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Step 1: (Define variables)
The data of 16 panels of Tavanir Regional Electricity Distribution Company in the period 1391 to 1396, in the Tobit regression model are divided into two groups before 1392 and after 1392 for the imaginary variable of privatization.
Control variables (environmental) include: 1- Privatization dummy variable (DUMPRIVATE) to control the ownership structure, 2- Ratio of underground network to total network length to control the structure of the network (UGR), 3- The ratio of home customers to all customers to control the consumer structure (CONSRESSHARE), 4- Network load coefficient (maximum asynchronous load ratio to total power consumption) (LF1), 5- Transformer capacity load factor (ratio of transformer capacity to electricity demand) (LF2) to control the intensity of grid and transformer use, respectively.
6- Circuit density as the ratio of the number of customers to the length of the network (CD2) and 7- Customer density is considered as the ratio of the number of customers to the area of coverage to control the operating environment (CD1).
In this research, the method of maximum straightness of the random panel has been used.
Also, the control variables that are placed in the well-known data envelopment analysis box as the inputs and outputs of the unit-independent SBM model are:
1- Length of network lines (km), 2- Capacity of transformers (MV), 3- Number of employees (persons) and 4- Transmission and distribution losses (percentage) as input variables and 1- Number of subscribers (thousand people), 2- The energy delivered to the subscribers (million kilowatt hours) is used as output variables.
Step 2: (Solve the two-stage model of SBM data envelopment analysis independent of the classical unit and Tobit regression)
The results of unit-independent SBM model efficiency and environmental variables will be included in a two-stage model of data envelopment analysis and Tobit regression. Then, the effect and the amount of the final effect of environmental variables on the average efficiency of regional electricity distribution and transmission companies are determined. Tobit regression in the present study is as described in relation (4):

$$Y_{it} = \alpha + \beta_1 x_{1it} + \beta_2 x_{2\,it} + \beta_3 x_{3\,it} + \beta_4 x\, 4_{it} + \beta_5 x_{5\,it} + \beta_6 x_{6\,it} + \beta_7 x_{7\,it} + u_{it}$$

Y_{it} symbolizes the amount of final influence of environmental variables on the average efficiency of units,
α is the symbol of intercept,
u_{it} is the symbol of the remaining error and has an independent and uniform distribution N (0, 6^2). The degree of freedom in the hypothesis test is 8.
Step 3: (Build the first GANN-DEA network)
Using the efficiency obtained with the unit-independent SBM model, during the years 2012 to 2017 and the input and output data values of the unit-independent SBM model during these years, we construct the GANN-DEA model. We use 70% of the data at this stage as training data, 15% as test data, and the remaining 15% as generalized data.
Then, the ranking of the units of Tavanir regional electricity companies in 2017 is determined and the separation of efficient and inefficient units is done at this stage.
Step 4: (Modeling for inefficient units with PSOGA)
Using the hybrid PSOGA algorithm, we present the values of the slack variables of inputs and outputs (4 inputs and 2 outputs) to be used to improve the efficiency values in the next year. We perform this step by placing the data values of 2017 in the unit-independent SBM model. And we try to bring the efficiency value of the PSOGA hybrid algorithm closer to the efficiency of the GANN-DEA target, to obtain the values of the slack variables for the GANN-DEA, and for each inefficient unit a hybrid PSOGA algorithm is needed. The SBM model, independent of the data envelopment analysis unit, is placed in the fitting function of this algorithm, and we try to achieve the efficiency of the GANN-DEA model by trial and error and different settings of the parameters of this complex algorithm. From the best local answers obtained, the values of the slack variables are obtained, which is the well-known modeling of the data envelopment analysis model.
Step 5: (Modeling for efficient units)
To rank and provide a model for efficient units, we use the clustering method of decision-making units introduced by Azar, Daneshvar, Khodadad Hosseini and Azizi (2012) [32] and Toloui Ashlaghi, Afshar Kazemi and Abbasi (2013) [33]. Of course, this model of data envelopment analysis by Cook and Green has

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also been done under the title "Power Plant Evaluation: A Hierarchical Model" for the electricity industry [34]. Toloei Ashlaghi et al., As well as Azar et al. in this method remove the units that are efficient at the level of each, from the inputs and outputs of the model, and measure the efficiency again for the remaining units to create several levels of the efficiency boundary. (Units that work in the first level will be removed in the run after the model); But to model reference units (which are efficient at the first level), we build a virtual unit; in this way, we select the lowest of all inputs for each index and the highest of all outputs for each virtual unit. A virtual unit is a unit that, although not objectified, it is possible to achieve such a unit with a set of experienced units. After adding the virtual unit to the other decision-making units, we run the model again. Units that have been efficient so far have a efficiency of less than 1, and thus a reference unit can be defined for reference units [33,32], and this step is solved by the SBM model independent of the classical unit.

