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Developing a new method using Artificial Immune System in order to High Productivity of Inefficient Units in Network DEA approach

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ABSTRACT

Objective: Most traditional DEA models treat their reference technologies as black boxes. To open the "black box" and get greater insight in to the production process, the network DEA model is constructed. **Methodology:** This paper describe the operation analysis of the NDEA that mainly it's aim is detecting of the efficient units in a network. In this paper, a new method based on the Network Data Envelopment Analysis and Artificial Immune system (FNDEA-AIS), for evaluating of DMUs efficiency and increasing the performance of inefficient units, is presented. Finally a numerical example will be presented for illustration the advantages of the presented method. **Results:** In this paper a new method based on pattern recognition and robustness of computational processes in AIS and FNDEA methods is designed. **Conclusion:** By using this method the inputs and outputs of decision units are modified subject to inefficient units will become efficient and predicting of the optimal values of inefficient units has done with high accurate.

1. Introduction

Data envelopment analysis, is introduced by Charnes and Neralic, (1990). In tradition DEA models, DMU is treated as a "black box", in which the inputs enter and outputs exist, neglecting the intervening steps (Liu et al., 2009). To open the "black box, the network DEA model is constructed to analyze the network structure of production by researchers, such as Fare and Grosskopf (N de Castro and Timmis, 2002), Lewis and Sexton (Liu et al., 2009), Sexton and Lewis (Nossal, 1994), Tone and Tsutsui (Pendharkar and Rodger, 2003). The first paper discussing this idea is probably Charnes et al. (1986), which found that army recruitment had two processes: the first created awareness through advertisements, and the second created contracts. Fare and Grosskopf (Smith and Timmis, 2008), first introduce network DEA model, wich was improved and extened by other researchers. Lewis and Sexton (Liu et al., 2009) propose a network DEA model for multi-stage system which is an extension of the two- stage DEA model propose by Sexton and Lewis (Nossal, 1994).
Cook, Liang, and Zhu (2010) reviewed a number of models for the basic two-stage system, in which the system has only two processes connected in series, and the second only consumes all the outputs from the first for production. Castelli, Pesenti, and Ukovich (2010) reviewed Shared -flow, multilevel, and some network models. The network models they reviewed are of the general network DEA form developed by Fare and Grosskopf (2000), leaving many others untouched. In real problems, inputs and outputs cannot be given exactly, in nature, which can be considered as a fuzzy model. Fuzzy DEA models are implemented in many applicable and practical problems. Widely an integrated DEA enhanced Russell measure (ERM) model in fuzzy context to select the best sustainable suppliers is developed (Charnes and Neralic, 1990). A comprehensive fuzzy DEA framework for solving performance evaluation problems with coexisting desirable input and undesirable output data in the presence of simultaneous input–output projection is presented (Damghani and Tavana, 2016).
Artificial neural network (ANN), as a black box approach, based on learning ability and generalization properties is a significant soft computing method. different methods, based on integrating DEA and ANN methods have proved (Athanassopoulos and Curram, 1996; Costa and Markellos, 1997). A fuzzy DEA neural network approach to measuring design service performance is used (Ching-Hwang et al., 2009). Immune system is one of the most intricate biological systems that has received a large amount of attention, in recent years. Similar to development of ANN which motivated by neural system, the

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motivation of this field inspired by immune system and it's primarily to extract useful metaphors from natural immune system and to create effective solutions to complex problems in a wide range of areas (Naganathan et al., 2008; Soliman and Tan, 2010). Various kinds of immune theories, like as, Negative selection mechanisms, clonal selection theory (Costa and Markellos, 1997; Burnet, 1959), and immune network theory (Dai et al., 2010), were proposed and used in AIS models. Some useful artificial immune systems can be found in (Smith and Timmis, 2008; Liu et al., 2009).

In this paper, a new method based on fuzzy network data envelopment analysis and artificial immune system (FNDEA-AIS), for evaluating of DMUs efficiency and increasing the performance of inefficient units by predicting the optimal values of them is presented. Numerical example illustrates the advantages of presented method.

This paper is organized in seven sections. Network DEA and Fuzzy Network DEA models is described, briefly in section two. Section three presents a useful review and design an algorithm of Artificial Immune System. Hybrid Fuzzy NDEA and Artificial Immune system algorithm are designed in section four. In section five, a numerical example for indicating the advantages of proposed algorithm is simulated. Finally in section six, conclusion of the paper is presented.

