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Assessment of Developing Countries Based on Their Level of Technology Use and Innovation

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Abstract

The content of the economic development in recent years has undergone a change towards competitiveness and innovation due to the technological advances and globalization. These changes, particularly in developing countries, have positive impacts such as significantly increase in productivity and ease of access to new markets. In this paper, a methodology was proposed by using fuzzy c-means clustering algorithm in order to classify countries based on their technology use and innovation indicators. According to the numerical application carried out for 52 developing countries, it was determined that proposed method gave remarkable results.

Keywords:

Innovation, technology, country classification, fuzzy c-means

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The innovation and investments in technology provide competitiveness, progress, productivity, and a sustainable economic growth (Juma et al., 2001). Therefore, the promotion of innovation in developing countries has evolved as an important research topic in recent years. As stated in OECD's Oslo Manual (2005) "Innovation is at the heart of economic change". Therefore, it is very important for developed and developing economies. Current generation experiences knowledge based economic development. Firms, who realize the importance of innovation, are getting more shares in national and international markets. Indeed, these firms contribute their country's economic growth and development. Moreover, it can be clearly seen that Asian Economies have had the highest growth rates among the other countries in last years. Undoubtedly, innovation has the greatest role in the prompt development of Far East countries. Because of this remarkable example, policy makers focus on their economy's innovation structure more than ever (Hall and Lerner, 2010; Nasierowski and Arcelus, 1999; 2003).

In neoclassical aspect, innovation is about investment decisions, product development and improvement of efficiency. In other words, innovation is a part of business planning and management (Galende, 2006). Another theory which emphasizes innovation is industrial organization theory. This theory focuses on firms' competitive positioning. In a paper by Guan et al. (2006) the quantitative relationship between technological innovation capability and competitiveness was investigated. According to Tirole (1995), firms need innovation to defend their existing competitive position as well as to seek new competitive advantages. Additionally, Rosenberg (1994) stated that decision making process of innovation was often constructed under uncertainty. As many things about future, upcoming developments in technology and applications of new technological ideas on economics can be unpredictable. Also, all sectors and markets have their own distinctive features that determine level of uncertainty. Therefore, relationship between innovation activities and uncertainty of related sector or market is getting very important for researchers.

In recent years, stability and sustainability are very well known concepts in economic growth research. It should be noted that idea of innovation effect both of these concepts (Grupp and Mogee, 2004; Williams and Mcguire, 2010). Because of this reason, understanding an economy's innovation capability carries a vital importance for managers of firms and policy makers of governmental institutes (Porter, 1991). However, there is a lack of data providing necessary information on innovation; this situation prevents researches to carry out required economic analysis. There are some institutions that have projects and surveys to collect the data on innovation. One of the most important sources is provided by Word Bank.

In general, most of the studies about innovation that use cluster analysis contain national or regional level objects. Furthermore, there is not any sufficient research that analyze Asian economies' innovation structure simultaneously. In a study by Lu and Jiao's (2008), 18 prefecture level cities of Chine's Henan province were clustered according to four variables which were called potential innovation resources, technological innovation input, research and development ability, and technological innovation output. In another study, Arvanitis and Hollenstein (1998) analyzed innovative activity and firm characteristic of Swiss manufacturing by using firm-level data. Firstly, they collected data from Swiss firms with surveys. Then they tried to group similar firms into innovation types based on a cluster analysis of nine innovation indicators and seventeen knowledge sources which are formed by their surveys. Their result yielded five innovation types which were characterized by additional structural properties (e.g. firm size) and factors relevant for innovation (e.g. market conditions). Davó et al. (2011) classified EU-15 countries according to technological innovation capacity and competitiveness. Researchers used data from Science and Technology Indicators 2009 published by Eurostat in addition to competitiveness indicators used by the European Commission, the World Economic Forum and IMD. Thus an empirical study was conducted (using a cluster analysis) with the technological innovation and competitiveness variables for each country during the period 1998 to

2008. As a result of the paper, they proposed five cluster entitled as "Leaders, Followers, Mediterranean, Moderate and Germany". Moreover, Ahire and Ravichandran (2001) investigated innovation in total quality management perspective, and Mielgo et al. (2009) indicated that there was strong relationship between working standards, quality control and innovation structure.