Step 6: (Build the second GANN-DEA network for efficient units and virtual units)

We implement and repeat the steps of the GANN-DEA model for the efficient units and the virtual unit described in step five. With the difference that for designing GANN-DEA model for efficient units, the data of 2016 and 2017 have been used. Also, 50% of the data was used as training data, 25% of the data was used as test data and the remaining 25% was used as generalized data due to the small data row.

\Step 7: (Modeling for efficient units with PSOGA algorithm)

The unit-independent SBM model described in the fifth step, with the data of 1396 we put in the hybrid PSOGA algorithm to modelling for efficient units, and again for each decision-making unit requires a separate PSOGA hybrid algorithm. The Conceptual framework of the present study is shown in Figure (1).

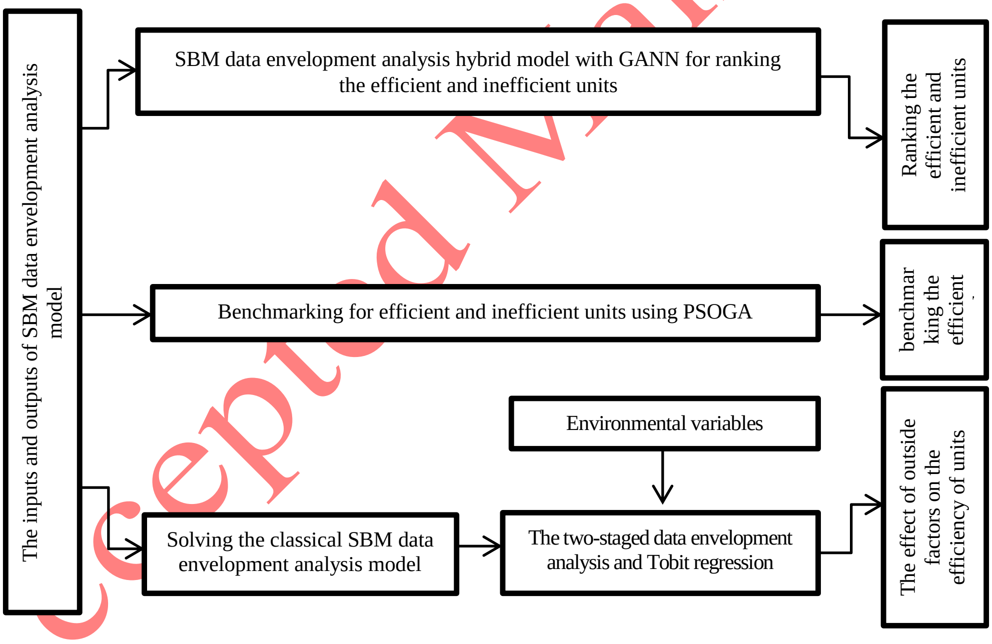

Figure (1) - Conceptual framework of the proposed model based on Tobit regression, GANN-DEA and PSOGA for evaluating the efficiency and modeling of efficient and inefficient units

Research Findings

Among efficient companies in 1396, the best efficiency belongs to 8 Region Electricity Company and the lowest super efficiency score belongs to 4 Region Electricity Company. The average efficiency scores of regional electricity companies have decreased slightly from 1392 to 1394, but from 1392 onwards, it continues its upward trend. Company 6 was recognized as efficient for the first time in 1396, while in previous years it has had a higher upward growth than other regional electricity companies. The efficiency values of Tavanir Regional Distribution and Transmission Companies using unit-independent SBM model and variable efficiency compared to the obtained scale are given in Table (2).

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Table (2) - Efficiency of SBM model independent of the unit and variable efficiency compared to the scale of Tavanir Regional Electricity Distribution and Transmission Companies during the years 2012 to 2017.

