1.013858	0
2	1.072211	0
3	1.402667	0.298517
4	3.090658	0
5	3.682132	0
6	0	0
7	0	0

Table 3: Fuzzy Coefficients of Malaysian Data.

n	p	c
0	163.9972	0
1	0	0.3322688
2	0.2284970	0.8459350
3	0.9931189	0.2905979
4	0.1645203	0.0859338

Ultimately, possibilistic fuzzy linear regression equation for the UK CO_2 emission data can be written as:

$$\tilde{y} = (0,0) + (1.013858,0)x_1 + (1.072211,0)x_2 + (1.402667,0.298517)x_3 + (3.090658,0)x_4 + (3.682132,0)x_5 + (0,0)x_6 + (0,0)x_7$$

It can be seen that the variable population is the most effective predictor for the UK model.

With the similar fashion, the possibilistic fuzzy linear regression equation for Malaysia CO_2 emission data can be written as:

$$\tilde{y} = (163.9972,0) + (0,0.3322688)x_1 + (0.2284970,0.8459350)x_2 + (0.9931189,0.2905979)x_3 + (0.1645203,0.0859338)x_4$$

Of the four variables, that is GDP variable is the most effective predictor for CO_2 emissions in Malaysia.

Using these two possibilistic fuzzy linear regression equations, the value of CO_2 emission can be predicted. The predicted and the actual values of CO_2 emission for the UK and Malaysia are given in Figure 1 and Figure 2 respectively.

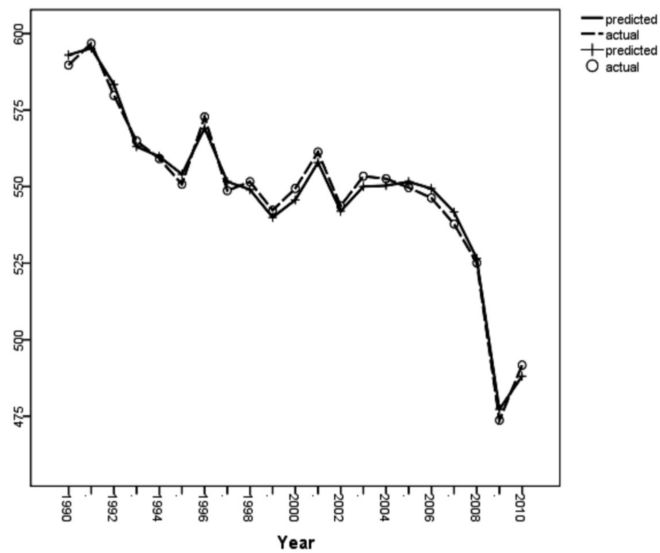

Figure 1: Actual and Predicted Values for CO_2 emission of the UK.

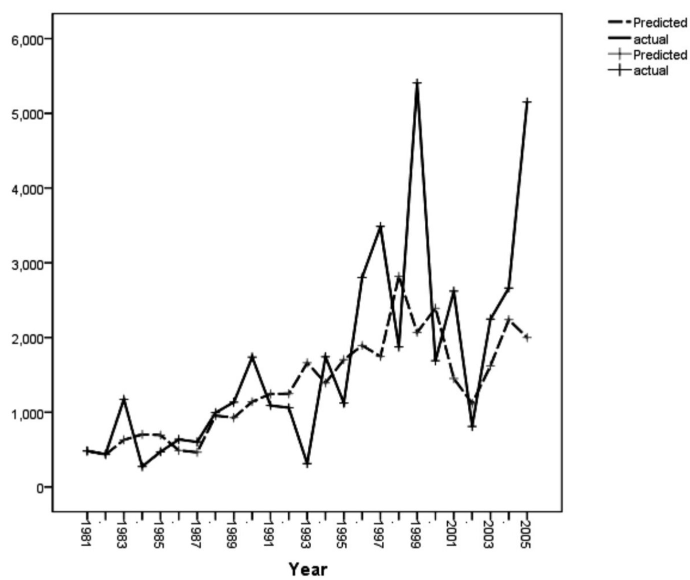

Figure 2: Actual and the Predicted Values for CO_2 emission of Malaysia.

It can be seen from the graphs of the two figures that the prediction model of the UK is better than Malaysia. To distinguish between the outputs of the predicted values and actual values and to check the performance of possibilistic fuzzy linear regression models for Malaysia and the UK data, Mean Average Percentage Errors (MAPE) and Root Mean Square Errors (RMSE) were calculated using the equation (11) and equation (12) .

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \qquad (12)$$

where A_t is the actual value and F_t is the predicted value.

The performance of the two possibilistic fuzzy linear regression models is shown in Table 4.

Table 4: Errors of the UK Model and Malaysia Model.

Model	MAPE	RMSE
Possibilistic Fuzzy linear regression model of the UK	0.00503	2.895
Possibilistic Fuzzy linear regression model of Malaysia	2.028522	1010.117

The two error measures explain the efficiency of the models. A comparison of the two errors reveals that the UK model has smaller error than the Malaysia model. The RMSE for the UK model was 2.895 while the same error measurement for Malaysia model was 1010.117. This trend was also consistent with the error measurement of MAPE. It indicates that the predictors of the UK performed better than predictors of Malaysia on CO_2 emission prediction.

Conclusion

An important element in predictive modelling of CO_2 emissions is a method which can take into account multiple variables with vague and incomplete data. The model should establish a decision to reflect the contribution of each accounted predictors toward CO_2 emissions. Apart from the identification of the best predictor, the method is also able to compare the efficiency of the predictors for two countries with different socioeconomic profiles. As to handle these issues, possibilistic fuzzy linear regression predictive models were proposed. The method was utilized to capture the predictive models and the best predictor of CO_2 emissions for the United Kingdom and Malaysian data. The fuzzy coefficients in the form of middle and spread values denote the fuzziness of the model. The approach has successfully offered the prediction models of CO_2 for the two countries from two different socioeconomic profiles. Population and gross domestic product were identified as the effective predictors for CO_2 emissions of the UK and Malaysia respectively. Furthermore, this paper also contributed to the identification of the better model for CO_2 emissions. The CO_2 emissions prediction model of the UK outperformed the model of Malaysia. The results imply that the chosen predictors of CO_2 emissions in the UK were the better predictors. On the other hand, the predictors of CO_2 emissions in Malaysia were not sufficient to be considered as good predictors. Therefore, it is suggested that several new predictors should be considered in predicting CO_2 emissions in Malaysia.

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