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Evaluating the performance of decision-making units using hybrid neural network model for predicting the performance and data envelopment analysis approach Case study: Khuzestan steel company treatment plant

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One of the main problems with using Data Envelopment Analysis (DEA) is the weak separability of the decision-making units. This is mainly due to the low number of units compared to the number of inputs and outputs of the model [1]. This problem is evident in evaluation of the performance of 144 decision-making units (2007-2014) of Khuzestan Steel Company industrial wastewater treatment plant due to the large number of inputs and outputs of the treatment system. Thus, in the present research, in order to evaluate the performance of the treatment plant in removal of environmental pollutants, first input-based CCR model was used to rank efficient units in the form of DEA models and weaknesses of the models in terms of calculation and separability of efficiency of the treatment plant. Then, in order to analyze and evaluate the efficiency of the treatment plant, neural networks for predicting the performance in the form of hybrid models of data envelopment analysis and artificial neural networks (Neuro/DEA) were used. The result of the analysis of the calculated efficiency of the units using these models suggested the strength of the network in calculation and separability of the treatment plant performance in terms of efficiency over the studied years.

Keywords: treatment plant, efficiency, data envelopment analysis, artificial neural networks (ANN), neuro-DEA

INTRODUCTION

Measurement of efficiency, due to its importance in evaluation of the performance of a system, has always been considered by researchers. In 1957, Farrel used a method similar to engineering efficiency measurement to evaluate the efficiency of a production unit. In his study, Farrel considered one input and one output. His study consisted of evaluating the technical efficiency and allocation and the efficient production function derivative. Farrel used his model to estimate the efficiency of USA agriculture section in comparison to other countries. However, he was not successful in presenting a model containing multiple inputs and outputs [2]. Charnes, Cooper and Rohdes developed Farrel's model and presented a model which had the ability to evaluate the efficiency using multiple inputs and outputs. This model was called Data Envelopment Analysis. Since this model was presented by Charnes, Cooper, and Rudez, it became known as CCR model, which stood for the initials of the names of these three researchers. The aim of this model is to evaluate and compare the relative efficiency of organizational units with multiple inputs and outputs similar to each other [3]. Evidently, creating an efficient system and optimal use of the resources will prevent from wasting substantial amounts of material and moral resources, that is, a small percentage of increase in efficiency can save a large amount of resources. Therefore, studying the level of efficiency in industrial treatment systems is essential. Although choosing the best process for the treatment of industrial waste is important, some quantitative studies have been conducted in this regard using numerous scientific and mathematical techniques and have had a good feedback [4].

To reach this goal, it is necessary to, first, evaluate and analyze the performance of the treatment systems and then identify the units that are not efficient, determine the causes of their inefficiency and try to remove them. Many methods for measuring efficiency have been proposed in the research literature, but in comparison to other models, DEA is a better method for organizing and analyzing the data, because it allows for changes in efficiency over time and requires no assumptions about efficiency limit [5]. Therefore, DEA has been

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used more than any other method for evaluating the performance and is a suitable technique for comparing the units in terms of efficiency. However, the efficiency limit obtained from DEA is sensitive to statistical turbulence and outlying data caused by measurement errors or any external factor and statistical turbulence or outlying data may shift the efficiency limit and deviate the analysis results [6]. Therefore, caution should be taken in using DEA to evaluate the performance of other decision-making units (DMU). Thus, recently Artificial Neural Networks have been used as a suitable alternative for estimation of efficiency limits for decision-making, because due to their learning ability and generalizability, the performance of neural networks is such that they are more resistant to outlying data and turbulence caused by inaccurate measurement [7].

In 2011, Salgado *et al.*, in a research entitled Evaluation of Efficiency of Wastewater Treatment Plants using Data Envelopment Analysis (DEA) Method, studied modern technologies for comparing the efficiency of wastewater treatment technologies. In order to calculate technological economic efficiency and Technological Gap Ratios (TGRs) of WasteWater Treatment Plants (WWTPs), a heterogeneous technological factor was used. This model included four alternative technologies: activated sludge, aerated lagoon, trickling filter and biological rotation. The results showed that the mean efficiency was relatively high and uniform across various technologies. Furthermore, analysis of the calculation of technological economic efficiency and technological gap ratios (TGRs) indicates that optimal technological economic efficiency for WWTPs is using activated sludge and basically, it could be stated that activated sludge is more efficient compared to other technologies [8].

Nasr (2012) used an artificial neural networks method to study the reduction of efficiency costs in a treatment plant in Egypt. In this study, the data including input Total Suspended Solids (TSS), Chemical Oxygen Demand (COD) and Biological Oxygen Demand (BOD), environmental temperature, pH, Mixed Liquor Suspended Solids (MLSS) concentration in aerated lagoon, nitrogen and phosphorus were used in the network for a year. The results showed that Feed Forward Back Propagation (FFBP) Neural Network with a correlation coefficient of 0.9 can estimate the return sludge in this treatment plant [9].

Neelakantan *et al*. (2014) used artificial neural networks to predict the qualitative factors of output wastewater of industrial/urban treatment plants in the United States. In this study, multilayer perceptron (MLP-7) artificial neural network, which is the most common neural network structure, was employed. They used the characteristics of sewage pH, COD and BOD in the neural network input in order to predict pH, COD and BOD in the wastewater. Their results showed good efficiency of the used neural network with minimum absolute percentage errors (MAPEs) of 4, 11 and 7 for pH, COD and BOD, respectively [10].

Steel industry is one of the main consumers of water and Khuzestan Steel Plant, due to its geographical location, has diverse and abundant water consumptions. In a process where sewage is collected and reused in the best way possible, efficiency has a special role in all the stages and can play a significant role in sustainable development of the country. This research develops and presents a new approach based on DEA models to evaluate the performance of wastewater treatment plant of Khuzestan Steel Company by which in addition to evaluating the current efficiency of the performance of treatment plant in removal of the pollutants, predictions can be made of the quality of the output wastewater in the future. In this research, it is tried to use neural networks, DEA and a combination of the two (Neuro/DEA) to measure the technical efficiency of the industrial treatment plant of Khuzestan Steel Company (2009-2014). After calculation of efficiency, the obtained results are compared with the conventional DEA results, because given the number of inputs and outputs, basic DEA models cannot rank the units. The rest of the article is arranged as follows. Section two contains an overview of the principles of DEA and section three briefly introduces neural networks. Section four describes the used method and structure of Neuro/DEA, and in section five the data are analyzed. Finally, section six includes conclusion and recommendations for future research.

RESEARCH METHOD

Studied area

Khuzestan Steel Company treatment plant

With an area of 3.8 square kilometers, Khuzestan Steel Company is located on the 10^{th} kilometer of Ahwaz-Imam Khomeini Port road. Khuzestan Steel Company wastewater treatment plant was established in 2006 and began operation in 2008. Wastewater treatment plant was constructed next to the south wing of the factory. The current capacity of the wastewater treatment plant is 3000 m^3/h and in the future, it can be increased to 5715 m^3/h. The wastewater produced by various units of Khuzestan Steel Complex enters the main canal through two (eastern-southern) canals.