Regional electric company	DEA model	variables		Year						Mean SBM
		input	output	2012	2013	2014	2015	2016	2017	
Company(1)	SBM	1- Length of network lines (km), 2- Capacity of transformers (MV), 3- Number of employees (persons) and 4- Transmission and distribution losses (percentage)	1- Number of subscribers (thousand people), 2- The energy delivered to the subscribers (million kilowatt hours)	1	1	1	1	1	1	1
	Super Efficiency			1.06	1.06	1.02	1.03	1.03	1.03	--
Company(2)	SBM			1	1	1	1	1	1	1
	Super Efficiency			1.06	1.14	1.19	1.17	1.15	1.14	--
Company(3)	SBM			0.71	0.75	0.71	0.70	0.77	0.77	0.73
	Super Efficiency			0.43	0.75	0.71	0.70	0.77	0.77	--
Company(4)	SBM			1	1	1	1	1	1	1
	Super Efficiency			1.55	1	1	1	1	1	--
Company(5)	SBM			1	1	1	1	1	1	1
	Super Efficiency			1.35	1.13	1.10	1.08	1.09	1.10	--
Company(6)	SBM			0.86	0.80	0.82	0.78	0.81	1	0.84
	Super Efficiency			0.51	0.80	0.82	0.78	0.81	1.01	--
Company(7)	SBM			0.83	0.86	0.84	0.85	0.80	0.80	0.83
	Super Efficiency			0.48	0.86	0.84	0.85	0.80	0.80	--
Company(8)	SBM			1	1	1	1	1	1	1
	Super Efficiency			1.49	1.28	1.34	1.37	1.34	1.36	--
Company(9)	SBM			0.99	0.99	1	0.99	0.99	1	0.99
	Super Efficiency			1.16	0.99	1.01	0.99	0.99	1.01	--
Company(10)	SBM			0.66	0.71	0.72	0.70	0.69	0.71	0.70
	Super Efficiency			0.45	0.71	0.72	0.70	0.69	0.71	--
Company(11)	SBM			0.55	0.58	0.58	0.60	0.62	0.66	0.60
	Super Efficiency			0.44	0.58	0.58	0.60	0.62	0.65	--
Company(12)	SBM			1	1	1	1	1	1	1
	Super Efficiency			1.25	1.16	1.17	1.11	1.17	1.20	--
Company(13)	SBM			1	1	1	1	1	1	1
	Super Efficiency			1.17	1.16	1.11	1.09	1.10	1.09	--
Company(14)	SBM			0.80	0.83	0.82	0.84	0.78	0.80	0.81
	Super Efficiency			0.49	0.83	0.82	0.84	0.78	0.80	--
Company(15)	SBM			0.85	0.80	0.81	0.80	0.79	0.84	0.81
	Super Efficiency			0.45	0.80	0.81	0.80	0.79	0.84	--
Company(16)	SBM			1	1	1	1	1	1	1
	Super Efficiency			1.07	1.05	1.06	1.06	1.07	1.07	--
Mean	SBM	--	--	0.89	0.89	0.89	0.89	0.89	0.91	--

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Factors affecting the efficiency of the unit-independent SBM model with variable returns to scale, which are the results of the two-stage model of data envelopment analysis and Tobit regression are listed in Table (3).

Table (3) - Factors affecting the efficiency of the two-stage model of data envelopment analysis and Tobit regression

Variable	The final impact of variables	Statistic t	Significance value (P-value)
α_0	--	***2/935	0/887
CONSRESSHARE	-0/956	***-1/55	30/243
UGR	-0/649	*0/158	-0/321
CD2	-0/891	*-1/559	0/651
CD1	6/704	*0/154	0/075
LF1	-8/221	**-1/485	-0/545
LF2	7/975	*-1/181	0/142
DUMPRIVATE	0/445	**0/050	0/510
Log Likelihood	-8/399		
Chi-squared statistic	--	139/09	0/000
Likelihood ratio test	--	37/64	0/000
Number of views	112(censored: 51)		
Number of companies	16		
*,**,*** are respectively significance level of 1 percent, 5 percent and 10 percent using a two-tailed test.			

All seven environmental variables do not have a significant effect on the average the efficiency. In this study, due to the limitation in the collection of statistical data in the years before 1391 in Tavanir Regional Electricity Company, we have studied the short-term of environmental variables on group efficiency.
To implement the GANN-DEA model, we first designed the NN-DEA model according to what has been proposed in the research background and theoretical framework, and then by trial and error we obtained the best settings for NN-DEA and the genetic algorithm that optimizes it. The best GA settings included roulette wheel for selection and with an initial population of 20, two-point coupling with a rate of 0.9, a mutation with a uniform function and a mutation rate of 0.01 and a 60-minute or 100-generation stop condition were obtained. Comparison of the efficiency values of Tavanir regional electricity distribution and transmission companies in 1396, which was obtained using the unit-independent SBM model and variable efficiency relative to scale, with the efficiency values of GANN-DEA is given in Table (4).

