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Estimating a Fuzzy Linear Regression For Energy Intensity in Iranian Industrial Sector

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Abstract:

In the present paper, a case of fuzzy regression model was estimated for Iranian industrial energy intensity. To do so, at first the trapezoidal fuzzy values of energy intensity observations were calculated based on the Minimizing Entropy Principle Algorithm(MEPA) and then a tripled recursive model was estimated for fuzzified energy intensity. Because of application of the partial adjustment model, we explored the short-run and long-run membership functions for each of the explanatory variable fuzzy coefficients. The estimation results show that the lagged energy intensity values are the only factor which has a positive effect on the industrial energy intensity attitude, whereas other explanatory variables including energy price, value added share and technical efficiency score have negative effect on energy intensity trend in the period (1982-2006). Moreover the estimation results indicated the numerous potential energy saving in Iranian industrial sector which is mainly emerged from pure energy intensity in short-run.

JEL classification**: C23, D24**

Keywords: *Fuzzy sets, Fuzzy Regression, Fuzzification, Energy Intensity*

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1. Introduction

The application of linear estimation of economic variables relationships is greatly important for empirical research and has a key role in our understanding of economic issues. Regression analysis is one of the favorite methods of estimation. The classical regression method only provides a crisp estimation for economic relations and is usually used in most economic surveys. However, there are numerous things which cause vague attributes in variables, coefficients, parameters and relations. Therefore, the use of a fuzzy method can be helpful for understanding these issues. Some of the reasons include inherent nature of some variables, errors in data collection and vague nature of parameters. In brief, the fuzzy nature of economic parameters and relations makes the causal analysis more difficult. Hence, it is necessary to apply a method for inferring the economic relationships in a fuzzy environment. Fuzzy theory is very helpful in understanding the vague problems, such as parameters, variables and relationships.

The fuzzy set theory was first proposed by Zadeh (1965) and has since been successfully applied to many fields, such as fuzzy controls, fuzzy expert systems, and fuzzy database systems. Basic concepts of fuzzy set, fuzzy number, linguistic value, and defuzzification methods are explained in many studies (Welkenhaur, 2001; Cheng et al. 2006).

Traditional econometric models typically assume that the underlying relationships are linear and that the relevant inputs and outputs are well-defined or crisp. Given that well-defined linear empirical models are always just approximations to the relationships suggested by theory, the important question is whether these approximations are sufficient to capture the behavior of real-world systems. In practice, however, there are cases in which observations are fuzzy in nature which cannot be described by probability distributions. The observations described by linguistic terms such as low, high, many, approximately equal to 5, etc. are typical examples. How to estimate the parameters under a fuzzy environment is a challenge to the classical regression analyses, too.

One way to handle these problems connected to uncertainty and imprecision of input values and theoretical relationships is to apply the fuzzy logic framework, based on the fuzzy set theory proposed by Zadeh (1965). For example, in the production theory, there are many types of functions defined for the production function which obviously differs from describing technological attributes.

The fuzzy regression model has first been introduced by Tanaka and Wang (2001). In the literature, several papers have addressed the issue of regression analysis under fuzzy environment. Recent articles. such as Sanchez and Gomez (2003, 2004), Sanchez (2006), Kao and Chyu (2003) and Ishibichi and Nii (2001). used fuzzy regression in their analyses.

In fuzzy regressions, the difference between the observed and the estimated values is assumed to be due to the ambiguity inherently present in the system. Two general approaches are used to fit the fuzzy regression model. One is *the possibilistic regression model* (Tanaka and Wang, 2001) which minimizes the fuzziness of the model by minimizing the total spreads of its fuzzy coefficients, subject to including the data points of each sample within a specified feasible data interval . The other is *the least squares fuzzy regression model*, which minimizes the distance between the output of the model and the observed output, based on their models and spreads (D`Urso & Gastaldi, 2000, 2001, 2002; D`Urso, 2003).

In both approaches, the notion of "best fit" incorporates the optimization of a functional form associated with the problem. In particular, in the possibilistic approach, "this functional takes the form of a measure of the spreads of the estimated output, either as a weighted linear sum involving the estimated coefficients in linear regression, or as quadratic form in the case of exponential possibilistic regression" (Diamond & Tanaka, 1998). In the least-squares approach, "the functional to be minimized is a quadratic distance between the observed and estimated outputs. This reduces to a class of quadratic optimization problems and constrained quadratic optimization" (Diamond & Tanaka, 1998).

In this paper, we apply a least-squares approach fuzzy regression model which was introduced by D`Urso(2003) for the estimation of the Energy Intensity regression equation, to Iranian Industrial sector. The model functional relationship is crisp and its data structure is crisp input-fuzzy output.

The layout of the paper is as follows: section 2 will describe some aspects of fuzzy concepts and a review of Fuzzy sets, numbers and relations. In section 3, the time series fuzzfication model is explained**.** In section 4 we shall introduce a fuzzy linear regression (FLR) model. The specifications of the data, variables and the model estimation are explained in section 5. In section 6, we will accomplish the fuzzification of energy intensity. Estimation results are presented in section 7 and section 8 is allocated to the summary and conclusion.