This treatment plant uses physical/chemical treatment methods in several stages during the operation (such as increasing polyelectrolyte and alum and directing the wastewater to settling basins in order to reduce suspended materials, etc.). The effluent is discharged directly to Maleh River by considering environmental standards and eventually, enters Shadegan international wetland and some of it is employed to irrigate the company's green area. (Khuzestan Steel Company Public Relations Department, 2012)

Due to the high volume of this wastewater, discharging it to the environment without observance of control measures can cause considerable damage to the environment. In recent decades, many legal regulations and restrictions on the methods of treatment and disposal of industrial wastewater to the environment have been established. Therefore, to solve the problem of wastewater, environmental experts have proposed two general ideas: reuse and final disposal.

The treatment process of this plant is shown in Figure 1.

Sampling and Analysis methods

In this research, the data from raw sewage and output wastewater of Khuzestan Steel Company industrial wastewater treatment plant were studied. Since for modeling data with a high degree of accuracy and richness in the studied period are required, parameters and quality indicators were used that create an output for an input (2009-2014). Thus, Oil, COD, TSS and pH factors were selected. Raw sewage and output wastewater were sampled to measure and monitor the above-mentioned parameters and based on the book *Standard Methods for the Examination of Water and Wastewater*, input sewage samples were kept in polyethylene and glass containers on which the date, time and place of sampling, as well as the water temperature at the time of sampling had been written and these containers were immediately transferred to the laboratory of Khuzestan Steel Company where tests were performed on the parameters (Table 1). To analyze the output wastewater, online monitoring systems were used, the specifications of which are given in the equipment and devices section.

Equipment and devices:

To analyze the output wastewater, online monitoring devices were used, the specifications of which are given in the following: HACH-LANGE FP 360 sc was used to measure Oil and G, HACH-LANGE UVAS Plus was adopted to measure COD, HACH-LANGE SOLITAX sc was employed to measure TSS and HACH-LANGE 1200-S/sc100 was used to measure pH.

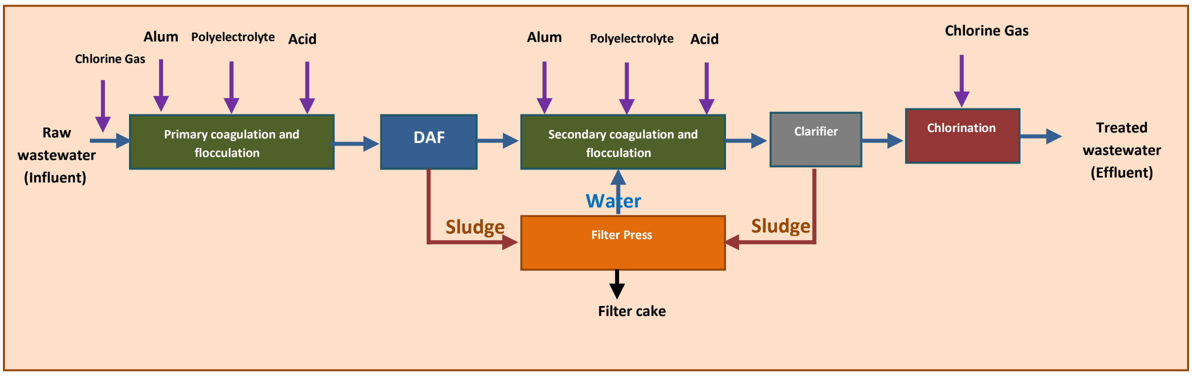

Fig. 1. Schematic of the process of Khuzestan Steel Company industrial wastewater treatment plant

Table 1. Methods of conducting the examinations (Standard methods for the examination of water and wastewater)

	Method number	Used method	Parameter	Number
4500 - M. B.	Section 4- p. 86	Electrometric method	pH*1	1
2540 D.	Section 2- p. 57	Total suspended solids dried at 10^3-10^5 CC *4	Total suspended solids*2	2
5220 .B.	Section 5- p. 13	Reading COD	Chemical oxygen demand*3	3
5220 .B.	Section 5- p. 35	Ben Marie– Oil&G	Oil	4

*1- Method of calculating pH: using pH Meter Metrohm type made in Switzerland.

*2- Method of calculating TSS: using vacuum pump.

*3- Method of calculating COD: kept for 2 h at a temperature of 150ºC in a DRB200 reactor (HACH Company) and read by DR5000 (HACH Company).

*4- Cubic centimeter

Table 2. Inputs and outputs of the model

Parameter	Output	Parameter	Input
Oil	O_1	Oil	I_1
COD	O_2	COD	I_2
TSS	O_3	TSS	I_3
pH	O_4	pH	I_4

Other devices that were used in the examinations were Memmert oven and incubator, Sartorius GM 502 digital scale with an accuracy of 0.00001. The chemicals used were products of Merck Company, Germany. It should be noted that all laboratory operations were carried out in the environmental laboratory of Khuzestan Steel Company and all the used devices belonged to this center.

Stages of the research

This research is conducted in four stages:

Stage one: Data collection;

Stage two: Reviewing, selecting and collecting data on wastewater and effluent quality index, according to the past years' statistics;

Stage three: Sampling and testing parameters and quality indices in the input wastewater and effluent from the treatment plant;

Stage four: Data analysis and modeling.

Steps in the analysis of performance and determining the efficiency of the treatment system:

First step: Collecting the data related to Decision Making Units (DMUs) input/output:

In the study of real systems, to calculate the efficiency, the first step is to determine the inputs and outputs of each DMU so that they reflect the efficiency. In analyzing the efficiency of treatment plants, determining inputs and outputs is particularly important, because each DMU or time period has numerous inputs and outputs and considering a lot of them or ignoring them will cause some problems. After determining the inputs and outputs of each DMU, to compare and measure the efficiency of DMUs, the data related to each DMU were collected.

Each year, 24 samples (2 samples per month) are taken for the 4 input and output parameters (Oil, COD, TSS, pH) and it could be stated that each year we had 24 DMUs and over a six-year research period, a total of 144 DMUs are calculated (Table 2).

Second step: After collecting the data, the efficiency of all DMUs is calculated using the CCR model. In this research, the data related to all DMUs from 2009 to 2014 (each year includes 24 DMUs, where DMU-1 represents August and DMU-24 represents July) are used for the input (Oil, COD, TSS, pH) and output (Oil, COD, TSS, pH) parameters. (Similar input and output parameters)

Third step: The data required for training the artificial neural network are obtained from the results of the DEA-CCR model.

Fourth step: In this stage, the artificial neural network (ANN) is trained using the data selected in the previous step.