Table (4) - Comparison of the efficiency of SBM model of data envelopment analysis unit-independent with GANN-DEA model in 2017.

	Regional electric company	SBM-DEA Model efficiency in 2017	GANN-DEA efficiency in 2017
1	Company(1)	1	0.99
2	Company(2)	1	0.99
3	Company(3)	0.77	0.77
4	Company(4)	1	1.00
5	Company(5)	1	1.00
6	Company(6)	1	1.00

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7	Company(4)	0.80	0.80
8	Company(8)	1	1.00
9	Company(9)	1	1.00
10	Company(10)	0.71	0.71
11	Company(11)	0.66	0.67
12	Company(12)	1	1.00
13	Company(13)	1	0.99
14	Company(14)	0.80	0.80
15	Company(15)	0.84	0.84
16	Company(16)	1	0.99
--	Mean	0.91	0.91

Efficiency estimation of 1396 with GANN-DEA with an average of 0.914704 and efficiency of 2017 with SBM model of data envelopment analysis with an average of 0.91278019 indicates acceptable learning of GANN-DEA network with data for six consecutive years. The efficiency of NN-DEA neural networks after optimization by genetic algorithm is given in Table (5).

Table (5) - Results of evaluation tools the function of genetic neural networks

Neural network performance	Output of neural network including all units	Output of neural network including efficient units
Mean squared error	0.0004	0.0001
Correlation coefficient	0.99	0.99

A summary of the optimization of the two neural networks with the genetic algorithm is presented in Table (6).

Table (6) - Summary of optimization with genetic algorithm for two NN-DEA neural networks

Optimization summary	Best fitness (neural network including all units)	Mean fitness (neural network including all units)	Best fitness (neural network including efficient units)	Mean fitness (neural network including efficient units)
Generation	4	5	5	7
Lowest mean squared error	0.0004	0.001	0.00	0.0001
Mean final Squared error	0.0004	0.001	0.00	0.0001

The lowest mean squared error and the mean squared value of the final error for a genetic neural network, one includes all the units and the other includes the efficient units and the virtual unit are all at an acceptable level.The best settings of PSOGA hybrid algorithm include perceptual and social component 1.5, maximum inertia coefficient 0.9 and minimum inertia coefficient 0.4, single point coupling with a rate of 0.85, mutation rate of 0.02, mutation with uniform function, initial population for each particle in genetic algorithm 10, minimum number of iterations in genetic algorithm 10, the highest number of replications in genetic algorithm is 20, the lowest number of individuals in genetic algorithm 1, the reduction rate of the number of individuals affected by genetic algorithm (γ) 10 and the maximum increase rate of replication of genetic algorithm (β) 15. The efficiency values estimated by the GANN-DEA and PSOGA algorithms for inefficient and efficient units as well as the slack variable values obtained for modeling inefficient units by the PSOGA hybrid algorithm are presented in Tables (7) and (8).

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Table (7) - GANN-DEA and PSOGA efficiency values for inefficient units and slack variable values for modeling the inefficient units by PSOGA

Regional electric company	GANN-DEA efficiency	PSOGA efficiency	S6(PSOGA)	S5(PSOGA)	S4(PSOGA)	S3(PSOGA)	S2(PSOGA)	S1(PSOGA)
Company(3)	0.778652	0.774007	5.01E-05	5E-05	0.199862	255.4729	2655.433	4075.862
Company(11)	0.676048	0.671708	4.97E-05	5.01E-05	0.027146	998.0688	8475.363	6153.824
Company(10)	0.710237	0.716365	5.26E-05	5.02E-05	0.542077	89.37919	1933.935	4786.697
Company(15)	0.847341	0.844972	920.3739	0	0.873357	104.7047	1884.729	1.09E-05
Company(14)	0.805315	0.803648	5.11E-05	4.98E-05	0.458319	130.4469	1723.022	1136.608
Company(7)	0.807656	0.804789	5.04E-05	5.01E-05	0.591003	155.0925	577.446	1044.265