2. Fuzzy sets and Data

The fuzzy set theory was first proposed by Zadeh(1965). It is primarily concerned with quantifying and reasoning, using natural language in which words can have ambiguous meanings. Fuzzy logic is an analytical approach that applies to multiple memberships of sets and different levels belonging to any one set. The fuzzy theory has a basic assumption that is a non-clear boundary between members and non-members of a set. The main research fields in fuzzy theory are fuzzy sets, fuzzy logic and fuzzy measure. Some essential definitions of fuzzy theory are described as follows (Tsai et al, 2006; Liu,2009; Lin & Wu,2008)

Definition 2-1: Let X be a universe of discourse, A is a fuzzy subset of X and x is a point of X. A is defined as:

$$A = \left\{ (x, \mu_A(x)) \middle| \, x \in X \right\}$$

where $\mu_A(x)$ is the membership function (MF) of associates x in A with a real number in the interval *[0,1]*. The value of $\mu_A(x)$ represents the membership grade of x. Suppose D_x is a domain of x. The mapping of the membership function will be:

$\mu_A(x): D_x \rightarrow [0,1]$. Fuzzy set A is sometimes represented as follows:

$$A = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + \frac{\mu_A(x_n)}{x_n}$$

Definition 2-2: The $\alpha - cut$ of fuzzy set A is defined as:
$A_\alpha = \{x \in X \mid \mu_A(x) \geq \alpha\}$,
where $\alpha \in [0,1]$.

Definition 2-3: Fuzzy set A is normal if $\max \mu_A(x) = 1$.

Definition 2-4: *N* is called a triangular fuzzy number and can be a triplet(ℓ, m, r), if the membership function of *N* or $\mu_N(x)$ is defined as:

$$\mu_N(x) = \begin{cases} 0, & x \leq \ell \\ (x-\ell)/(m-\ell), & \ell \leq x \leq m \\ (r-x)/(r-m), & m \leq x \leq r \\ 0, & x \succ r \end{cases}$$

Where ℓ , m and r are real numbers and $\ell \leq m \leq r$. The triangular fuzzy number is shown in Fig.1. Indeed if there is $\ell = r$, then the fuzzy number will be called *homogenous (symmetric)*, otherwise *non-homogenous(non-symmetric)*. A *homogenous (symmetric)* fuzzy number can be written in the form of (m, c) and $c = \ell = r$. If the fuzzy number is written as (m, c^L, c^R), $c^L = \ell$, $c^R = r$, then this is called a non-symmetric 6 ′ number or an LR fuzzy number. In all these types, m is the middle point.

Definition 2-5: N is called a trapezoidal fuzzy number and can be a four(ℓ, m_1, m_2, r), if the membership function of N or $\mu_N(x)$ is defined as:

$$\mu_N(x) = \begin{cases} 0, & x \le \ell \\ (x-\ell)/(m_1-\ell), & \ell \le x \le m_1 \\ 1, & m_1 \le x \le m_2 \\ (r-x)/(r-m_2), & m_2 \le x \le r \\ 0, & x \succ r \end{cases}$$

where ℓ, m_1, m_2 and r are real numbers and $\ell \le m_1 \le m_2 \le r$. The trapezoidal fuzzy number is shown in Fig. 2.

Definition 2-6: Fuzzy relations are fuzzy sets defined on universal sets which are Cartesian products. They capture the strength of association among elements of two or more sets, not just whether such an association exists or not. Let A and B be two fuzzy sets, the fuzzy relation from A to B is denoted by $R = A \times B$ given by

$$R = \left\{ \left((x, y)\ ,\ \min\left(\mu_A(x), \mu_B(y)\right) \right) \middle|\ \forall x \in A, y \in B \right\}$$

Fig 1: A triangular fuzzy number N

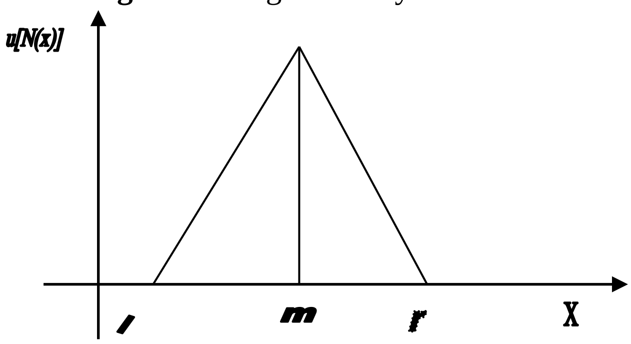
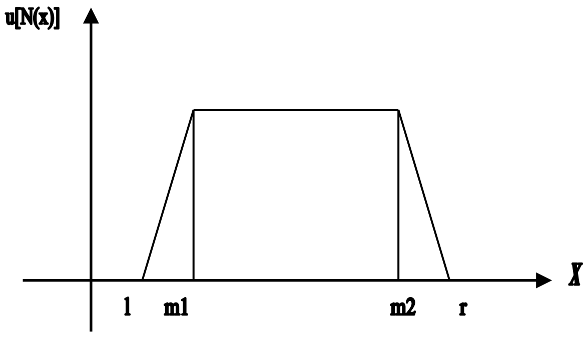


Fig 2: A trapezoidal fuzzy number N



3. The Time Series fuzzification model

In the Fuzzy regression analysis on time series data, model variables may be crisp or fuzzy numbers, but observations on the variables are usually crisp. This is also true about both dependent and explanatory variables. The main difference between the traditional time series and fuzzy time series is that the observed values of the former are real numbers while the latter are fuzzy sets or linguistic values.

Definition 1-3: $Y(t)(t=1,2,3,............)$ is a subset of R^1. Let $Y(t)$ be the universe of discourse defined by the fuzzy set $\mu_i(t)$. If $F(t)$ consists of $\mu_i(t)(i=1,2,.......)$ then $F(t)$ is called a fuzzy time series on $Y(t)$ (Liu, 2009).

There are two important techniques which can be used for fuzzifying historical data (crisp time series) and constructing the fuzzy time series These techniques are the Sang and Chisson method (1993) and Minimizing Entropy Principle Algorithm (MEPA) (Christensen,1980). The first can be applied to make homogeneous fuzzy numbers, and the second for non-homogenous fuzzy numbers. In this paper, we will apply the MEPA method. The purpose of this technique is to fuzzify real-value data sets and partition the data set into a number of fuzzy sets and then to construct membership functions objectively. The entropy of a probability distribution is a measure of the uncertainty of the distribution (Yager & Filev, 1994). To subdivide the data into membership functions, establishing the threshold between classes of data is needed. The MEPA method determines the threshold line and then starts the segmentation process by dividing the data into two classes. Therefore, a repeated partitioning with threshold value calculations will allow us to partition the data set into a number of fuzzy sets (Ross, 2000).