Fifth step: The efficiency of the performance of the industrial wastewater treatment plant of Khuzestan Steel Company is predicted using artificial neural networks (ANNs).

Data Envelopment Analysis (DEA)-(DEA-CCR model):

Data Envelopment Analysis (DEA) is a method adopted to measure the relative efficiency of decision making units (DMUs). In DEA, the criteria are not weighed by the decision maker and this is done by the model in a way that each DMU achieves its highest level of efficiency. A DMU is an institution which turns the data into outputs. DMUs are units that perform similar types of tasks and share the same goals and ideals. DMUs which are used in DEA must be homogeneous and have the same kind of data and outputs [11].

Efficiency is defined as the ratio of the output to input. When there are multiple inputs and outputs, efficiency is defined as the ratio of weighed total outputs to weighed total inputs. If the values of the inputs and outputs are known, efficiency is simply calculated as follows (Equation 1):

$$TE_i = \frac{u_1 y_{1i} + \ldots + u_s y_{si}}{v_1 x_{1i} + \ldots + v_m x_{mi}} \qquad \text{(Eq.1)}$$

where v is the input value and u is the output value of the i^{th} unit. But the difficulty is in determining the value of inputs and outputs. If the units under evaluation are manufacturing units, evaluating or pricing the inputs and outputs is not difficult but if they are not manufacturing units, determining the real value of the inputs and outputs is difficult and perhaps impossible. Therefore, in the DEA method the value of the inputs and outputs is assumed variable and in order to calculate efficiency, the following fractional model was presented by Charnes, Cooper and Rhodes in 1978, which is known as CCR model. (Equation 2):

$$\max \quad \frac{\sum_r u_r y_{rp}}{\sum_i v_i x_{ip}}$$
$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \le c$$
$$st \qquad u_r, v_i \ge 0 \qquad \text{(Eq.2)}$$

where c is an arbitrary constant which is usually assumed to be 1. In fact, the above model considers all possible weights for the inputs and outputs of the pth unit and finds weights for which the objective function will be maximized. Due to the constraints of the problem, maximum objective function value can be c. If the pth unit is inefficient compared to other units, in the process of maximizing the objective function, constraints related to efficient units in the set of constraints first reach the value of c and force the pth unit to reach a level lower than c. However, if the pth unit is efficient, the objective function reaches the value of c is without destroying the feasibility of the constraints. [12]

It should be noted that the CCR model described above is fractional and in practice, its linear type is used. In the following, some of the most widely used models of DEA are described. (Equation 3)

Above models are all input models; that is, they determine the efficiency frontier in a way that the input is minimized to the extent that the output is not reduced. A similar model with an output nature can also be written. Output models determine the efficiency frontier in a way that the output is maximized to the extent that the input is not increased. [12]

Artificial neural networks (ANNs)

Artificial neural networks are mathematical models that imitate human brain's function and are capable of extracting patterns from the observed data without the need for assumptions about the relationships among the variables. In neural networks, a neuron is the smallest processing unit and is the basis of a neural network. In Figure 2 a neuron with one input is shown. This simple neuron is composed of two simple elements: weight (w) and transfer function (f).

Input (p) is applied to the neuron and is weighed by multiplying it by weight (w). The result is applied to transfer function (f) as an input and the final output is obtained. By adding bias to the

Multiplier form of BCC (Banker, Charnes and Cooper) model [18]

$$\begin{aligned}
Max \quad & \sum_{r=1}^{s} u_r y_{rp} + u_0 \\
st \quad & \sum_{i=1}^{m} v_i x_{ip} = 1, \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u_0 \le 0, \quad j = 1,\dots,n \\
& u_r \ge \varepsilon, \qquad r = 1,\dots,s \\
& v_i \ge \varepsilon, \qquad i = 1,\dots,m \\
& u_0 \;\; free\, in\, sign
\end{aligned}$$

Multiplier form of CCR model

$$\begin{aligned}
Max \quad & \sum_{r=1}^{s} u_r y_{rp} \\
st \quad & \sum_{i=1}^{m} v_i x_{ip} = 1, \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1,\dots,n \\
& u_r \ge \varepsilon, \qquad r = 1,\dots,s \\
& v_i \ge \varepsilon, \qquad i = 1,\dots,m
\end{aligned} \qquad \text{(Eq.3)}$$

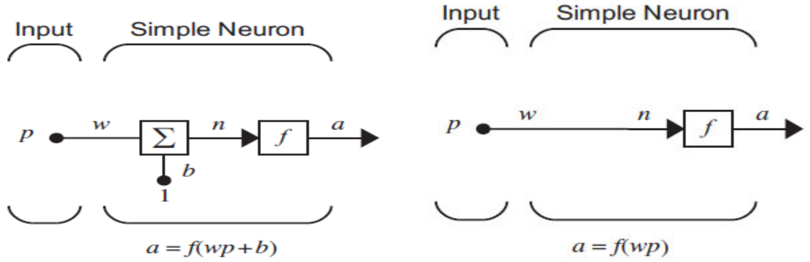

Fig. 2. Simple biased neuron (left) and nonbiased neuron (right) [13]

structure of the neuron in the previous figure, a biased neuron (on the left) is created. b and w are two regulating parameters in the neurons [14]. The main idea of neural networks is that by changing the values of w and b, the network makes a decision. In the used tool in MATLAB, bias has been considered but using it is optional. Neural networks can have more than one layer. They are called multilayer networks. Generally, neural networks can be divided into two types of feedforward and recursive networks. In feedforward networks, no feedback is given to the network input from the network output. But in recursive networks, at least one recursive signal is sent from one neuron to the same neuron or neurons in the previous layer(s). Also, neural networks can be divided into fully connected networks and partially connected networks. In partially connected networks, some of the synaptic connections have been removed [15].

Learning in neural networks:

Simply put, learning in neural networks means that synoptic weights (w, b) change in a way that the neuron input/output relation is adjusted to a specific goal. Learning in neural networks is often done in two ways: supervised learning and unsupervised learning. In supervised learning, a set of data pairs, known as learning data, are applied. A learning pair {(xi ,ti),i,1,2,...m} in which xi is network input and ti is the desirable output for xi. After applying xi input to the network, in the network output, Oi is compared with ti and then learning error is calculated and used to adjust the network factors. In unsupervised learning (self-organizing learning), neural network factors are only modified and adjusted by system's response. In other words, the input merely comprises the data received by the network from the environment and optimal vector is not applied to the network [16]. One of the most common and most widely used neural networks are multilayered perceptron neural networks with backpropagation algorithm. In backpropagation algorithm, frequent input data are given to the network and the output is compared with optimal output and error is calculated in each repetition. This error is propagated across the network and synoptic weights are adjusted in a way that reduces the error in each repetition [17].