Table (8) - GANN-DEA and PSOGA efficiency values for efficient units and slack variable values for modeling the efficient units by PSOGA

Regional electric company	GANN-DEA efficiency	PSOGA efficiency	S6(PSOGA)	S5(PSOGA)	S4(PSOGA)	S3(PSOGA)	S2(PSOGA)	S1(PSOGA)
Company (1)	0.344872	0.340418	787.828	0.009154	0.945692	872.8638	6549.98	5932.302
Company (2)	0.404413	0.404158	5350.029	19122.69	0.510794	521.3247	13542.99	7569.992
Company (5)	0.381241	0.382902	4888.003	24094.56	0.508069	2167.97	35128.99	6882.992
Company (6)	0.291241	0.29752	0.040636	20010.93	1.166796	1884.068	21156.98	6458.989
Company (8)	0.926037	0.928995	7580.16	36352.14	0.191	81.53098	0.001055	0.001321
Company (9)	0.499521	0.495196	34892.85	1.519953	612.2031	1031.076	5333.992	0.439948
Company (13)	0.689944	0.682042	948.7077	2275.122	1.12	437.9996	2217.995	604.9967
Company (16)	0.742596	0.748482	7539.807	34205	0.001	192.0088	2476.154	1545.257
Company (4)	0.291444	0.2952163	0.001	0.001	0.6377	2222	35130.007	6882.999
Company (12)	0.560727	0.5673636	7067.6872	30429.006	1.1889	0.00287	5623.0078	6028.922

With the PSOGA algorithm, we try to obtain the performance value in a way that is close to the GANN-DEA performance value. The values obtained with the slack variables will be the patterns of the decision units. By decreasing the values of the input variables and increasing the values of the output variables.

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For example, the regional electricity company 3 in Table (7) should, reduce the length of grid lines by 4075.862 km, the capacity of transformers by 2655.433 mV, the number of employees by 255 and the transmission and distribution losses by 0.199862%. And increase the number of subscribers to 0.00005 thousand people and the energy delivered to the subscribers by 0.0000501 million kilowatt hours to reach the efficient border.

Of course, the same interpretation applies to Table (8), but the regional power companies in this table are efficient and try to reach the virtual efficiency limit, which has the lowest values of input variables and the highest values of output variables, Reaches.

NN-DEA models have not been able to modeling the decision-making units in research to date. However, in the present study, this was made possible by the PSOGA hybrid algorithm. The addition of modeling for efficient units is another feature of the present study that was not possible to date for the NN-DEA model. Also, NN-DEA network optimization has been done for the first time in the current research, which has a faster rate of NN-DEA network convergence.

Considering that the data collection of Tavanir Regional Electricity Transmission and Distribution Companies are updated every two months or even less, the above proposed model will be able to evaluate the new conditions with a training once available from the existing 6-year data. And provide the proposed values for increasing or decreasing data on network lines length(km), transformer capacity (megavolt amperes), number of employees (person) and transmission and distribution losses(percentage), number of subscribers(thousand people) , and energy delivered to subscribers (million kWh).

Tobit regression in the proposed model will be able to determine the final effect of environmental variables (exogenous) on the average of efficiency of units and the direction of their effect (positive or negative).

Research Limitations

In the present study, due to the limitation of collecting statistical data in the years before 1391 in Tavanir Regional Electricity Company, we have been satisfied with a short-term study of environmental variables on group efficiency.

Conclusions and suggestions

The proposed model based on Tobit regression, GANN-DEA and PSOGA for evaluating the efficiency and modeling of efficient and inefficient units, in addition to having the features and capabilities of classical data envelopment analysis models, is a tool that has new capabilities, including considering the efficiency of several consecutive years to estimate the efficiency of the last year, very little impact on disturbance data, providing a model for inefficient units with considering GANN-DEA efficiency , and also modeling for efficient units considering GANN-DEA efficiency .

It can also measuring the impact of environmental variables that are not under the control of the organization's senior managers on the average the efficiency of the unit-independent SBM and provide for the organization's evaluators. For future research, it is suggested that Malcom Quist, multi-stage and fuzzy data envelopment analysis models be designed similar to the multi-stage proposal model of this research. Of course, bio-efficiency models of data envelopment analysis with very similarity to the current research will be feasible. Corporate development budget index and climate indicators (such as humidity, salt content and particulate matter) are also suggested for designing propositional models similar to the present research.

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