Assume that a threshold value is a sought for sample in the range between x_1 and x_2. An entropy equation with each value of x is written for the regions $[x_1, x_1 + x]$ and $[x_1 + x, x_2]$, and we mark the first region p and the second region q.An entropy with each value of x in the region between x_1 and x_2 is explained as:

$$S(x) = p(x)S_p(x) + q(x)S_q(x)$$

where

$$S_p(x) = -[p_1(x)\ln p_1(x) + p_2(x)\ln p_2(x)]$$

$$S_q(x) = -[q_1(x)\ln q_1(x) + q_2(x)\ln q_2(x)]$$

where $p_k(x)$ and $q_k(x)$ are conditional probabilities that the class k sample has in the regions $[x_1, x_1 + x]$ and $[x_1 + x, x_2]$, respectively. $p(x)$ and $q(x)$ are probabilities that all samples are in the regions $[x_1, x_1 + x]$ and $[x_1 + x, x_2]$ respectively, and $p(x) + q(x) = 1$.

A value of x that gives the minimum entropy is the optimum threshold value. The value estimates of $p_k(x)$, $q_k(x)$, $p(x)$ and $q(x)$, are calculated as follows:

$$p_k(x) = \frac{n_k(x) + 1}{n(x) + 1}$$

$$q_k(x) = \frac{N_k(x) + 1}{N(x) + 1}$$

$$p(x) = n(x)/n$$

$$q(x) = 1 - p(x)$$

where

$n_k(x) =$ number of class k samples located in $[x_1, x_1 + x]$

$n(x) =$ the total number of samples located in $[x_1, x_1 + x]$

$N_k(x) =$ number of class k samples located in $[x_1 + x, x_2]$

$N(x) =$ the total number of samples located in $[x_1 + x, x_2]$

$n =$ total number of samples in $[x_1, x_2]$.

While moving x in the region $[x_1, x_2]$, we calculate the values of entropy for each position of x, as in Fig.3. The value of x in the region that holds the minimum entropy is called the primary threshold (PRI) value. Repeating this process, secondary threshold values can be determined which are denoted as SEC1 and SEC2. To develop seven partitions, we need tertiary threshold values, here denoted as TER1, TER2, TER3 and TER4 (Chen & Cheng, 2008; Tsaur et al., 2005).

This method is based on a schema that describes the input and output relationships for a well established database. The induction is performed by the entropy minimization principle, which clusters most optimally the parameters corresponding to the output classes. By minimizing the entropy, we can find intervals in which the distribution of samples of any class is as relatively uniform as possible. The steps of the Minimize Entropy Principle Approach (MEPA) are described below (Cheng et al, 2006; Chen & Cheng, 2008):

Step 1: Determine the class of each data entry.

In the Minimize Entropy Principle Approach, each data has to be assigned a class initially. There is no specific rule to determine the number of classes and the class of each data due to the 10 acteristics of entropy. After doing some experiments, this paper assigned three classes to each data entry.

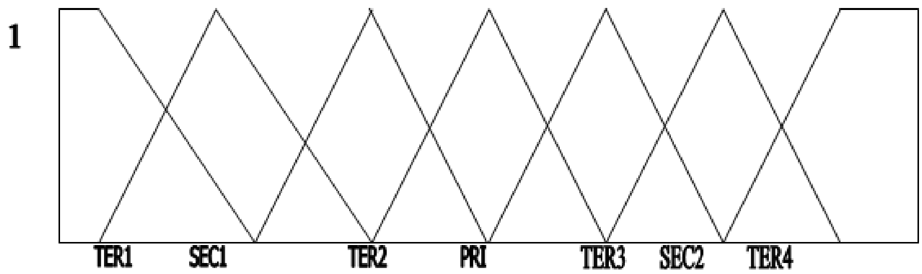
Step 2: Calculate the threshold value (PRI, SEC1, SEC2, TER1, TER2, TER3, TER4).The entropy value of each data entry is computed by the entropy equation proposed by Christensen

(1980) described above. The dataset must be sorted based on the value of each year. We must calculate the entropy values between every two adjacent data to obtain the minimal entropy value. By repeating this procedure to subdivide the data, the thresholds can be obtained.

Step 3: Determine the length of intervals and build membership functions.
Using the thresholds from Step 2 as the midpoint of the triangular fuzzy number, the membership function of Minimize Entropy Principle Approach can be established.

Step 4: Fuzzify the historical data.
According to the membership function in Step 3, the membership degree of each data is calculated to determine its linguistic value.

Fig 3: Partitioning process of Minimize Entropy Principle Approach



4. Fuzzy Linear Regression (FLR) Model

Regression analysis is one of the common methods of parameters estimation. The classical regression method only provides a crisp estimation for parameters in economic models. However, there are numerous things which cause vague attributes in variables, coefficients, parameters and relations. Therefore, the use of a fuzzy estimation method can be helpful for understanding the vague nature of phenomena in the economic surveys. Like any regression technique, the objective of the fuzzy regression model is to determine a functional relationship between a dependent variable and a set of independent variables. In fuzzy regression model, functional relationships can be obtained when the observations over independent variables, dependent variable, or both, are not only crisp values but also intervals or fuzzy numbers.