Hybrid model of neural networks and data envelopment analysis (Neuro/DEA):

In the present research, a combination of neural networks and data envelopment analysis is used to evaluate the performance of Khuzestan Steel Company wastewater treatment plant. The potential of neural networks for identifying patterns, estimating functions, prediction and clustering makes it possible to combine them with DEA in order to evaluate the efficiency of the units. Hybrid models of neural networks and DEA used in this research include two approaches (scenarios) which will be discussed in detail in the following section.

In the following, to implement the Neuro/DEA model, first the data are collected. Then, the collected data are saved in the form of EXCELL files in MATLAB software. The networks used in this research include multilayer, feedforward networks and self-organizing networks, which were discussed in the previous section.

Modeling the defined scenarios:

In the present research, two main approaches have been adopted to model the scenario. Before describing these two approaches, to model the scenario, the data must be normalized. In leading neural networks with backpropagation learning algorithm, activation functions errors in the input and latent layers are tangent sigmoid and in the last layer, linear activation function is used. Since sigmoid functions are saturated for values larger than 1 and smaller than -1, input and output values must be scaled to prevent saturation. In addition, the output must also be scaled to be proportionate to the sizes obtained from the neural network. Radial neural network is also composed of a middle layer and an external layer. Activation function of the main layer is a Gaussian radial function, which varies between 0 and 1 and its external layer is a linear activation function. Both neural networks need scaling inputs and outputs. There are various methods for normalization of the data. In this project, mapstd was used to normalize the data in a way that the mean of the data was zero and their standard deviation was one. After scaling and normalization of the input and output data, the following two approaches (scenarios) were considered and the normalized data were entered into the model.

First approach: performance prediction network:

In the first approach in hybrid Neuro/DEA-1 models, a multilayer perceptron network was used to predict the performance of the decision-making units, which as a simulator can simulate the performance of the units in the coming years and analyze the sensitivity of the units. 8 data including Oil_i ‹COD_i ‹TSS_i ‹pH_i ‹Oil_o ‹COD_o ‹ TSS_o ‹pH_o as well as the efficiency calculated by DEA (input-based multiple CCR model) are taught to the network. The network learns the efficiency pattern of the units based on network topology and Scaled Conjugate Gradient (SCG) and Levenberg–Marquardt (LM) learning algorithms and establishes a nonlinear mapping between inputs and outputs. The calculated output is actually the efficiency of the data in the new year, that is, 2014. Therefore, we call the first network "performance prediction network". Our goal is to be able to predict the outputs based on these inputs. To do so, we will consider the first five years data as training data and the sixth year data as test data.

Second approach: efficiency calculation network:

In the second approach in hybrid Neuro/DEA-2 models, also a multilayer perceptron network was used. At this stage, the aforementioned neural network calculates the efficiency of the units. 5 data including Oil_i ،COD_i ،TSS_i ،pH_i ،DEA-CCR are considered as inputs and 4 data including Oil_o ، COD_o ،TSS_o ،pH_o as outputs. The available data for the units from 2009 to 2014 are divided into learning data and test data. Test data are selected randomly from units' data and are entered into the network along with their efficiency which is calculated by DEA (input-based CCR model). The network learns the pattern of efficiency between inputs and outputs and then, calculates the efficiency of the new data which have been kept as test data. This network is referred to as efficiency calculation network. Our aim is to be able to predict the outputs based on these inputs. To this end, we will consider the first five years data as training data and the sixth year data as test data.

The method employed in hybrid Neuro/DEA models (first and second approach) to evaluate the units:

In the present research, to evaluate the performance of Khuzestan Steel Company industrial wastewater treatment plant during 2009-2014, DMUs of inputs and outputs are determined and efficiency is measured using DEA (input-based CCR model).

To measure efficiency, the data related to the inputs and outputs of the treatment plant during the mentioned years were used as Fig. 3.

For measuring the technical efficiency of each industrial treatment plant in terms of reducing wastewater parameters to the standard environmental level, COD, pH, TSS and Oil can be considered as model inputs and the treatment plant outputs corresponding to the mentioned parameters can be considered as model outputs. Nevertheless, there are numerous parameters that are considered while evaluating technical efficiency of a treatment plant and it could be stated that efficiency of each industrial treatment plant can be a function of the abovementioned variables and changes in each of them affects the performance of the company. Under such conditions, the assumption of linearity of the relationship between the variables can be ignored and based on the law of diminishing returns and by considering the interactions between the variables, efficiency function of the i^{th} unit, that is, fi=(x1,x2,x3,x4,y1,y2,y3,y4), can be a nonlinear function. The aim of Neuro/DEA model is to minimize the number of inputs required to achieve the desired output. To measure the efficiency of the treatment plant using Neuro/DEA model, first based on the mentioned approaches, 5 scenarios are introduced as shown in Table 3. In this table, the inputs and outputs corresponding to each scenario are described. Then, a suitable neural network model is simulated and after that, using the data for initial processing as well as preprocessing data, the network is trained using a suitable output calculated by DEA so that the network can learn the reference model and based on it, calculate the efficiency of the units. Then, the observed results are studied using DEA/CCR and Neuro/DEA models.

Fig. 3. Khuzestan Steel Company industrial treatment plant inputs and outputs.

Table 3. Inputs and outputs corresponding to each scenario.

Scenario No.	Model inputs	Model output
1	Oil_i, COD_i, TSS_i, pH_i, Oil_o, COD_o, TSS_o, pH_o + DEA-CCR	DEA-CCR sixth year (2014)
2	Oil_i, COD_i, TSS_i, pH_i, DEA-CCR	pH_o
3	Oil_i, COD_i, TSS_i, pH_i, DEA-CCR	TSS_o
4	Oil_i, COD_i, TSS_i, pH_i, DEA-CCR	COD_o
5	Oil_i, COD_i, TSS_i, pH_i, DEA-CCR	Oil_o

Table 4. Inputs and outputs of decision making units (DMUs)*.