2. Materials and methods

2. Fuzzy Network DEA model

2.1 Fuzzy logic

Fuzzy sets were introduced by zadeh in 1965 for representing data and information possessing non-statistical uncertainties.

Definition 1. Let X be a nonempty set. Fuzzy set A in X is characterized by its membership funct

$$A = \{(x, \mu_A(x) / x \in X)\} \quad (1)$$

Such that $\mu_A(x)$ is interpreted as the degree of membership of element x in fuzzy set A for each x∈ X.

Definition 2. Let A be a fuzzy subset of X; the support of A, denoted supp(A), is the crisp subset of X whose elements all have nonzero membership grades in A:

$$supp(A) = \{x \in X \,/\, \mu(x) > 0\} \quad (2)$$

Definition 3. Let $S(X)$ denote the support of X, the ($\boldsymbol{\alpha}$-cut) of X is defined as:

$$X^{\alpha} = \{x \in S(X);\ \mu(x) \geq \alpha\} \qquad \alpha \in [0\ 1] \quad (3)$$ (3)

In this paper, the triangular fuzzy number for inputs and outputs is used.

Definition 4. A fuzzy number A is said to be triangular if its membership function is given by

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{u-a}, & a < x \leq u \\ \frac{x-b}{u-b}, & u < x \leq b \\ 0 & x \geq b \end{cases} \quad (4)$$

Where a, u, b are given numbers. Therefor the real numbers a, u, b define the triangular fuzzy number A which will be denoted by $\tilde{A} = (a; u; b)$.

2.2 Serial Network DEA model

Consider the p-stage process pictured in Fig. 1. We denote the input vector to stage 1 by x_0. The output vectors from stage $p\ (p = 1, \dots, P)$ take two forms, namely y_p^1 and y_p^2 . Here, y_p^1 represents that output that leaves the process at this stage and is not passed on as input to the next stage. The vector y_p^2 represents the amount of output that becomes input to the next $(p + 1)$ stage. This types of intermediate measures are called links in Tone and Tsutsui (2009). In addition, there is the provision for new inputs x_p^3 to enter the process at the beginning of stage $p + 1$ (D.Cook et al., 2010).

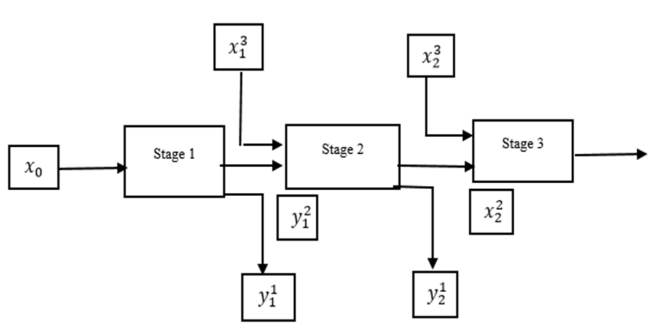


Figure 1. Serial multistage DMU

Then we calculate the overall efficiency θ using multistage processess by :

$$\text{Max} \quad \sum_{p=1}^{P}\left(\sum_{r=1}^{R_p} u_{pr} y_{pr}^{o1} + \sum_{k=1}^{S_p} \eta_{pk}\, x_{pk}^{o2}\right)$$

$$\text{Subject to} \quad \left\{\sum_{i=1}^{l_0} v_{0i} x_{0i}^{o} + \sum_{p=2}^{P}\left(\sum_{k=1}^{S_{p-1}} \eta_{p-1k} y_{p-1k}^{o2} + \sum_{i=1}^{l_p} v_{p-1i}\, x_{p-1i}^{o3}\right)\right\} = 1,$$

$$\left(\sum_{r=1}^{R_l} u_{1r} y_{1r}^{j1} + \sum_{k=1}^{S_1} \eta_{1k}\, x_{1k}^{j2}\right) \le \sum_{i=1}^{l_0} v_{0i} x_{0i}^{j}, \tag{5}$$

$$\left(\sum_{r=1}^{R_p} u_{pr} y_{pr}^{j1} + \sum_{k=1}^{S_p} \eta_{pk}\, x_{pk}^{j2}\right) \le \left(\sum_{k=1}^{S_{p-1}} \eta_{p-1k} y_{p-1k}^{j2} + \sum_{i=1}^{l_p} v_{p-1i}\, x_{p-1i}^{j3}\right)$$