Selection of appropriate method for evaluation of the country's level of innovation is considered to be an important issue. Due to the overlapping structure of the group boundaries, with classical statistical methods, it becomes difficult to determine the actual classification structure. Traditional clustering algorithms are organized based on the idea that each object belongs to a cluster with the exact boundaries. However, the boundaries of these clusters may not always be precisely defined (Nefti and Oussalah, 2004). Fuzzy methods allow partial belongings (membership) of each observation to the clusters, so they are effective and useful tool to reveal the overlapping structure of clusters (Zhang, 1996). In such cases and if there exist complex multiple factors, fuzzy set methodology provides an efficient way to create a model that would represent the system well (Ostaszewski, 1993). Thus, with proposed fuzzy type of clustering (Bezdek, 2013), more information about the memberships of patterns were intended to provide. According to Fuzzy c-means (FCM) clustering method, clusters may include patterns with different degrees of membership (Nayakvd., 2015). In a study performed by Höppner et al. (1999), FCM clustering method was examined in a comprehensive way.

In this paper, we would like to draw an adequate framework which shows comparative structure of developing countries with respect to their innovation and technology variables. For this purpose, a methodology was proposed by using fuzzy c-means clustering algorithm with the data from Word Bank's Enterprise Surveys Database. Undoubtedly, for policy makers of governments, considering the innovation situation activities before policy decisions have vital importance. This study holds a light for alternative policy decisions which focus on innovation and technology.

Material and Methods

Description of the Data

The main objective of this paper was to classify developing countries based on their level of technology use and innovation. The data source is World Bank's Enterprise Surveys Database. These surveys are conducted across all geographic regions and cover small, medium, and large companies. The universe of the survey includes the entire manufacturing sector, the services sector, and the transportation and construction sectors. The surveys provide indicators that describe several dimensions of technology use and innovation. The definition of each variable is summarized in Table 1.

Our study was performed at an individual level by taking into consideration the time period 2013-2014. The sample consisted of 52 developing countries which take part in World Bank List of Developing Countries.

Table 1. Technology Use and Innovation Indicators, Their Explanations

Variable	**Explanation**
Certification	Percent of firms with an internationally-recognized quality certification
Technology	Percent of firms using technology licensed from foreign companies
Web Site	Percent of firms having their own Web site
e-mail	Percent of firms using e-mail to interact with clients/suppliers
Financial Statement	Percent of firms with an annual financial statement reviewed by external auditors

Fuzzy C-Means Clustering Algorithm

Fuzzy clustering methods are used for calculating the membership function that determines to which degree the objects belong to clusters and used for detecting overlapping clusters in the data set (De Oliveira and Pedrycz, 2007). Fuzzy c-means (FCM) clustering algorithm is one of the most widely used method among fuzzy associated models (Bezdek and Pal, 1992).

Let $X = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$ denote a set of n objects and each i object $(i = 1, 2, \dots, n)$ be represented with d dimensional vector $\mathbf{x}_i = [x_{1,i} x_{2,i} \dots x_{d,i}]^T \in \Re^d$. So, $n \times$

d dimensional data matrix, composed of a set of n vectors is

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d} \end{bmatrix}. \tag{1}$$

A fuzzy clustering algorithm separates data matrix, X into c overlapping clusters in accordance with the design of a fuzzy partition matrix, U. Fuzzy partition matrix, U is composed of the degrees of memberships of objects, $\mathbf{x}_i$ $(i = 1, 2, \ldots, n)$ in every cluster k $(k = 1, 2, \ldots, c)$. The degree of membership of i. vector in cluster k is represented by $\mu_{k,i} \in \mathrm{U}$. Accordingly, the partition matrix is given by

$$U = \begin{bmatrix} \mu_{1,1} & \mu_{2,1} & \cdots & \mu_{c,1} \\ \mu_{1,2} & \mu_{2,2} & \cdots & \mu_{c,2} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{1,n} & \mu_{2,n} & \cdots & \mu_{c,n} \end{bmatrix}. \tag{2}$$