Year		Input (Oil)	Input (COD)	Input (TSS)	Input (pH)	Output (Oil)	Output (COD)	Output (TSS)	Output (pH)
2009	Mean	9.733	85.817	58.092	7.938	4.242	43.929	14.000	7.700
	Std. Dev.	8.470	59.619	53.557	0.186	4.311	23.760	7.945	0.232
	Min	1.3	26	9	7.5	0.3	11	3	7.2
	Max	37	254	271	8.3	20	115	35	8.1
2010	Mean	4.317	69.333	45.775	8.075	1.883	25.458	12.896	7.850
	Std. Dev.	4.473	53.921	35.277	0.217	2.676	10.371	4.191	0.159
	Min	0.6	25	14	7.8	0.2	3	6	7.6
	Max	22	261	150	8.6	11	40	22	8.2
2011	Mean	4.279	55.133	55.825	7.942	2.333	38.500	21.750	7.725
	Std. Dev.	2.960	9.644	26.411	0.289	1.001	6.711	8.774	0.285
	Min	1.2	40	26	7.1	0.6	25	6	6.9
	Max	15	81	129	8.5	4.5	53	48	8.2
2012	Mean	7.435	62.058	71.446	7.982	2.863	33.083	13.917	7.663
	Std. Dev.	8.430	20.317	38.274	0.261	0.283	13.897	5.770	0.300
	Min	2.9	22	17	7.5	2.4	6	4	7
	Max	40	103	162	8.6	3.5	62	32	8.5
2013	Mean	4.571	65.221	74.168	8.079	3.596	20.747	15.333	7.854
	Std. Dev.	1.926	23.135	39.179	0.257	1.434	10.448	11.126	0.195
	Min	2.9	33.8	20	7.6	2.6	13	9	7.5
	Max	11.3	111	210	8.6	10.1	64	66	8.2
2014	Mean	3.617	46.625	61.583	8.004	2.775	23.417	20.833	7.800
	Std. Dev.	0.725	14.832	33.628	0.146	0.182	6.928	17.264	0.147
	Min	2.8	29	23	7.7	2.2	12	11	7.4
	Max	5.1	98	143	8.3	3.1	40	99	8

* According to the table, the measurement unit of Oil, COD and TSS parameters in the input and output of the treatment plant is mg/L.

RESULTS AND FINDINGS OF THE RESEARCH

The present research was conducted based on the data gathered over the period of six years from 2009 to 2014.

The results of the analyses conducted on Oil, COD, TSS and pH parameters of the raw sewage entering the treatment plant and the output wastewater, are presented in Table 4 in the form of decision making units (DMUs).

As can be seen, the range of annual mean of Oil in the raw input sewage varies from 3.62 mg/L in 2014 to 9.73 in 2009 and in the output wastewater from 1.88 mg/L in 2010 to 4.24 in 2009. The total mean in the raw input sewage and in the output wastewater was estimated to be 5.66 and 2.95 mg/L respectively.

Also regarding TSS, BOD and pH parameters, according to Table 4, the range of annual mean of COD in the raw input sewage varies from 46.63 mg/L in 2014 to 85.82 in 2009 and in the output wastewater from 20.75 mg/L in 2013 to 43.93 mg/L in 2009. The total mean in the raw input sewage and output wastewater was estimated to be 63.84 and 30.86 mg/L, respectively. The range of annual mean of TSS in the raw input sewage varies from 45.78 mg/L in 2010 to 74.17 in 2013 and in the output wastewater from 12.92 mg/L in 2010 to 21.75 in 2011. The total mean in the raw input sewage and the output wastewater was estimated to be 61.15 and 16.45 mg/L, respectively. Finally, the annual mean of pH in the range of the raw input sewage varies from 7.93 in 2009 to 8.08 in 2013 and in the output wastewater varies from 7.66 mg/L in 2012 to 7.86 in 2013. The total mean in the raw input sewage and the output wastewater is estimated to be 8 and 7.77, respectively.

Results of process performance evaluation using DEA

In this section, the real application of the proposed model in water and wastewater industry is explained. As noted above, our study includes 144 homogeneous decision making units, each of which has four input variables and four similar output variables. As explained above, in order to measure efficiency and compare the units, the data from 2009 till 2014 were used. Decision making units (DMUs), which are the years studied in this research, are presented in Table 4. Efficiency of the treatment system during these years was calculated based on inputs and outputs using DEA-RCC, the results of which are shown in Table 5. According to the results, the number of efficient units in 2014, 2013, 2012, 2011, 2010 and 2009 was 7, 7, 9, 8, 12 and 10, respectively, and the number of inefficient units in 2014, 2013, 2012, 2011, 2010 and 2009 was 17, 17, 15, 16, 12 and 14, respectively (Table 5).

Results of Neuro/DEA section:

First scenario: DEA/CCR prediction of the performance in the sixth year (2014)

The results of the first scenario are presented in Table 6 and Figure 4. Figure 4 shows the outputs simulated by the neural network and the output already existing, corresponding to the learning data. The color blue stands for the existing outputs and red stands for simulated outputs. Ideally, the two graphs should match each other. Following the implementation of the program, we observe that the same thing occurs and the two graphs approximately match each other, which shows that our network has been properly trained for learning data. In this graph, the x axis shows the number of the used test data and the y axis shows the DEA/CCR value.

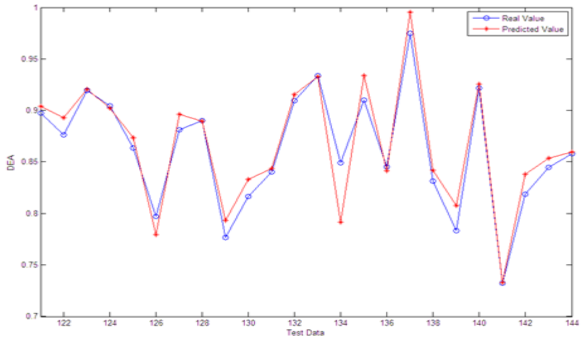

Fig. 4. Comparison of the output of the neural network with the real values of the first scenario.

Table 5. The results obtained from the DEA-RCC model.

	2009	2010	2011	2012	2013	2014
DMU01	0.7725	1	1	1	0.9133	1
DMU02	0.7844	0.9083	1	1	1	0.9727
DMU03	0.7958	0.8589	1	0.9398	0.8331	1
DMU04	0.8638	0.88	0.8658	0.9674	0.9204	0.9443
DMU05	0.785	0.8967	0.9551	0.9917	1	0.9429
DMU06	0.7956	1	0.8404	1	1	0.8661
DMU07	0.8907	0.8626	0.7691	0.9257	0.8966	1
DMU08	0.7252	1	1	1	0.9217	1
DMU09	0.8779	0.9269	0.9039	0.8701	0.7732	0.9047
DMU10	0.6869	0.9609	1	0.9368	1	0.9326
DMU11	1	1	0.9813	0.9499	0.8907	0.9573
DMU12	0.9331	0.9707	1	1	0.9405	0.9769
DMU13	1	0.9487	0.9815	0.8352	1	1
DMU14	0.8512	0.8611	1	0.9688	1	1
DMU15	1	1	0.955	0.967	0.8197	1
DMU16	0.8149	0.9298	0.89	0.9318	0.9185	0.9612
DMU17	0.9565	0.9084	1	1	1	1
DMU18	0.9006	0.9076	0.8591	0.9336	0.8992	0.9194
DMU19	1	0.8569	0.9433	0.9255	1	0.8817
DMU20	1	0.7996	0.9183	0.9683	1	1
DMU21	1	0.9231	0.7956	0.8819	0.8172	0.839
DMU22	0.8895	1	0.9532	0.8811	1	0.9161
DMU23	0.8362	1	0.8483	1	1	0.9657
DMU24	1	0.8827	1	1	1	1
# of efficient units	7	7	9	8	12	10
# of inefficient units	17	17	15	16	12	14

Real values- First scenario:

The results of the second through fifth scenarios:

To better compare the value predicted by the neural network to the expected values in the test data, in the second through fifth scenarios, the following graphs are used. In these graphs, the x axis is the number of the used test data and the y axis shows the value of the predicted output parameter. The (predicted) neural network output values are shown in red and the real values of the test data in blue.