$$\forall j,\ u_{pr},\ \eta_{pk},\ v_{pi}\ v_{0i} > 0.$$

2.3 Fuzzy Network DEA Model

If $\tilde{x}_{pi} = (x_{pi}^{l}, x_{pi}^{m}, x_{pi}^{u})$ and $\tilde{y}_{pr} = (y_{pr}^{l}, y_{pr}^{m}, y_{pr}^{u})$ are ith input and the rth output for $DMU_o\ (j = o)$, respectively then the fuzzy additive model corresponding to the model (1) is:

$$\text{Max} \sum_{p=1}^{P}\left(\sum_{r=1}^{R_p} u_{pr} \tilde{y}_{pr}^{o1} + \sum_{k=1}^{S_p} \eta_{pk}\, \tilde{x}_{pk}^{o2}\right)$$

$$\text{Subject to} \quad \left\{\sum_{i=1}^{l_0} v_{0i} \tilde{x}_{0i}^{o} + \sum_{p=2}^{P}\left(\sum_{k=1}^{S_{p-1}} \eta_{p-1k} \tilde{y}_{p-1k}^{o2} + \sum_{i=1}^{l_p} v_{p-1i}\, \tilde{x}_{p-1i}^{o3}\right)\right\} = 1,$$

$$\left(\sum_{r=1}^{R_l} u_{1r} \tilde{y}_{1r}^{j1} + \sum_{k=1}^{S_1} \eta_{1k}\, \tilde{x}_{1k}^{j2}\right) \le \sum_{i=1}^{l_0} v_{0i} \tilde{x}_{0i}^{j}, \tag{6}$$

$$\left(\sum_{r=1}^{R_p} u_{pr} \tilde{y}_{pr}^{j1} + \sum_{k=1}^{S_p} \eta_{pk}\, \tilde{x}_{pk}^{j2}\right) \le \left(\sum_{k=1}^{S_{p-1}} \eta_{p-1k} \tilde{y}_{p-1k}^{j2} + \sum_{i=1}^{l_p} v_{p-1i}\, \tilde{x}_{p-1i}^{j3}\right)$$

$$\forall j,\ u_{pr},\ \eta_{pk},\ v_{pi}\ v_{0i} > 0.$$

By using the $\boldsymbol{\alpha}$-cut method (Esmaeili and Horri, 2014):

$$\breve{y}_{pr} = \left[y_{pr}^{m} - (1-\alpha) y_{pr}^{l}, y_{pr}^{m} + (1-\alpha) y_{pr}^{u}\right] \tag{7}$$

$$\breve{x}_{pi} = \left[x_{pi}^{m} - (1-\alpha) x_{pi}^{l}, x_{pi}^{m} + (1-\alpha)\, x_{pi}^{u}\right] \tag{8}$$

Therefor by integrated of any crisp distance, we produce a crisp data for any input or output:

$$\hat{x}_{pi} = 1/2 \int_0^1 \left[x_{pi}^{m} - (1-\alpha) x_{pi}^{l}, x_{pi}^{m} + (1-\alpha) x_{pi}^{u}\right] \mathrm{d}\alpha = \frac{1}{4}\left(x_{pi}^{l} + 2\, x_{pi}^{m} + x_{pi}^{u}\right) \tag{9}$$

$$y_{pr} = 1/2 \int_0^1 \left[y_{pr}^{m} - (1-\alpha) y_{pr}^{l}, y_{pr}^{m} + (1-\alpha) y_{pr}^{u}\right] \mathrm{d}\alpha = \frac{1}{4}\left(y_{pr}^{l} + 2\, y_{pr}^{m} + y_{pr}^{u}\right) \tag{10}$$