In fuzzy clustering method, each cluster is represented with a vector of cluster centers which is usually identified as the centroids of d objects, e.g., average of all the datum of the corresponding cluster (Celikyilmaz andTürksen, 2009). The algorithm calculates c number of cluster center vectors $V = \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_c\} \in \mathcal{R}^{c \times d}$ where each cluster center is denoted as $\mathbf{v}_k \in \Re^d$, $k = 1, 2, \ldots, c$.

FCM clustering algorithm is a simple and convenient method. In this method, the number of clusters, c is assumed to be known or at least fixed. Because this assumption is considered to be unrealistic in many data analysis problems, the method for determining the number of clusters such as Cluster Validity Index (CVI) analysis has been developed in FCM clustering algorithm (Celikyilmaz and Türkşen, 2008; Pal and Bezdek, 1995; Kim and Ramakrishna, 2005).

FCM clustering method is based on a constrained optimization problem reaching the optimum solution with the minimum of the objective function. The mathematical model of this optimization problem with two prior information such as number of cluster, c and fuzziness parameter, m is identified as

$$\min J(\mathrm{X}; \mathrm{U}, \mathrm{V}) = \sum_{k=1}^{c} \sum_{i=1}^{n} \left(\mu_{k,i}\right)^m d^2(\mathbf{x}_i, \mathbf{v}_k)$$

$$0 \le \mu_{k,i} \le 1 \ , \quad \forall i, k$$

$$\sum_{k=1}^{c} \mu_{k,i} = 1 \ , \quad \forall i > 0 \tag{3}$$

$$0 < \sum_{i=1}^{n} \mu_{k,i} < n \ , \quad \forall k > 0$$

where each cluster is represented by a prototype, $\mathbf{v}_i$ (Bezdek, 2013). The value of $m \in (1, \infty)$ in objective function is expressed as the degree of fuzziness or fuzzifier, and it determines the degree of overlapping of clusters. The situation of "$m = 1$" which means that the clusters are not overlapping represents the crisp clustering structure (Hammah and Curran, 1998). Here, $d^2(\mathbf{x}_i, \mathbf{v}_k)$ is the measure of distance between i. object and k. cluster center. FCM clustering algorithm specifically uses Euclidean distance. Quadratic distance ensures that the objective function is not negative definite, $J > 0$ (Hammah and Curran, 1998).

Optimum membership values and cluster centers derived from the solution of optimization problem in (3) with the method of Lagrange multipliers are calculated as

$$\mu_{k,i}^{(t)} = \left[\sum_{l=1}^{c} \left(\frac{d\left(\mathbf{x}_i, \mathbf{v}_k^{(t-1)}\right)}{d\left(\mathbf{x}_i, \mathbf{v}_l^{(t-1)}\right)} \right)^{\frac{2}{m-1}} \right]^{-1} \tag{4}$$

$$v_k^{(t)} = \frac{\sum_{i=1}^{n} \left(\mu_{k,i}^{(t)}\right)^m \mathbf{x}_i}{\sum_{i=1}^{n} \left(\mu_{k,i}^{(t)}\right)^m} \ , \quad \forall k = 1, 2, \ldots, c \tag{5}$$