In general, the fuzzy linear regression model can be described as (Wu, 2003; Kao & Chyu, 2003; Shapiro, 2005):

$$Y_j = f(x, A) = A_1 + A_2 x_{2j} + A_3 x_{3j} + ... + A_k x_{kj} + U_i \quad , j = 1,2,......,m \qquad (1)$$

where, Y_j , $j = 1,2,......,m$, is the output observation j that may be a non-fuzzy(crisp) or fuzzy observation, x_{ij} , $i = 1,2,....,k$, $x_{1j} = 1$ and $j = 1,2,...,m$ is the model input which crisp. A_i , $i = 1,2,.....,k$, are the fuzzy coefficients which can be defined in the form of asymmetric or non-asymmetric fuzzy numbers. Indeed, U_j is the fuzzy error associated with the regression model. According to the output observations attribute, two types of fuzzy regression are identified as follows.

In both types, the output is a fuzzy number but the inputs are crisp as before. Indeed, the coefficients of the model are fuzzy numbers continuously. In the first type, the fuzzy output is represented by a triangular fuzzy number in the form of symmetric $Y_j = (y_j, e_j)$, and, in the second type, the fuzzy output has the form of trapezoidal fuzzy number or LR-type $Y_j = (y_j, e_j^L, e_j^R)$, $j = 1,2,.....,m$. Both types and those membership functions are described in section 2. In this paper, I apply the LR-
12 fuzzy regression. Eq.(1), for LR- type of the fuzzy coefficients and output can be written as below

$$\begin{aligned} Y_j = (y_j, e_j^L, e_j^R) &= (a_1, c_1^L, c_1^R) + (a_2, c_2^L, c_2^R) x_{2j} + (a_3, c_3^L, c_3^R) x_{3j} + ... \\ &... + (a_k, c_k^L, c_k^R) x_{kj} + (\varepsilon_{1j}, \varepsilon_{2j}, \varepsilon_3 j) \quad , j = 1,2,......m \end{aligned} \qquad (2)$$

where, (a_i, c_i^L, c_i^R) *for* $i = 1,2,....,k$ is the regression parameters in the form of triangular fuzzy number. And $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ is the regression error term in the form of triangular fuzzy number.

As stated earlier, in this paper we apply a fuzzy regression model based on the least squares approach that is supplied by Pierpalo D`Urso(2003). In this model, the dependent variable is a trapezoidal fuzzy number, but the explanatory variables are crisp. This fuzzy regression model in its structural form is,

$$y_j = a_1 + a_2.x_{2j} + a_3.x_{3j} + ... + a_k.x_{kj} + \varepsilon_{1j} \quad , j = 1,2,......m \tag{3}$$

$$e_j^{\ L} = d + b.y_j + \varepsilon_{2j} \quad , j = 1,2,......m \tag{4}$$

$$e_j^{\ R} = h + g.y_j + \varepsilon_{3j} \quad , j = 1,2,......m \tag{5}$$

Where, b, d, g *and* h are regression parameters for $e^L, e^R;$ equations. Other variables and parameters are introduced latter. This model has a recursive structure, which is an important type of simultaneous equations model. In this model, all the explanatory variables and ε_1 determine y . y is the predetermined variable with respect to Eqs.(3) and (4). Then y determines e^L and e^R, with ε_2 and ε_3, respectively. Recursive models are always exactly identified (Interligator,1978). By incorporating y from Equ.(3) in Eqs.(4-5) we have,

$$e_j^{\ L} = (b.a_1 + d) + b.a_2.x_{2j} + b.a_3.x_{3j} + ... + b.a_k.x_{kj} + \varepsilon_{2j} \quad , j = 1,2,......m \tag{6}$$

$$e^R = (g.a_1 + h) + g.a_2.x_{2j} + g.a_3.x_{3j} + ... + g.a_k.x_{kj} + \varepsilon_{3j} \quad , j = 1,2,......m. \tag{7}$$

Eqs. (6-7) are the reduced form of the Eqs. (4-5), respectively. Incorporating Eqs. (6-7) to Equ (2) we have,

$$Y_j = (y_j, e_j^L, e_j^R) = (a_1, ba_1 + d, ga_1 + h) + (a_2, ba_2, ga_2)x_{2j}$$
$$+ (a_3, ba_3, ga_3)x_{3j} + ... + (a_k, ba_k, ga_k)x_{kj} + (\varepsilon_1 + \varepsilon_2 + \varepsilon_3) \quad (8)$$
$$, j = 1,2,......m$$

which is the reduced form of the Equ. (2).

5. Specification of Data, Variables and model estimation

As noted in previous sections, the purpose of the present paper is to estimate the fuzzy regression model based on the least squares approach for annual end-use energy intensity on its determinant factors for Iranian industrial activities. Here, the annual End-Use energy is equal to the annual sum of the consumed energy carriers' quantities in MBOE[37] measures by industrial groups. The energy carriers include oil derivatives, electricity and natural gas. Hence, the End-Use energy intensity is calculated as the total End-Use energy divided by the industrial real value-added (see Patterson 1996, Ang 1994 & Sun 2001 for details).

According to the literature on the energy economic, there is a supposition that factors which can determine energy intensity consist of end-use energy cost, structural change in industrial activities, energy carriers' combination in end-use energy bundles and technical efficiency progress (for instance, Boyd and Pang, 2000, Ang 1994 & Farla et al 1998). Associated with these factors, we introduce, in the present study, explanatory variables such as the end-use energy average price, each sector's share in industrial total value-added for the index of structural changes, the share of natural gas in total end-use carriers and technical efficiency score calculated by the DEA method[38] for carriers combinations and technical change progress factors, respectively.

In this study, industrial activities are classified into 9 main groups associated with ISIC. Our database consists of 225 pooled observations on response and explanatory variables within 9 industry groups in the period1982-2006, which were collected from Iranian Statistical Center publications. All monetary values

[37] Million Barrels of Oil Equivalents

[38] Data Envelopment Analysis

such as prices and value-added are deflated by an industrial price index based on 1999 constant prices.