Then the fuzzy additive model change to following α model:

$$\text{Max} \sum_{p=1}^{P}\left(\sum_{r=1}^{R_p} u_{pr} \hat{y}_{pr}^{o1} + \sum_{k=1}^{S_p} \eta_{pk}\, \hat{x}_{pk}^{o2}\right)$$

$$\text{Subject to} \quad \left\{\sum_{i=1}^{l_0} v_{0i} \hat{x}_{0i}^{o} + \sum_{p=2}^{P}\left(\sum_{k=1}^{S_{p-1}} \eta_{p-1k} \hat{y}_{p-1k}^{o2} + \sum_{i=1}^{l_p} v_{p-1i}\, \hat{x}_{p-1i}^{o3}\right)\right\} = 1, \tag{11}$$

$$\left(\sum_{r=1}^{R_l} u_{1r} \hat{y}_{1r}^{j1} + \sum_{k=1}^{S_1} \eta_{1k}\, \hat{x}_{1k}^{j2}\right) \le \sum_{i=1}^{l_0} v_{0i} \hat{x}_{0i}^{j},$$

$$\left(\sum_{r=1}^{R_p} u_{pr} \hat{y}_{pr}^{j1} + \sum_{k=1}^{S_p} \eta_{pk}\, \hat{x}_{pk}^{j2}\right) \le \left(\sum_{k=1}^{S_{p-1}} \eta_{p-1k} \hat{y}_{p-1k}^{j2} + \sum_{i=1}^{l_p} v_{p-1i}\, \hat{x}_{p-1i}^{j3}\right)$$

$$\forall j,\ u_{pr},\ \eta_{pk},\ v_{pi}\ v_{0i} > 0.$$

Definition 5. Network DEA is net$\alpha -$ efficient if and only if each Pth- layer is $\alpha^P -$ efficient [9].

When $\alpha = [\,\alpha_1, \alpha_2, \dots, \alpha_p]$ Net (12)

Definition 6. DMU_o^P is α^P --efficient if $s_j^{+*}(\alpha^P)$ and $s_i^{-*}(\alpha^P)$ are zero for $i = 1,2,\dots,p$ And , $j = 1,2,\dots,q$ where $s_j^{+*}(\alpha^P)$ and $s_i^{-*}(\alpha^P)$ are optimal solution of (13) (Kang et al., 2011).

$$\begin{gathered}
\text{Max } \sum_{i=1}^{p} s_i^- + \sum_{j=1}^{q} s_j^+ \\
\text{Subject to: } \sum_{k=1}^{n} \tilde{x}_{ki}{}^{P} \lambda_k = \tilde{x}_{oi}{}^{P} - s_i^-, \quad i = 1,2,\dots,p \\
\sum_{k=1}^{n} \tilde{y}_{kj}{}^{P} \lambda_k = \tilde{y}_{oj}{}^{P} + s_j^+, \quad j = 1,2,\dots,q \qquad (13) \\
\sum_{k=1}^{n} \lambda_k = 1 \\
\lambda_{j;k} \geq 0, \quad k = 1,2,\dots,n \\
s_i^- \geq 0, \quad i = 1,2,\dots,p \\
s_j^+ \geq 0, \quad j = 1,2,\dots,q.
\end{gathered}$$

Theorem 1. An α^P-inefficient DMU_o^P becomes $(\hat{x}_o^P, \hat{y}_o^P) = (\tilde{x}_o^P - s^{-*}(\alpha^P), \tilde{y}_o^P + s^{+*}(\alpha^P)),$ α^P-efficient if where $s^{-*}(\alpha^P)$ and $s^{+*}(\alpha^P)$ are optimal solution of (13) (Kang et al., 2011).

3. Artificial Immune Systems

3.1 Review of an Immune Network

Natural immune system is comprised of cells, molecules and rules that work together to protect the host against foreign invaders' attacks (Esmaeili and Horri, 2014). Immune network theory, proposed by Jerne, indicates that the immune system, even in the absence of foreign stimuli, must display an eigen-behavior resulting from cell to cell interactions within the immune system [5, 3].

3.2 Artificial Immune Model

In this section, we introduce an immune network model based on artificial immune system model. As shown in Figure. 1, this model consist of three layers: pre-processing layer (APC layer), competitive layer (TH cell layer), and stimulation-inhibition layer (B cells layer) (Costa and Markellos, 1997). For recognizing an antigen two routes, Bcell direct recognition and T cell dependent antigen recognition, are accomplished. The pre- processing layer process and transforms the antigen to the competitive layer. In TH cell layer, one and only one TH cell which receives the maximum input stimuli is activated.. In the following, we will describe the proposed model mathematically in detail (Dai et al., 2010).