In eq. (4), $\mathbf{v}_k^{(t-1)}$ denotes cluster center vector for cluster i obtained in $(t-1)$th iteration. $\mu_{k,i}^{(t)}$in eqs. (4) and (5) denotes optimum membership values obtained at t. iteration. According to this operation, the membership values and cluster centers seem to be dependent on each other. Therefore, Bezdek (2013) proposed an iterative formula for determining membership values and cluster centers. Accordingly, at each iteration t, objective function $J^{(t)}$ is determined by

$$J^{(t)} = \sum_{k=1}^{c} \sum_{i=1}^{n} \left(\mu_{k,i}^{(t)}\right)^m d^2\left(\mathbf{x}_i, \mathbf{v}_k^{(t)}\right) > 0 \tag{6}$$

FCM algorithm is ended at the end of a particular iteration or according to a termination rule defined as $\left|v_k^{(t)} - v_k^{(t-1)}\right| \le \mathcal{E}$ (Celikyilmaz andTürksen, 2009).

Empirical Investigation: Predicting Country Innovation Group

In order to evaluate countries according to the innovation factors given in Table 1, the steps outlined below are performed.

Step 1. Optimum value of the number of cluster (c^*) and degree of fuzziness (m^*) are determined by utilizing CVI analysis.

In order to assess the goodness of the partition obtained from the FCM clustering, validity measures such as Bezdek's Partition Coefficient (Pal and Bezdek, 1995), Xie-Beni Index (Kim and Ramakrishna, 2005; Xie and Beni, 1991) were used. In the cluster validity index formulas given in Table 2, μ represents the membership values, and $\mathbf{v}_i$ is the center vector of ith cluster. Optimum parameters of FCM were determined by using the grid search taking number of clusters, $c = 2, 3, \ldots, 10$ and degree of fuzziness, $m = 1.1, 1.2, \ldots, 3.5$.

Table 2. Cluster Validity Measures Used for Assessing The Goodness of The Partition

Cluster Validity Indices	Formulations
Bezdek's Partition Coefficient	$v_{pc}(c) = (1/n)\sum_{i=1}^{n}\sum_{k=1}^{c}\mu_{k,i}^2$
Xie-Beni (XB*) Index	$v_{XB^*}(c) = \dfrac{\max_{i=1,\ldots,c}\left\{(1/n)\sum_{k=1}^{n}\mu_{k,i}^2\lVert\mathbf{x}_k-\mathbf{v}_i\rVert^2\right\}}{\min_{i,j\neq i}\lVert\mathbf{v}_i-\mathbf{v}_j\rVert^2}$

The graphs of the results obtained from two cluster validity indexes, i.e., Bezdek's Partition Coefficient and Xie-Beni (XB*) Index are displayed in Fig. 1. By synthesizing these measures, optimum number of clusters that satisfies the maximization of Bezdek's Partition Coefficient and minimization of Xie-BeniIndex were observed when $c^* = 4$. In order to determine the optimum value of degree of fuzziness, we utilized the same validity measures, which are at their optimum values when $m^* = 1.8$. Thus, our investigation to model the solar radiation was executed for $c^* = 4$and $m^* = 1.8$.