Let us point out again that the response variable is supposed to be a fuzzy time series which is scaled by linguistic indexes. In order to provide such indexes, we must first fuzzify the original observations on energy intensities by means of one of the two approaches introduced in section 3, that is, the Sang and Chisson method and Minimizing Entropy Principle Algorithm (MEPA). Because of high differences between industrial groups in terms of energy intensity, we prefer to use the second approach (**MEPA)** for fuzzifing the energy intensity time series observations. Applying this approach, we can make the LR-type fuzzy numbers for response variables.

Based on Equ.(2) and the variables explained above, our fuzzy regression equation will be,

$$\begin{aligned}&(Log(eninmed), Log(spreleft), Log(spreright))_{it} = (a_0, c_0^L, c_0^R)\\&+(a_1, c_1^L, c_1^R)Log(eninmed)_{it} + (a_2, c_2^L, c_2^R)Log(enpric)_{it}\\&+(a_3, c_3^L, c_3^R)Log(valuads)_{it} + (a_4, c_4^L, c_4^R)Log(effscor)_{it}\\&i = 1,2,......,9\ ,\ t = 1,2,..........,25\end{aligned} \tag{2b).}$$

Based on Equs. 3-5, our selected recursive model for estimating the fuzzy regression (2b) can be rewritten as bellow:

$$\begin{aligned}&Log(eninmed)_{it} = a_0 + a_1 Log(eninmed(t-1))_{it} + a_2 Log(enpric)_{it}\\&+a_3 Log(valuads)_{it} + a_4 Log(effscor)_{it} + \varepsilon_{i1}\\&i = 1,2,........,9;\ t = 1,2,.............,25\end{aligned} \tag{3b}$$

$$\begin{aligned}&Log(spreleft)_{it} = 1.d + b.Log(eninmed)_{it} + \varepsilon_{i2}\\&i = 1,2,........,9;\ t = 1,2,.............,25\end{aligned} \tag{4b}$$

$$\begin{aligned}&Log(spreright)_{it} = 1.h + g.Log(eninmed)_{it} + \varepsilon_{i3}\\&i = 1,2,........,9;\ t = 1,2,.............,25\end{aligned} \tag{5b}$$

where, *eninmed* is the med-point value of energy intensity(fuzzy number), *spreleft and spreright* are left and right spreads, *eninmed(t-1)* is the lagged value of *eninmed, Enpric, valuads and effiscor* are the energy average price, industry sector value added share and efficiency score, respectively, *i* and *t* are the time and the industry sector subscripts and *Log* is the natural logarithm assignment.

Equation 6b is one type of autoregressive regression model sets. We suppose that there is a long-run or desired path for the energy intensity variable which is determined by the explanatory variables: *enpric, valuads and effscor*. Therefore, Eq. 6b is a partial adjustment to the model. The distance between the observed (current) value of energy intensity and its desired value is called the error term. The energy intensity partially adapts to its long-run path in the short-run. The error term in this model would be modified by error correction phenomena.

In the partial adjustment models, the lagged dependent variable is independent of the disturbance term, thus this model can be estimated with the OLS procedure. In Eq.3b, $1-a_1$ is called the dynamic adjustment rate coefficient. Based on the partial adjustment model structure, in Eq.3b the explanatory variables coefficients are short-run model coefficients. Long-run model coefficients are obtained by dividing the short-run coefficient by the partial adjustment rate ($1-a_1$). For example, a_2 is the short-run price elasticity, whereas $\frac{a_2}{1-a_1}$ is its long- run value (Chow, 1983).

According to estimation rules for the recursive model mentioned above, in our model, Eq. (3b) could be estimated by the OLS technique. Then Eqs. (4b) and (5b) would be estimated by associated techniques such as 2SLS and 3SLS with instrumental variables which include the model predetermined bles: eninmed(t-1), Enpric , valuads and effiscor.

7. Fuzzification of energy intensity data

In this section, we calculate the fuzzy values for the energy intensity observations based on the Minimizing Entropy Principle Algorithm (MEPA) introduced in section 3. The energy intensity database in this study includes 25 annual observations for each industrial group and, as a result, 225 pooled observations for all groups. The MEPA procedure, with an energy minimizing screen process, subdivides the energy intensity data with threshold values, which allows us to partition the dataset into a number of fuzzy sets with associated membership functions (Tsai, 2006).

The number of the fuzzy sets depends on repeating screen processes. To determine the maximum partitions during the screen process repetition, we must calculate the entropy value of every potential threshold point by MEPA equations (in section 2-3) until there is no extra partition process. With the application of the MEPA method, the attained maximum number of partitions for the energy intensity observations is seven. Hence, there are 7 membership functions and 7 linguistic values for our respond variable too.

Table (1) shows the calculated threshold points. These points can be used to construct the linguistic values and membership functions for the energy intensity variable that are represented in table (2) and figure (4), respectively.

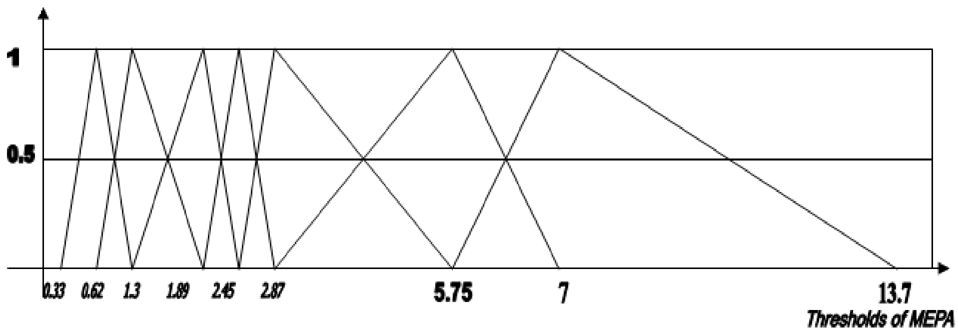
Table 1: Thresholds of MEPA

Thresholds	TER1	SEC1	TER2	PRI	TER3	SEC2 EC2	TER4
Value	0.62	1.30	1.89	2.45	2.87	5.75	7.00