DISCUSSION AND CONCLUSION

Selection of the superior model or approach to evaluate the performance and rank the decision-making units (during the studied years)

Data Envelopment Analysis model

In Data Envelopment Analysis models, only input-based multiple CCR approach (model) has been used and evaluation of the performance of Khuzestan Steel Company treatment plant during the studied years has been done using the mean of the data, which, given the final conclusion in Table 5, reveals that in 2009 and 2010 most of the units have been inefficient and some of the units have had almost equal efficiency. Therefore, it suggests poor separation of the performance of the units using the aforementioned model in 2009 and 2010.

This problem in evaluation of the performance of the units is also evident in 2011 and 2012, because in 2011, 9 DMUs had efficiency of 1 and some of the units had almost equal efficiency, and in 2012, 8 DMUs were considered efficient. In 2013, 12 DMUs had the highest level of efficiency (1) and in 2014, 10 DMUs were considered efficient and the rest of the DMUs had equal efficiency. Evaluation of the performance of the units using the mean of the data during the studied years (2009-2014) may have a better evaluation logic in comparing the efficiency of the units during the studied years (2009-2014), but evaluation of the performance using multiple input-based CCR model indicates poor separability of this model in analyzing efficiency. Because according to Table 5, it is shown that in this evaluation, 53 DMUs have had the highest efficiency (1) during 6 years (2009-2014) and some other have had similar performance. Also, based on the obtained results, the most important parameter affecting the efficiency of the treatment plant system is pH. In other words, by removing or changing pH, changes will occur in the performance of the treatment plant, which can be due to the significant impacts of this parameter on different phases of wastewater treatment including the process of removal of dissolved metals and wastewater chlorination. In the event that wastewater with acidic or basic pH enters receiving waters, depending on the conditions, it can have severe environmental consequences for the water ecosystem.

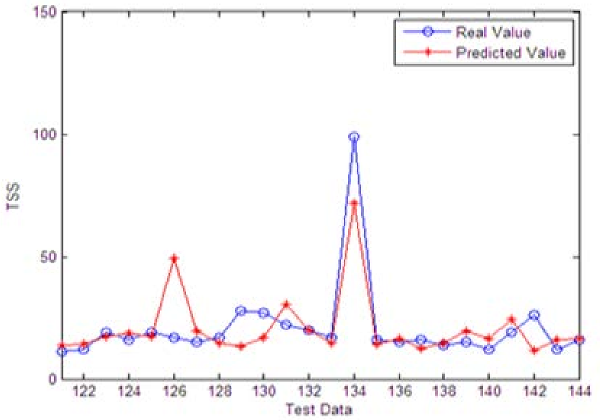

Fig. 5. Comparison of the output of the neural network with the real values of the second scenario.

As we know about the Data Envelopment Analysis method, this method is a nonparametric method and the efficiencies calculated by this method have relative values. In this method, unlike the parametric method, the function has no predetermined shape and the efficiency limit is determined based on the location of the data. Thus, it is natural to speak of the contribution of each unit or index in forming the limit.

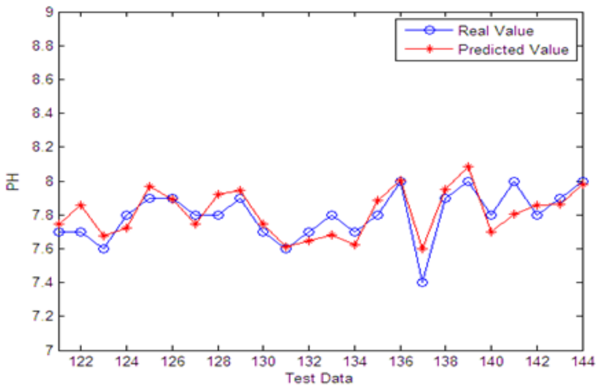

Fig. 6. Comparison of the output of the neural network with the real values of the third scenario.

Because any change in the data shifts the production function and particularly the efficiency of each unit, this will be discussed while analyzing sensitivity. In this section by removing each of the indices, we study the change in efficiency of the units. It should be noted that there is a direct correlation between the input and output indices and removing each of the input indices will lead to the removal of its corresponding output index. In general, it could be said that considering the used models and conducted analyses in each section, it is evident that in none of the results obtained from the models employed in this research, except for few of the units, there has been a remarkable difference between the performances of the units. Regardless of the individual performance of the units, it could be stated that there is a perceptible balance in the system.

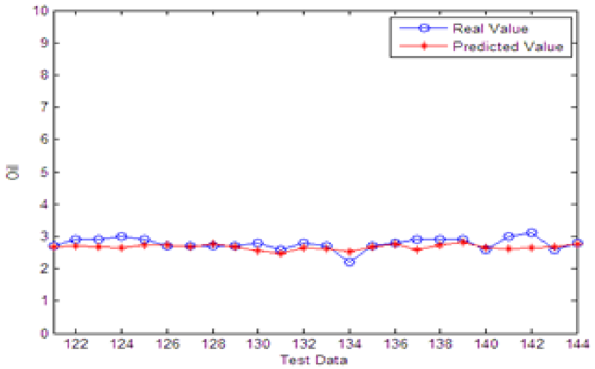

Fig. 7. Comparison of the output of the neural network with the real values of the fourth scenario.

Therefore, considering the conducted analysis, it seems that Data Envelopment Analysis models are not a suitable approach to analyze and evaluate the units in a comprehensive and complete way. Thus, hybrid Neuro/DEA models were adopted to evaluate the performance of the treatment plant during the studied years.

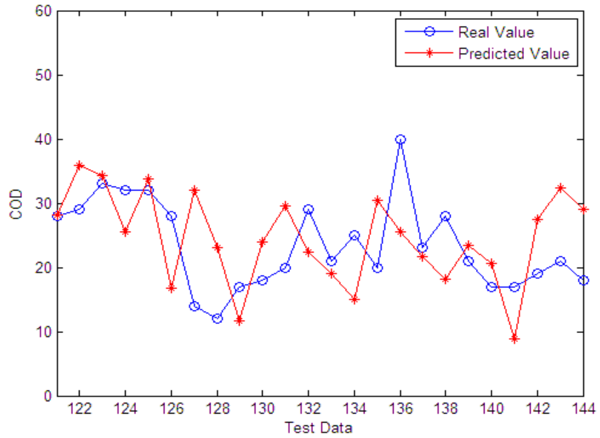

Fig. 8. Comparison of the output of the neural network with the real values of the fifth scenario.