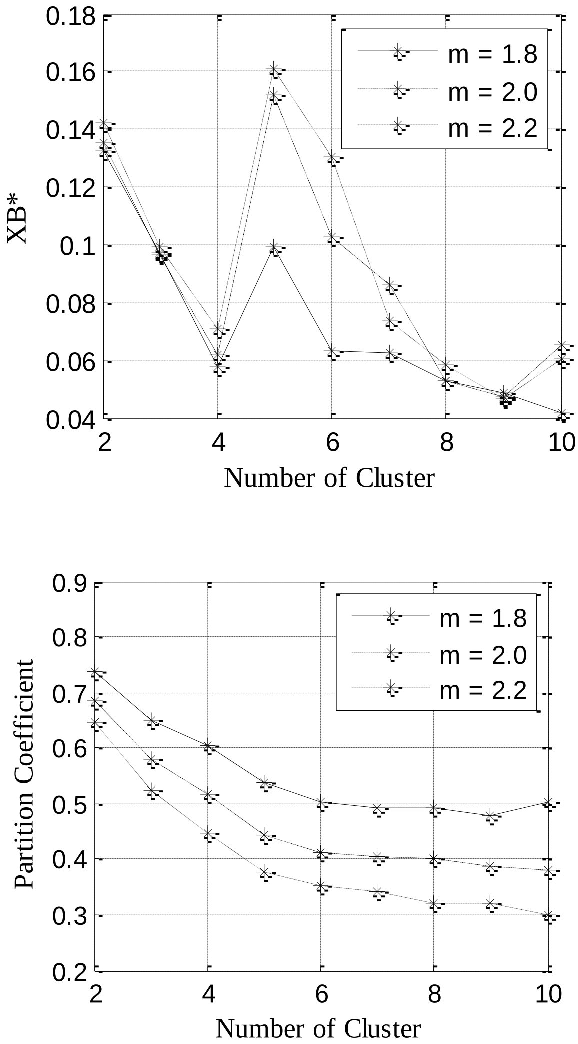

Figure 1. The Change in Cluster Validity Indices According to The Number of Cluster, (left) Xie-Beni index, (right) Bezdek's partition coefficient

Step 2. Cluster center vectors and partition matrix are determined by applying FCM clustering algorithm with the prior information, $c^*$and m^*, obtained at first step.

For $c^* = 4$ and $m^* = 1.8$ by applying FCM clustering method, cluster center vectors, $V = \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_c\} \in \mathcal{R}^{c\times d}$were determined as

$$V = \begin{bmatrix} 25.708 & 17.651 & 62.022 & 86.713 & 32.703 \\ 21.044 & 13.135 & 55.118 & 78.791 & 70.110 \\ 12.983 & 15.759 & 34.680 & 63.429 & 48.571 \\ 9.885 & 11.362 & 23.346 & 37.413 & 29.710 \end{bmatrix}.$$

Step 3. Euclidean norm is calculated for each cluster center vector.

In this paper, it was claimed that the norm values allow an assessment of the general level of innovation for each cluster. Thus, while the value of the calculated norm for each cluster increases, the level of innovation rises in accordance with defined factors, and while the norm value becomes smaller, the level of innovation of cluster will be reduced similarly. As a result, calculated Euclidean norms for center vectors of 4 cluster are given in Table 3.

Table 3. Euclidean Norms Calculated for The Cluster Center Vectors

Cluster Number	Norm (h_i)
1	115.79
2	121.56
3	89.45
4	55.26

Step 4. The advantage of FCM clustering algorithm is to produce the degree of membership of each country to c cluster. Let the degree of memberships of i. country to c number of cluster be denoted as $\boldsymbol{\mu}_i = [\mu_{1,1}, \mu_{2,1}, \dots, \mu_{c,1}]$ and the vector consisting of the norms of cluster center vectors be represented by $\boldsymbol{h}$. Accordingly, the value of innovation for each country is determined with the formula,

$$r_i = \boldsymbol{\mu}_i \boldsymbol{h}$$

Step 5. Innovation rate of each country, $R_i, i = 1, 2, \dots, n$ which is normalized values of r_i is calculated as

$$R_i = \frac{r_i - r_{min}}{r_{max} - r_{min}} \cdot 100, \quad i = 1, 2, \dots, n$$

All the values with normalization were scaled to the range [0, 100]. In this study, countries with a score higher than 50% were considered as innovative countries (SI = 1), and below 50% were considered as non-innovative countries (SI = 0).As a result, the assessment of 52 countries based on their level of innovation is given in Table 4.