Table 2: Membership function of MEPA

Linguistic value	Lower bound	Midpoint	Upper bound	Length of interval
L1 (very very low)	0.33	0.62	1.30	0.97
L2 (very low)	0.62	1.30	1.89	1.27
L3 (low)	1.30	1.89	2.45	1.15
L4 (moderate)	1.89	2.45	2.87	0.98
L5 (high)	2.45	2.87	5.75	3.30
L6 (very high)	2.87	5.75	7.00	4.13
L7 (vey very high)	5.75	7.00	13.70	7.95

FIG 4: Membership function of MEPA for Energy Intensity



8. Estimation results

We use the software EVIEWS to estimate the recursive model as specified in Eqs. 3b-5b. Eq.3b is estimated by iterative WLS[39] whereas, because of the selected model structure, Eqs. 4b-5b are estimated by the 2SLS method. As noted above, our observations are pooled (panel) data, thus during the estimation we examined different effective procedures for panel data such as none, fixed and random effects. The fixed-effects model supplies the best results compared to others for Eq. 3b. Hence, the constant terms in equations have one estimated value for each of 9 industrial sectors. Tables 3-4 report the short-run and long-run estimated results for Eq.(3b) and Eqs.4b-5b.

[39] Weighted Least Square Estimator

Table 3: Estimation results for equation 3b.[The response variable is $Log(eninmed)_{it}$] The estimation method is WLS

variable	Short- run estimated coefficient	Long- run estimated coefficient
$Log(eninmed(t-1))_{it}$	0.413 (7.84)	--------
$Log(Enpric)_{it}$	-0.155 (-6.26)	-0.263
$Log(valuads)_{it}$	-0.105 (-2.64)	-0.178
$Log(effiscor)_{it}$	-0.158 (-2.93)	-0.268
Sector fixed effects terms [min to max]	[1.65 - 3]	[2.8 - 5]
R^2	0.968	------------
D.W statistics	1.9	---------------

Table 4: Estimation results for equation 4b and 5b.The estimation method is TSLS

Equation and Respond variable	Constant and Variable term	Estimated coefficients
Equation 7b $Log(spreleft)_{it}$	Constant ($\hat{d}$)	[-0.97- -0.22]
	$Log(eninmed)_{it}$	0.295 (3.27)
	R^2	0.36
	D.W statistics	2.1
Equation 8b $Log(spreright)_{it}$	Constant ($\hat{h}$)	[-0.4- 0.22]
	$Log(eninmed)_{it}$	0.332 (2.73)
	R^2	0.64
	D.W statistics	2.01

The short-run and long-run coefficients for fuzzy regression Eq.2b can be calculated by the estimated results of the recursive model as shown in above tables. Table 5 reports the estimated coefficients of predetermined variables for Eq.2b. And so, the fuzzy fixed effects terms of Eq.2b are shown in table 6.

Table 5: Estimation results for equation 2b

	$(\hat{a}_1, \hat{c}_1^L, c_1^R)$	$(\hat{a}_2, \hat{c}_2^L, c_2^R)$
Short-run coefficients	(0.413,0.122,0.137)	(-.155,-.045,-.05)
Long-run coefficients	(0.703,0.207,0.233)	(-.267,-.076,-.085)

Table 5:continuation

	$(\hat{a}_3, \hat{c}_3^L, c_3^R)$	$(\hat{a}_4, \hat{c}_4^L, c_4^R)$
Short-run coefficients	(-.105,-.03,-.03)	(-.158,-.046,-.05)
Long-run coefficients	(-.179,-.05,-.05)	(-.27,-.07,-.09)

Based on estimated results, we can explore the short-run and long-run membership functions for each fuzzy regression coefficient as specified in Eq. 2. This allows us to calculate two α_{cut} intervals under the membership functions associated with α quantity for each coefficient. Tables 7-8 show the trapezoidal fuzzy numbers for our model coefficients (Eq.2b) in selected α_{cut} levels. The estimation results of fuzzy fixed effect coefficients are shown in table 6. As it is seen, higher fixed effect coefficients belong to the energy intensive industries such as chemical, mineral and metallic industries groups.

Table 6: Estimation results of fuzzy fixed effects terms for equation2b

Industry sector	Short-run $(\hat{a}_0, \hat{c}_0^L, \hat{c}_0^R)$	Long-run $(\hat{a}_0, \hat{c}_0^L, \hat{c}_0^R)$
Food industries	(2.5 , 0 , 0.6)	(4.25 ,0.28,1.2)
Textile industries	(2.2 ,0.09,0.5)	(3.7 ,0.53,0.54)
Wood industries	(2 , 0 , 0.47)	(3.4 ,0.22,0.93)
Paper and press industries	(2.2 , 0 , 0.11)	(3.7 , 0.30 ,0.6)
Chemical industries	(2.4 , 0 , 0.37)	(4.08 ,0.4 ,0.92)
Non-metal Mineral industries.	(3 , 0.66 , 2)	(5.1 ,1.28 ,0.63)
Main metallic industries	(2.8 , 1 , 1.18)	(4.77,0.97,1.78)
Machinery and Equipment industries	(1.98 , 0, 0.32)	(3.37,0.08,0.78)
Other industries	(1.65 , 0 ,0.15)	(2.81,0.11,0.53)

Table 7: α_{cut} s intervals of the short-run estimated coefficients for equation 2b

$\hat{a}_i$ \ α_j	$\hat{a}_1$			$\hat{a}_2$		
	Lower bound	Med point	Upper bound	Lower bound	Med point	Upper bound
$\alpha_1 = 0$	0.291	0.413	0.55	-.195	-.155	-.105
$\alpha_2 = 0.25$	0.322	0.413	0.516	-.189	-.155	-.118
$\alpha_3 = 0.5$	0.352	0.413	0.482	-.178	-.155	-.130
$\alpha_4 = 0.75$	0.383	0.413	0.447	-.166	-.155	-.143
$\alpha_5 = 0.9$	0.40	0.413	0.427	-.159	-.155	-.150