Let, $AB = (\,ab_1.ab_2.\dots\ ab_N)$ and $AG = (\,ag_1.ag_2..\ ag_M)$ are antibody and antigen vectors, respectively. The weights between $i - th$ member of pre-processing layer (APC layer) and $j - th$ member of competitive layer (TH -layer) are expressed as $w_{ij}\ for$ i = 1.2. .... M and j = 1.2. .... N and the weights between competitive layer and stimulation-inhibition layer are expressed as $V = (v_{ji}, j = 1,2,\dots,N; i = 1,2,\dots,M)$, where M and N are numbers of TH cell and antibodies vectors dimension, respectively

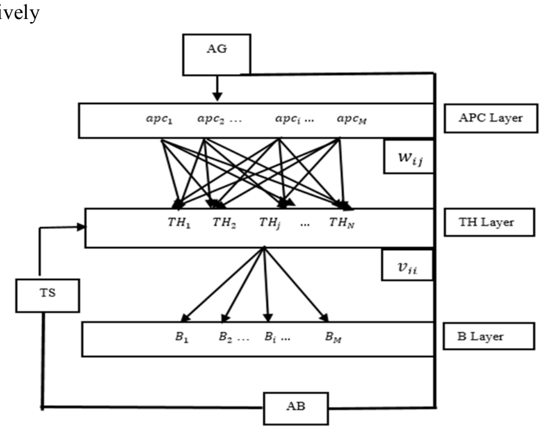


Figure. 1 Schema of the artificial immune network theory based on artificial immune system

In this research we apply an affinity based linear idiotypic network. In fact, affinity is defined as a vital link between immune cell and antigen in the natural immune system. AB and / or AG can be declared as a set of real-valued coordinates. It is straightforward to measure the affinities between immune cell and the antigen by their Euclidean distance (Dai et al., 2010). One can consider the weight V^k as a memory pattern of input antigen. Distance between input antigen and memory pattern can be calculated by:

$$D(k)=E(B',V^k)=\sqrt{\sum_{i=1}^{M}(b_i'-v_{ji}^k)^2} \qquad j=j\max, \qquad k=1,2,..,N \qquad (14)$$

The minimum value of D(k) therefore indicates the most antibody's affinity with the presented antigens. Let,

$$A(k)=M-D(k) \qquad (15)$$

If E_{a1} and E_{aN} are defined as the error between input antigen and cells B_{a1} , B_{aN} respectively, the stimulation-inhibition rule can be expressed as follows:

$$\frac{dB_i}{dt}=\varphi(E_{a1},\eta,S(t),t,P_S(i))\gamma-(1-\gamma)\psi(E_{aN},\eta,S(t),t,P_I(i)) \qquad (16)$$

Where γ , $\varphi(*)$, η , $S(t)$ and $P_S(i)$ are the balanced factor, the excitation function, learning rate, modulation function of T_s cell and distance between B_i cell and stimulation cell B_{a1} , respectively. Also $\psi(*)$ and $P_I(i)$ are the inhibition function and distance between cell B_i and inhibition cell B_{aN} , respectively (Esmaeili and Horri, 2014).
Also,) the other updating rules are:

$$v^k(t+1)=v^k(t)+\frac{dB_K}{dt} \qquad (17)$$

$$p_S(k)=\frac{N-k}{N-1},\ p_I(k)=\frac{k-1}{N-1} \qquad (18)$$

4. Fuzzy Artificial Immune Network DEA algorithm

In this article, according to the advantage of AIS in pattern recognition and remove the effects of uncertainties (robustness), a method is provided for improving the performance of DMUs. Toward this end, the AIS network is designed based on the units' efficiency patterns which are calculated by FNDEA method. This approach is presented as the AIS-FNDEA method to predict the optimal values of inefficient units. In general, the FNDEA-AIS calculation process can be presented as follows:

Step 1: Let $P=1$ (P is number of layers).
Step 2: Calculate the efficiency value of DMU_o^P, by using (11).
Step 3: If the unit is inefficient by using theorem 1, modify the corresponding inputs and outputs, to become α^p-efficient unit.
Step 4. Generation of the antigen and antibody population and initialization of parameters (set the modified values of step3, as antigen to artificial immune network.
Step 5. Normalizing the population values.
Step 6. Determine $\varepsilon = 0.015$ for the condition of stopping the algorithm.
Step 7. Loading of the training populations of antigens.
Step 8: Based on (14), (15), if $D(K)$ is less than ε , we have reached the final answer, else go to step 9.
Step 9: By using (17), (18), update V and come back to step 8.
Step 10: Pridicting the optimal values of inefficient DMUs by test dataset**.**
Step 10: Let P=P+1 and repeat the algorithm until the last layer.
After using this algorithm we found several optimal points for inefficient units that we choose the best of them. At the end of the algorithm, the inefficient units will become fully efficient.