Table 6. Results obtained from scenario one

Scenario	Year	name	Oil_i	COD_i	TSS_i	pH_i	Oil_o	COD_o	TSS_o	pH_o	Output DEA-CCR	Output Neuro-DEA
			Input									
First	2014.07.23	DMU-121	3.1	35	60	8	2.7	28	11	7.7	0.8972	0.9039704
	2014.08.13	DMU-122	3.1	40	55	8.1	2.9	29	12	7.7	0.8762	0.8926328
	2014.08.27	DMU-123	3.9	54	25	7.9	2.9	33	19	7.6	0.9196	0.9203327
	2014.09.10	DMU-124	3.1	35	50	7.9	3	32	16	7.8	0.9047	0.902035
	2014.09.24	DMU-125	3.9	46	32	8.1	2.9	32	19	7.9	0.8636	0.8733432
	2014.10.15	DMU-126	5.1	32	136	8.3	2.7	28	17	7.9	0.7974	0.7795509
	2014.11.05	DMU-127	4.5	45	43	7.9	2.7	14	15	7.8	0.8812	0.8961407
	2014.11.11	DMU-128	3.2	61	23	8.2	2.7	12	17	7.8	0.8904	0.8895371
	2014.11.25	DMU-129	4.5	58	85	8.1	2.7	17	28	7.9	0.7765	0.7931143
	2014.12.09	DMU-130	3.1	63	78	7.9	2.8	18	27	7.7	0.8167	0.83287
	2014.12.24	DMU-131	3.2	49	114	7.7	2.6	20	22	7.6	0.8402	0.8434945
	2015.01.06	DMU-132	3.2	37	56	7.8	2.8	29	20	7.7	0.9093	0.9157205
	2015.01.21	DMU-133	2.8	29	49	7.9	2.7	21	17	7.8	0.9338	0.9327067
	2015.02.03	DMU-134	2.9	36	143	7.8	2.2	25	99	7.7	0.8489	0.7917352
	2015.02.25	DMU-135	3.1	35	32	8.1	2.7	20	16	7.8	0.9101	0.9336293
	2015.03.11	DMU-136	3.5	50	34	8.1	2.8	40	15	8	0.8454	0.8413867
	2015.04.08	DMU-137	3.1	36	32	7.9	2.9	23	16	7.4	0.9748	0.9952334
	2015.04.15	DMU-138	3.1	45	61	8.1	2.9	28	14	7.9	0.8315	0.8420976
	2015.04.29	DMU-139	3.4	57	59	8.2	2.9	21	15	8	0.7833	0.8076925
	2015.05.13	DMU-140	3	31	50	7.9	2.6	17	12	7.8	0.9217	0.9257734
	2015.05.22	DMU-141	5.1	98	104	8.1	3	17	19	8	0.7326	0.7329739
	2015.06.05	DMU-142	4.9	51	70	8	3.1	19	26	7.8	0.8185	0.8379982
	2015.06.22	DMU-143	3.9	42	62	8	2.6	21	12	7.9	0.8446	0.8538165
	2015.07.06	DMU-144	4.1	54	25	8.1	2.8	18	16	8	0.8579	0.859641

Evaluating the approaches (scenarios) in the form of hybrid Neuro/DEA models

In the first approach (scenario) in hybrid Neuro/DEA models, a multilayer perceptron network was used to predict the performance of the decision-making units during the studied years, which as a simulator can simulate the performance of the units in the coming years and analyze the sensitivity of the units. 8 data including Oil_i ‹ COD_i ‹TSS_i ‹pH_i ‹Oil_o ‹COD_o ‹TSS_o ‹ pH_o, as well as the efficiency calculated by DEA (input-based multiple CCR model) are taught to the network. The network learns the efficiency pattern of the units based on network topology and SCG and LM learning algorithms and establishes a nonlinear mapping between inputs and outputs. The calculated output is actually the efficiency of the data in the new year, that is, 2014. Therefore, we call the first network “performance prediction network”. As shown in Table 6, all the units that have high efficiency have been separated, which indicates high separability of this model. Therefore, this approach (neural networks for predicting the performance) can be considered a suitable approach for evaluating DMUs of Khuzestan Steel Company treatment plant. In the second through fifth approaches (the first through fifth scenarios), the performance of 144 decision-making units (2007-2014) of Khuzestan Steel Company wastewater treatment plant has been calculated using the neural network for calculation of performance. Our goal is to be able to predict the outputs based on these inputs. To do so, we will consider the first five years data as training data and the sixth year data as test data. In this approach also a perceptron network is used which calculates the efficiency of the units. Test data are selected randomly from units’ data and are entered into the network along with their efficiency which is calculated by DEA (input-based CCR model). The network learns the pattern of efficiency between inputs and outputs and then, calculates the efficiency of the new data which have been kept as test data. This network is referred to as efficiency calculation network. Our aim is to be able to predict the outputs based on these inputs. Analysis of the results obtained from this approach indicates high separation power of the scores of efficiency of the units in this network. The obtained results show that this model has high power in separation and calculation of the scores of efficiency of the units. Furthermore, in calculation of efficiency by DEA, as the results indicate, efficiency scores are equal, which shows that this model cannot separate the units from each other in terms of efficiency. Whereas, the neural network eliminates this weakness of the DEA model, through separation and calculation of efficiency. Based on the results of several tests, we came to the conclusion that it is better to use four single-output neural networks instead of one four-output neural network. In this way we will be able to use a neural network with a specific structure for each output and produce minimum error in predicting each of the outputs. In the following, both networks have been evaluated and compared based on the efficiencies calculated by DEA/CCR and Neuro/DEA models.

Evaluation of the modelings:

To evaluate the modelings, the following parameters are used (Equation 4):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(T_{actual} - T_{forecast})^2}{n}}$$

$$NRMSE = \frac{RMSE}{T_{average}}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(T_{actual} - T_{forecast})^2}{\sum_{i=1}^{n}(T_{actual} - T_{average})^2}$$

$$MAE = \frac{\sum_{i=1}^{n}|T_{actual} - T_{forecast}|}{n}$$

$$NMAE = \frac{MAE}{T_{average}}$$

(Eq.4)

Table 7. Summarization of the results of simulations.