Table 7:continuation

$\hat{a}_i$ \ α_j	$\hat{a}_3$			$\hat{a}_4$		
	Lower bound	Med point	Upper bound	Lower bound	Med point	Upper bound
$\alpha_1 = 0$	-.135	-.105	-.075	-.204	-.158	-.108
$\alpha_2 = 0.25$	-.128	-.105	-.083	-.192	-.158	-.121
$\alpha_3 = 0.5$	-.120	-.105	-.09	-.181	-.158	-.133
$\alpha_4 = 0.75$	-.133	-.105	-.098	-.169	-.158	-.146
$\alpha_5 = 0.9$	-.108	-.105	-.102	-.162	-.158	-.153

Table 8: α_{cut} s intervals of the long-run estimated coefficients for equation 2b

$\hat{a}_i$ / α_j	$\hat{a}_1$			$\hat{a}_2$		
	Lower bound	Med point	Upper bound	Lower bound	Med point	Upper bound
$\alpha_1 = 0$	-------	------	-------	-0.34	-.264	-.179
$\alpha_2 = 0.25$	-------	------	-------	-.321	-.264	-0.2
$\alpha_3 = 0.5$	-------	------	-------	-.302	-.264	-.222
$\alpha_4 = 0.75$	-------	------	-------	-.283	-.264	-.242
$\alpha_5 = 0.9$	-------	------	-------	-.272	-.264	-0.26

Table 8:continuation

$\hat{a}_i$ / α_j	$\hat{a}_3$			$\hat{a}_4$		
	Lower bound	Med point	Upper bound	Lower bound	Med point	Upper bound
$\alpha_1 = 0$	-.229	-.179	-.129	-0.34	-0.27	-0.18
$\alpha_2 = 0.25$	-.216	-.179	-.141	-0.32	-0.27	-0.2
$\alpha_3 = 0.5$	-.204	-.179	-.154	-.305	-0.27	-.225
$\alpha_4 = 0.75$	-.191	-.179	-.167	-.287	-0.27	-0.25
$\alpha_5 = 0.9$	-.184	-.179	-.174	-.277	-0.27	-0.26

9. Summary and Conclusions

Compared to developed countries, energy intensity in the Iranian economy is very high. According to an IEA[40] report, energy intensity based on exchange rates in Iran was almost 7 times as much as that of OECD, 6.8 times that of U.S, 14.7 times that of Japan and 3.5 times that of Turkey. The gradual price increases during the Iranian development programs have to be regarded as an important government effort for managing the energy demand

[40] International Energy Agency

side. For example, observations on the average real price of energy carriers reveal an increasing trend especially after 1968.

Iranian industrial sectors consume about 20 percent of the total End-use energy. In 2001-08, the industrial end-use energy in the Iranian economy grew nearly 9% annually. In this study, industrial energy intensity is computed as end-use energy divided by real value added based on the 1990 constant price. Our computations show that industrial energy intensity has had a moderate declining trend after 1968 or at the beginning of the first development plan.

Energy intensity attitude can be affected by many factors. These factors can be autocorrelation behavior, relative technical efficiency changes, structural changes and energy carriers' price factors. Therefore the end-use energy changes in the production process are decomposed into three effects: energy pure intensity effect[41], structural changes effect[42] and production growth effect[43]. The autocorrelation factor is an index of the integrated based factors which can be determined by the main pattern of End-Use energy in economic activities. In this paper, these factors were explained by lagged energy intensity.

Technical changes indicate improvements in the inputs' combination required for achieving the frontier production function. In this study, technical changes were indexed by yearly efficiency scores computed based on data envelopment analysis (DEA) method during the surveyed period. The DEA method allocated relative efficiency scores to decision making units (DMUs). Each year in the studied period was taken as a DMU. In other words, the efficiency score for each year was computed as a percentage of the "best practice". Obviously, it is expected that a

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[41] Pure energy intensity is a part of energy intensity which independent of the activity level and production structure

[42] Structural changes effect is a part of energy end-use changes which depended to the firm value added share in industry.

[43] Production growth effect is a part of energy intensity which depended to the firm production growth.

relative improvement in technical efficiency raises the End-Use energy productivity.

In this paper, analyses and observations were based on a partial adjustment model. The fundamental assumption in this model was the current value of the respond variable approaches its long-term value or its desired value. The long-term value was determined by a functional relationship between the respond variable and explanatory variables. An important coefficient in this model was the dynamic adjustment rate which explains the proportion of the speed of the short-run energy intensity motion to its long-run trend. In other words, this rate is equal to the current value of energy intensity divided by its desired value.

The estimation of the fuzzy regression model for the Iranian industrial sector shows that the lagged energy intensity variable is the only factor which has had a positive effect on the industrial energy intensity attitude. The lagged energy intensity coefficient has a trapezoidal fuzzy number equal to 0.413, 0.122 and 0.137. On the other hand, other explanatory variables, including energy price, value added share and technical efficiency scores, have had a negative effect on the energy intensity trend in the period (1982-2006).

The fuzzy dynamic adjustment rate has a trapezoidal value equal to (0.587, 0.122, 0.137). This means that the observed energy intensity would be varieties in [0.465-0.724] around its desired value. The price elasticity of energy intensity has a fuzzy number equal to (-0.155,-0.045, -0.05) in the short-run and (-0.264 , -0.076 , -0.083) in the long-run. These indicate that energy intensity is price inelastic, thus the energy pricing policies have had a low effect on the end-use energy behavior in the industrial activities in our studied period.