3. Discussion and results

Consider the following example

Table 1. Fuzzy values of inputs and outputs corresponding to any unit (stage1).

DMUj	Input1	Input2	Input3	Output1	Output2	Output3
DMU1	(8,9,9.5)	(46, 50, 52)	(0.5, 1, 1.5)	(19, 20, 22)	(8.8, 10, 12)	(4.7, 5, 5.8)
DMU2	(9, 10, 13)	(14, 18, 20)	(9.5, 10, 10.5)	(8.2, 10, 11)	(14, 15, 17)	(6, 7, 7.8)
DMU3	(8.5, 9, 10.5)	(30, 30, 30)	(2.5, 3, 3.5)	(7, 8, 9.5)	(18, 20, 22)	(1.6, 2, 2.7)
DMU4	(3.4, 8, 4.8)	(21, 25, 2.6)	(0.5, 1, 1.5)	(19.3, 20, 22)	(18, 20, 21)	(9.4, 10, 11)
DMU5	(5.9, 10, 7.1)	(38, 40, 41)	(4.5,5,5.5)	(12, 15, 18)	(19, 20, 23)	(4, 5, 6)
DMU6	(5.9, 7, 7.1)	(38, 35, 41)	(1, 2, 3.5)	(36, 35, 37.7)	(9, 10, 13)	(4.3, 5, 5.3)
DMU7	(5, 7, 8)	(29, 30, 32)	(2, 3, 3.5)	(8.9, 10, 11)	(24, 25, 27)	(7.3, 8, 9)
DMU8	(10, 12, 13)	(38, 40, 41)	(4.5, 4, 5.8)	(19, 20, 21)	(23, 25, 26)	(4.5, 4, 5.5)
DMU9	(8.3, 9, 10.5)	(24,25,26)	(1.4,2, 3.5)	(8.9, 10, 11)	(9, 10, 12)	(4.3, 5, 5.9)
DMU10	(9, 10, 11.2)	(47, 50, 52)	(1, 1, 1)	(18, 20, 22)	(13.9, 15, 17)	(7.3, 9, 10)

Table 2. Fuzzy values of inputs and outputs corresponding to any unit (stage2).

DMU j	Input1	Input2	Input3	Output1	Output2	Output3
DMU1	(19, 20, 22)	(8.8, 10, 12)	(4.7, 5, 5.8)	(7, 8, 11)	(95, 100, 103)	(23, 25, 26)
DMU2	(8.2, 10, 11)	(14, 15, 17)	(6, 7, 7.8)	(8, 10, 14)	(65, 70, 72)	(19, 20, 23)
DMU3	(7, 8, 9.5)	(18, 20, 22)	(1.6, 2, 2.7)	(7, 8, 9)	(88, 96, 98)	(28, 30, 31)
DMU4	(19.3, 20, 22)	(18, 20, 21)	(9.4, 10, 11)	(9.3, 10, 12)	(75, 80, 82)	(18, 20, 24)
DMU5	(12, 15, 18)	(19, 20, 23)	(4, 5, 6)	(12, 15, 22)	(81, 85, 86)	(14, 15, 18)
DMU6	(36, 35, 37.7)	(9, 10, 13)	(4.3, 5, 5.3)	(4, 5, 7)	(85, 90, 92)	(31, 35, 36)
DMU7	(8.9, 10, 11)	(24, 25, 27)	(7.3, 8, 9)	(8.5, 10, 13)	(94, 100, 103)	(28.5, 30, 33)
DMU8	(19, 20, 21)	(23, 25, 26)	(4.5, 4, 5.5)	(7, 8, 11)	(115, 120, 128)	(8.2, 10, 13)
DMU9	(8.9, 10, 11)	(9, 10, 12)	(4.3, 5, 5.9)	(13, 15, 22)	(99, 110, 114)	(14, 15, 17)
DMU10	(18, 20, 22)	(13.9, 15, 17)	(7.3, 9, 10)	(9, 10, 13)	(72, 80, 83)	(19, 20, 23)

Tables 1, 2 show the triangular fuzzy inputs and outputs of the presented Network DEA model.