Table 4. The Assessment of Innovation by Using FCM Clustering Algorithm

Country Name	Innovation Rate R_i	State of Innovation (SI)	Country Name	Innovation Rate R_i	State of Innovation (SI)
Afghanistan	38.70	**0**	Macedonia, FYR	87.00	1
Albania	46.80	**0**	**Myanmar**	4.00	**0**
Armenia	89.30	1	Montenegro	60.90	1
Azerbaijan	52.10	1	Mongolia	90.30	1
Burundi	54.10	1	Mauritania	70.90	1
Bangladesh	2.40	**0**	Malawi	73.50	1
Bulgaria	92.60	1	Namibia	69.00	1
Bosnia and Herzegovina	93.50	1	**Nigeria**	2.90	**0**
Belarus	88.40	1	Nepal	52.70	1
China	86.90	1	Pakistan	59.90	1
Djibouti	58.60	1	Romania	92.40	1
Egypt, Arab Rep.	53.90	1	Sudan	81.10	1
Georgia	71.80	1	Senegal	50.70	1
Ghana	54.40	1	Serbia	91.00	1
India	100.00	1	**South Sudan**	23.60	**0**
Jordan	57.90	1	Tajikistan	51.60	1
Kazakhstan	75.30	1	Tunisia	95.90	1
Kenya	94.00	1	Turkey	91.50	1
Kyrgyz Republic	93.40	1	**Tanzania**	5.20	**0**
Cambodia	21.90	**0**	**Uganda**	35.80	**0**
Kosovo	91.20	1	Ukraine	90.50	1
Lao PDR	4.90	**0**	**Uzbekistan**	0.90	**0**
Lebanon	95.10	1	**West Bank and Gaza**	44.30	**0**
Morocco	90.00	1	**Yemen, Rep.**	6.10	**0**
Moldova	75.60	1	**Congo Dem. Rep.**	0.00	**0**
Madagascar	50.60	1	**Zambia**	46.20	**0**

First group of countries, SI = 1, shows evidence of strong innovation effort. In this group, range of innovation rate R_i starts with 100 and ends with 50, and India tops the overall ranking. According to innovation rate, it can be said that countries, which have innovation rate score especially bigger than 90 promise better innovative development for future. There are 16 countries that succeed 90 score or above. Innovation situation of the other 24 countries in the first group can be evaluated as sufficient but not enough. These economies need extra focus on innovation related polices. On the other hand, the other group of countries, SI = 0, shows evidence of weak innovation effort. In this group, economies suffer from the lack of development that based on information and technology. 15 countries placed in this group and worse ones are Bangladesh, Uzbekistan and Congo Democratic Republic. It should be remembered that these countries also experience deficiency of basic needs that directly affect innovative development. For instance, regular electricity supply and easy accessible internet services are two important input for innovation and these services are not provided sufficiently in related societies. Therefore, second group economies should urgently take action for structural policies which aim to achieve building basics of innovative development. Structural policies should involve legal and institutional regulations which are designed according to ongoing development path of science and technology.

Conclusions

Global economic crises, political instabilities and large-scale social events constitute major obstacles for countries to be able to realize its growth targets, so it is important to support innovation as a driving force. It is known that there is a strong correlation between the stability and sustainability which are the dynamics of economic growth and innovation. Therefore, evaluation of countries based on their level of innovation has significance both for the country itself and the general trend of the world economy.

In this paper, we aimed to investigate selected developing countries' innovation position with five variables which come from a new database of World Bank. Using a large data set that includes 52 developing countries for the period 2013 - 2014, we classified countries to try to better understand their innovation level with FCM algorithm. By using this method, we can overcome the problems associated with the findings functional form of the innovation indicator. Ranking of the world's 52 developing countries by FCM algorithm takes a more objective and unbiased approach to the question, focusing on five tangible variables that contribute to innovation. The results provide critique information for pre-decision period of policy development process.

Difficulties frequently faced by developing countries in an attempt to improve their economic situation stem from a low level of innovation. Insufficient education, inappropriate business and governance climates are considered as genuine obstacles to innovation Thus, innovative approaches which are adapted to the possibilities and needs of the country should be investigated. Moreover, in order to provide permanence of economic development, innovation activities should have incremental and continuous characteristics.

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