The estimated value added share coefficient shows that increasing the relative scale of industry activity helps improve energy productivity. This means that the larger groups have been higher energy savers. The value added share coefficient attains the fuzzy number (-0.105, -0.03 , -0.03) in the short-run and (-0.179 , -0.05 , -0.05) in the long-run. Infact the estimated fuzzy coefficient of the efficiency score indicates that technical efficiency changes in industrial groups have had a modifying effect on the energy intensity behavior in the surveyed period.

Results reveal that the energy pure intensity was the main factor explaining the end-use energy changes in the Iranian industrial sector. This means that high energy intensity in this sector is mainly due to low productivity of employing energy carriers and so there is much potential for energy saving in the Iranian industrial sector which mainly emerges from pure energy intensity in the short-run. Moreover, the results reveal that all of the explanatory, such as energy price, value added share and relative efficiency variables, have had a negative effect on the energy efficiency. In fact, according to the estimated value of the dynamic adjustment rate parameters, this negative effect has almost doubled in the long run compared to short run.

In sum, based on the model estimation results, it is recommended to improve price and technical policies for moderating end-use energy intensities, although this effectiveness was not rich enough in the study period. Indeed, the estimated domain of the gap between actual and desired states of energy intensity is about (0.54-0.26), which shows that the energy supply management system in Iranian economic should make more effort to modify, redesign and execute the price and non-price policies.

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APPENDIX 1: **Estimation Results of Eq 3b**

Method: Pooled EGLS (Cross-section weights)
Date: 10/10/09 Time: 00:21
Sample: 1362 1385
Included observations: 24
Total panel (balanced) observations 216
White Heteroskedasticity-Consistent Standard Errors & Covariance

Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.0000	7.840679	0.052745	0.413559	LOG(INTFUZ?(-1))
0.0000	-6.265649	0.024814	-0.155478	LOG(ENPRIC?)
0.0088	-2.644006	0.039739	-0.105071	LOG(VALUDR?/VALUDR TOT)
0.0037	-2.934772	0.053813	-0.157928	LOG(EFFIC?)
				Fixed Effects (Cross)
			2.487969	_S31--C
			2.236914	_S32--C
			2.081433	_S33--C
			2.243700	_S34--C
			2.461819	_S35--C
			3.046376	_S36--C
			2.788599	_S37--C
			1.981767	_S38--C
			1.659993	_S39--C

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

1.215091	Mean dependent var	0.968390	R-squared
1.442237	S.D. dependent var	0.966522	Adjusted R-squared
14.13626	Sum squared resid	0.263888	S.E. of regression
2073.014	F-statistic	51.08571	Log likelihood
0.000000	Prob(F-statistic)	1.883090	Durbin-Watson stat

APPENDIX 2: Estimation Results of Eq 4b

ystem: SYSFUZZYRIGHTNEW
Estimation Method: Iterative Weighted Two-Stage Least Squares
Date: 10/10/09 Time: 01:51
Sample: 1362 1385
Simultaneous weighting matrix & coefficient iteration
Convergence achieved after: 19 weight matricies, 20 total coef iterations

Prob.	t-Statistic	Std. Error	Coefficient	
0.3903	-0.860855	0.257615	-0.221769	C(331)
0.0067	2.739911	0.121353	0.332497	C(333)
0.0000	9.664383	0.054303	0.524802	C(1)
0.0000	-11.08450	0.061598	-0.682785	C(332)
0.3839	-0.872675	0.220319	-0.192267	C(313)
0.0515	-1.958387	0.318382	-0.623515	C(334)
0.1557	-1.424814	0.296445	-0.422379	C(335)
0.0009	3.383511	0.313409	1.060422	C(336)
0.4238	0.801425	0.335443	0.268833	C(337)
0.0681	-1.833981	0.185095	-0.339461	C(338)
0.0126	-2.517715	0.156162	-0.393170	C(339)
		2.79E-08	Determinant residual covariance	

Equation: LOG(INTFUZZR) = C(331) + C(333)*LOG(INTFUZ)
+[AR(1)=C(1)]
Observations: 24

0.086845	Mean dependent var	0.638807	R-squared
0.918698	S.D. dependent var	0.604407	Adjusted R-squared
7.011539	Sum squared resid	0.577826	S.E. of regression
		0.908672	Durbin-Watson stat

APPENDIX 3: **Estimation Results of Eq 5b**

System: SYSFUZZILEFTNEW
Estimation Method: Iterative Weighted Two-Stage Least Squares
Date: 10/10/09 Time: 01:50
Sample: 1362 1385
Sequential weighting matrix & coefficient iteration
Convergence achieved after: 14 weight matricies, 47 total coef iterations

Prob.	t-Statistic	Std. Error	Coefficient	
0.0000	-10.04101	0.096806	-0.972032	C(111)
0.0012	3.279823	0.090159	0.295707	C(222)
0.0000	6.214892	0.059441	0.369417	C(1)
0.0000	-10.17383	0.055919	-0.568909	C(112)
0.0005	-3.540409	0.222000	-0.785969	C(113)
0.0000	-8.281503	0.094077	-0.779095	C(114)
0.0000	-4.193251	0.182870	-0.766821	C(115)
0.2484	-1.157649	0.194590	-0.225267	C(116)
0.1171	-1.573747	0.274355	-0.431765	C(117)
0.0000	-11.78435	0.077511	-0.913412	C(118)
0.0000	-7.011782	0.102477	-0.718546	C(119)
		4.60E-11	Determinant residual covariance	

Equation: LOG(INTFUZL) = C(111) + C(222)*LOG(INTFUZ)
+[AR(1)=C(1)]
Observations: 24

-0.698626	Mean dependent var	-0.009598	R-squared
0.159884	S.D. dependent var	-0.105750	Adjusted R-squared
0.593586	Sum squared resid	0.168125	S.E. of regression
		0.394540	Durbin-Watson stat