Table 3. Performance results of the FNDEA model and its actual values (inputs and outputs) (stage1).

DMUs	Input1	Input2	Input3	Output1	Output2	Output3	Efficiency
DMU01	9	50	1	20	10	5	1
DMU02	10	18	10	10	15	7	1
DMU03	9	30	3	8	20	2	0.8
DMU04	8	25	1	20	20	10	1
DMU05	10	40	5	15	20	5	0.67
DMU06	7	35	2	35	10	5	1
DMU07	7	30	3	10	25	8	1
DMU08	12	40	4	20	25	4	0.77
DMU09	9	25	2	10	10	5	0.5
DMU10	10	50	1	20	15	9	1

Table 4. Performance results of the FNDEA model and its actual values (inputs and outputs) (stage2).

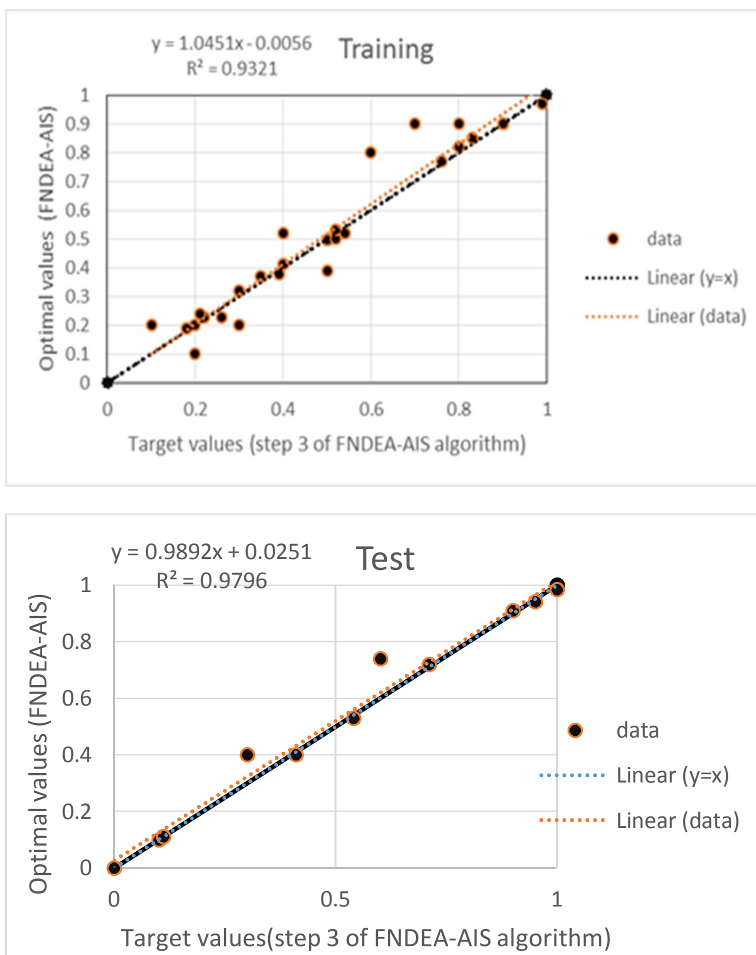
DMU j	Input1	Input2	Input3	Output1	Output2	Output3	Efficiency score
DMU01	**20**	**`10**	**5**	**8**	**100**	**25**	**1**
DMU02	**10**	**15**	**7**	**8**	**70**	**23**	**0.805**
DMU03	**8**	**20**	**2**	**8**	**96**	**30**	**1**
DMU04	**20**	**20**	**10**	**10**	**80**	**20**	**0.627**
DMU05	**15**	**20**	**5**	**15**	**85**	**15**	**0.604**
DMU06	**35**	**10**	**5**	**5**	**90**	**35**	**1**
DMU07	**10**	**25**	**8**	**10**	**100**	**30**	**0.833**
DMU08	**20**	**25**	**4**	**8**	**120**	**10**	**1**
DMU09	**10**	**10**	**5**	**15**	**110**	**15**	**1**
DMU10	**20**	**15**	**9**	**10**	**80**	**20**	**0.668**