Item	Scenario No	MODELING	RMSE	NRMSE	R	MAE	NMAE
1	1	DEA-CCR	0.0423	0.8344	0.8267	0.0683	1.3494
2	1	Neuro-DEA	0.0032	40.6721	0.9902	0.0330	59.1425
3	2	DEA-CCR	0.0349	0.6345	0.7967	0.04321	1.0056
4	2	Neuro-DEA	0.0186	101.8391	0.8418	0.1132	203.1523
5	3	DEA-CCR	0.0349	0.6345	0.7489	0.04321	1.0056
6	3	Neuro-DEA	0.036	110.8391	0.8618	0.0932	188.1167
7	4	DEA-CCR	0.0987	52.6382	0.4588	0.1753	64.8007
8	4	Neuro-DEA	0.0564	37.479	0.5388	0.08301	52.5800
9	5	DEA-CCR	0.0887	47.6382	0.5488	0.1523	71.7695
10	5	Neuro-DEA	0.0564	0.7902	0.6788	0.04321	1.0056

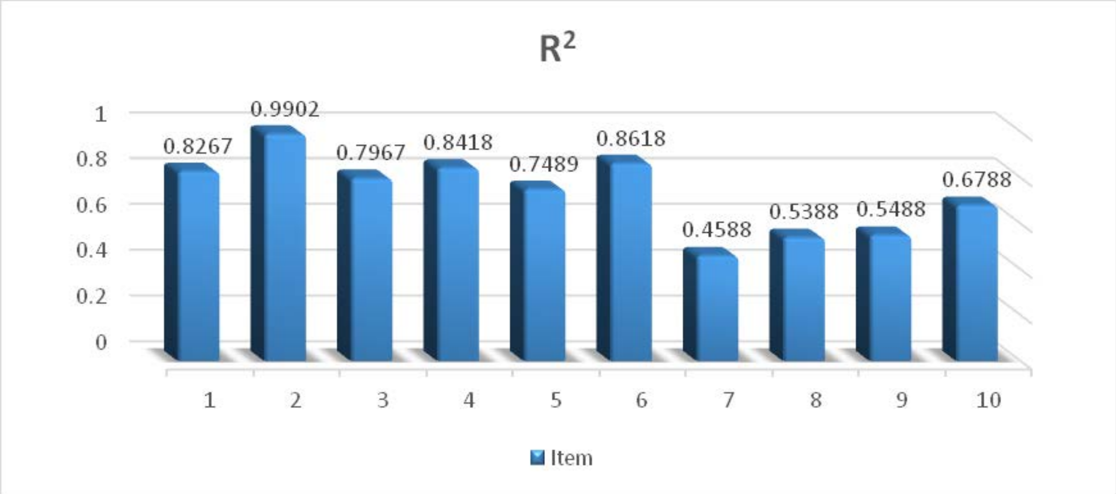

Fig. 9. Comparison of the correlation coefficients in various scenarios

In Figure 9, a comparison of the correlation coefficients in various scenarios is presented.

As shown in Table 7 and Figure 9, in all the defined scenarios, the best correlation coefficients are observed in Neuro/DEA models. In other words, hybrid models (including leading neural and artificial networks using error backpropagation model and DEA) have the best performance and are capable of predicting the data with minimum error (in most cases since the value of R is close to 1, there is a good linear relationship between the observed and modeled values) and real results are within a suitable range, because the ups and downs of the graphs simulated for various scenarios in order of priority include: the first scenario with 0.99, the third scenario with 0.86, the fifth scenario with 0.67 and the fourth scenario with 0.53 in the specific intervals in the model are consistent with reality. Also in most time points, the values obtained from simulation are very close to the real values. On the whole, the most accurate modeling for evaluation of the performance of Khuzestan Steel Company treatment plant during the studied years (2009-2014) is that of Neuro/DEA rather than DEA. On the other hand, the hybrid Neuro/DEA model not only evaluates the performance but also predicts the performance of the treatment plant in the coming years and this is one of the unique features of this model.

RECOMMENDATIONS FOR FUTURE RESEARCH

The results of the research showed that neural networks have a high capability to learn efficiency patterns, yet it is noteworthy that the network should be properly trained. A combination of DEA and neural networks can be employed in cases where basic models cannot separate and identify the units.

Given the fact that Neuro/DEA hybrid model has not been implemented in the treatment plants of the country, by using the findings of this research and modeling Khuzestan Steel Company treatment plant in terms of efficiency, other industrial treatment plants in the country can be studied to determine whether or not they are efficient and also strategies for improving efficiency can be presented. In this regard, other input and output criteria of the industrial treatment plants of the country can be extracted, the efficiency of the units can be evaluated and the units can be ranked using Neuro/DEA model.

Using Neuro/Fuzzy model and entering external factors as the inputs of the neural network and determining the efficient units in the future based on the changes in these factors can also be an area for future research. In subsequent studies, basic DEA models can be used to conduct more extensive research on this subject. Efficiency calculation networks and self-organizing networks can be used to create a network that analyzes efficiency independently of DEA. Since in DEA, the calculated weights are the most suitable weights for maximizing the efficiency of the units, it is expected that the efficiency of all units will be equal to one.

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ХИБРИДЕН ПОДХОД НА НЕВРОННА МРЕЖА И АНАЛИЗ НА ОБХВАТА НА ДАННИТЕ ЗА ОЦЕНКА И ПРЕДСКАЗВАНЕ НА ЕФЕКТИВНОСТТА НА ЕДИНИЦИ ЗА ВЗЕМАНЕ НА РЕШЕНИЕ НА ПРИМЕР НА СИСТЕМА ЗА ПРЕЧИСТВАНЕ НА ИНДУСТРИАЛНИ ОТПАДЪЧНИ ВОДИ НА КОМПАНИЯ ЗА ПРЕРАБОТКА НА СТОМАНА В ХУЗЕСТАН

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(Резюме)

Един от основните проблеми, свързани с подхода за анализ на обхвата на данните (Data Envelopment Analysis, DEA)) е липсата на чувствителност при оценка на ефективността на отделните единици за вземане на решение, които представляват резултати от анализа на параметрите на входящите и изходящи потоци на системата за пречистване на отпадъчни води. Този проблем се дължи на малкия брой единици в сравнение с броя на входовете и изходите на модела. Доказателство за това е разглеждането на пример за оценка на ефективността на 144 единици за вземане на решение за периода (2007-2014) на система за пречистване на отпадъчни води на Khuzestan компания за преработка на стомана с голям брой входове и изходи. За да се изчисли ефективността на пречиствателната система за преработка на замърсителите, първоначално е използван CCR подход за моделиране, основаващ се на анализ на данните за входовете на системата, който служи за подреждане на ефективните единици чрез прилагане на DEA модели. Показани са основните недостатъци на този подход, а именно наличието на трудности при отделянето на резултатите за ефективността на разглежданите единици за вземане на решение. С цел постигане на по-висока чувствителност модела за анализ на обхвата на данните е комбиниран с модел на изкуствена невронна мрежа за предсказване на ефективността на единиците за взимане на решения чрез създаване на т.н. хибриден Neuro/DEA модел. Резултатите от проведения анализ на ефективността на единиците за вземане на решение показват по-високата чувствителност на изкуствените невронни мрежи при изчисляване на ефективността на разглежданите единици за вземане на решения за определен период от време.