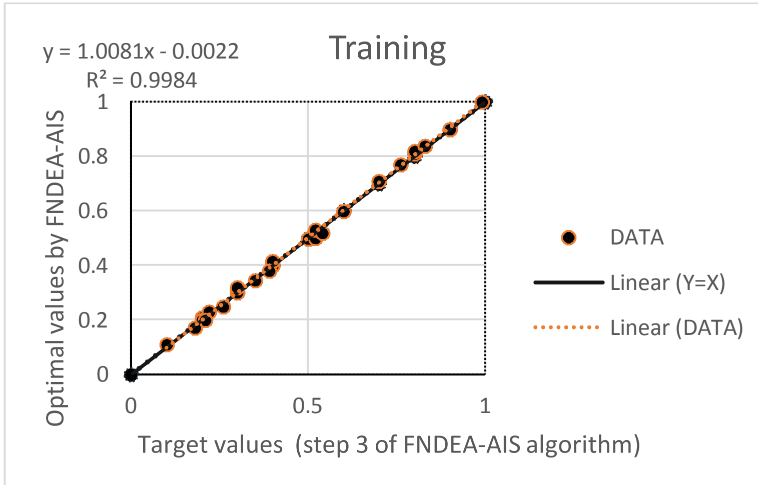
The results of the FNDEA (fuzzy network DEA) model show the relative efficiency scores of inefficient. Units and their actual values which called antibodies here.

Table 5. Adjusted parameters of artificial immune network.

Parameters	Value
The sum of antibody and antigens	**108**
Learning rate	**0.18**
Balanced factor	**0.85**
Epochs (max)	**500**
Error tolerance	**0.015**

To find the best structure, 70 percent of the data set was selected for training of AIS and to validate the prediction power of the model, the 30 percent remained of the model was used as test dataset which is out of the training dataset.
Figure 7 shows the two samples of the test and the train regression charts for the proposed AIS. Figure 7 displays the good quality of the trained network prediction.
After predicting the optimal outputs by the AIS, the DEA model. Must be selected for calculating the efficiency of inefficient units.





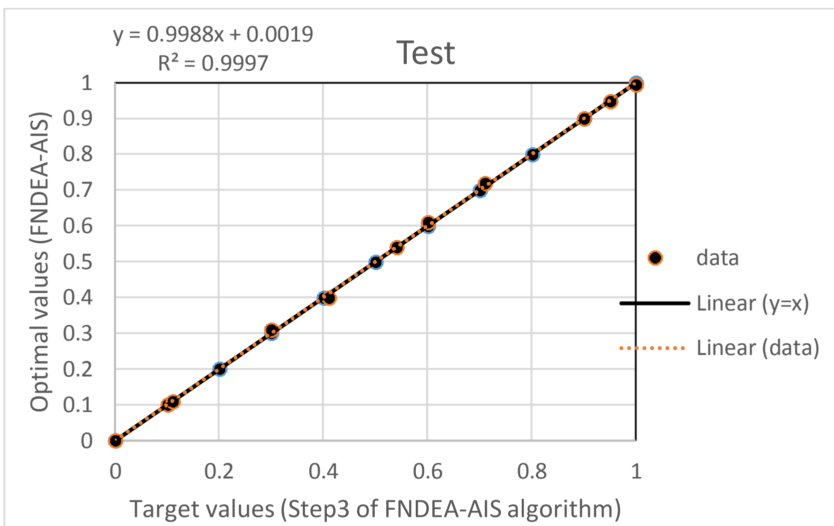


Figure 7. Training and testing charts

Table 6- Results of Overall performance rating of DMUs by FNDEA and FNDEA-AIS model.

DMUs	Efficiency score	Efficiency score
DMU01	0.924	1
DMU02	0.864	1
DMU03	0.858	1
DMU04	0.773	1
DMU05	0.620	1
DMU06	1	1
DMU07	0.904	1
DMU08	0.928	1
DMU09	0.780	1
DMU10	0.754	1

Table. 6 evaluates the DMUs by FNDEA and FNDEA-AIS models. It can be seen that all inefficient DMUs in FNDEA model will be effective by FNDEA-AIS model, this table shows that antigen recognition has done with high accuracy.

4. Conclusion

In this paper a new method based on pattern recognition and robustness of computational processes in AIS and FNDEA methods is designed. By using this method the inputs and outputs of decision units are modified subject to inefficient units will become efficient and predicting of the optimal values of inefficient units has done with high accurate. This model compared with DEA-ANN has a higher precision and predicts several optimal points for inefficient units. An example for demonstrating the advantages of the proposed FNDEA-AIS method is presented.

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