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Estimating Efficiency of Bank Branches by Dynamic Network Data Envelopment Analysis and Artificial Neural Network

Javad Niknafs, Mohammad Ali Keramati*, Jalal Haghighat Monfared

Department of Industrial Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran

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ABSTRACT

Network data envelopment analysis models assess efficiency of decision-making unit and its sections using historical data but fail to measure efficiency of its units and their internal stages in the future. In this paper we aim to measure efficiency of stages of bank branches and obtain efficiency trend of stages during the time, then to estimate their efficiency in the future therefore we can be aware of stages inefficiency before occurrence and prevent them. First, a two-stage structure including deposit collection and loan giving was designed for bank branches using literature review and comments of experts. Human forces and fixed assets were considered as input variables of the first stage, deposit as mediator variable, delayed claims as interim variable, and loan amount as output variable of the second stage. Then, a dynamic network data envelopment analysis model was formulated and stages efficiency were obtained for 16 consecutive periods. Therefore, efficiency trend of stages was obtained during the time. In the following, efficiency of various stages of branches were estimated using artificial neural network and some recommendations are provided according to obtained amounts in order to prevent inefficiency before occurrence.

1 Introduction

Data envelopment analysis (DEA) has been used in assessment of relative efficiency of bank branches [1-3]. Charnes and his colleagues proposed this technique in 1978 to evaluate decision-making units that have similar tasks [4]. Since activities of bank branches in the current time depend on their activities in the past, banks efficiency assessment in consecutive periods is of considerable importance [5-6]. Dynamic DEA is used for overall efficiency calculation. However, the structure of units is still considered as a black box. Classic models of DEA use the black box approach and do not pay attention to internal structure. Therefore, it cannot be specified that inefficiency of a unit to which a stage is related and it cannot be determined which stage of a unit must be considered in order to increase efficiency. Färe and Grosskopf [7], trying to appraise the internal structure of decision-making units [8], proposed network DEA in 2000. Then, dynamic models were developed in order to assess units in consecutive periods, and network models were provided to remove the deficiency of black box approach considering the internal structure of units. For this purpose, a model is required, which considers both time and unit's internal structure. Therefore, dynamic network data envelopment analysis (DNDEA) models were developed [9]. In these models, efficiency in consecutive periods is calculated and analysed for stages. Dynamic network models are used in various [10-13]. Traditional models of Network data envelopment analysis (NDEA) and dynamic NDEA cannot forecast future efficiency of

* Corresponding author. Tel.:*+989123872393*
E-mail address: *mohammadalikeramati@yahoo.com*

decision making units (DMUs). In other words, all models of NDEA and dynamic NDEA evaluate and rank DMUs and their internal structure based on past performance. This paper opens a new perspective to realm of NDEA as it proposes a transition from previous supervising models to a future planning approach which contains novel contributions. On the other hand, network DEA models depend on historical data and are not able to estimate the efficiency trend of decision-making units and their internal structure. The main goal of this paper is to estimate the efficiency trend of decision-making units (bank branches) and their internal structure in the future. This issue is of significant importance since the occurrence of inefficiency in network structure can be prevented. Moreover, some suggestions can be proposed based on the amount of efficiency amount in the future to make inefficient unit more efficient. Artificial neural network is used in clustering, classification and ranking. In addition, it is applicable in future predictions [14-15]. In this paper, DNDEA has been used together with artificial neural network to estimate the efficiency of internal structure of decision-making units (bank branches) in future. By doing this, decision-makers can detect sources of efficiency in the internal structure of bank branches before their occurrence and decide about them. Therefore, estimating the amount of efficiency can control future efficiency. Controlling the efficiency of a decision-making unit and its stages, maintaining the efficiency of efficient units and preventing the inefficiency of stages of a decision-making unit before occurrence of inefficiency are of necessities for the current research.

2 Literature Review

2.1 Network Data Envelopment Analysis

Classic models of DEA consider decision-making units as black box and neglect internal structure of units and relationships between them [16-17]. Therefore, useful information in case of sources of inefficiency of a unit's stages will be lost and this is a fundamental weakness [18-19] and can lead to the lack of accurate calculation of efficiency [20]. Färe and Grosskopf [21] utilized a network approach and implemented efficiency using a model with intermediate product. Kao and Hwang [22] designed a two-stage model in which outputs of the first stage are considered as inputs of the second stage and are referred to as intermediate amounts and the second stage itself has outputs which are called final output of the model. Overall efficiency will also will be obtained from efficiencies of both stages. Kao [23] used serial and parallel structures to assess decision-making units in which overall efficiency obtained from multiplying efficiency of stages. Cook et al. [17] introduced multi-stage models in which the outputs of each stage could be considered as the final output and get out of the systems, or could be entered as input variable at the next stage. In this model, each stage can also take inputs from the external environment. Zhou et al. [24] proposed a two-stage model based on the theory of games. The model calculates the efficiency of sub-systems so that overall efficiency does not change. Chen et al. [18] provided a model having two hypotheses of fixed return to scale and variable return to scale so that overall efficiency is obtained from weighted sum of two stages. Kao [25] classified all studies in the field of network DEA and recommended some suggestions for further studies one the was dynamic network models.

2.2 Dynamic Network Data Envelopment Analysis

Dynamic network models consider both structure and time in assessment of stages efficiency of a unit. Tone and Tsutsui [26] provided a dynamic network model based on deficient variables in which interim variables can have positive or negative impact on the next period. This model has also been used in other studies. Soltanzadeh and Omrani [27] have used this model with fuzzy inputs and outputs in airlines. In addition, Khushalani and Ozcan [28] used this model to evaluate efficiency of hospitals. Other studies also have been conducted to develop dynamic network models [9,11,29-31].

2.3 Banks Efficiency Assessing

Given the rapid development of the banking sector, it is reasonable to expect that the performance of banks has become the centre of attention among bank managers, stakeholders, policy makers, and regulators [32] As the main symbol of the money market, banks and financial institutions, can play an important role in the cash and credit flow and consequently, in economic growth and development, in Iran [33]. Assessment of bank efficiency has been conducted using network and dynamic network models in following studies. Fukuyama and Weber [34] utilized a network DEA based on deficiency variables to appraise efficacy of Japanese banks. Holod and Lewis [35] considered deposit as an intermediate variable and used a non-radial network model. Lin and Chiu [6] considered a network model in banks of Taiwan. Akther et al. [36] considered bank structure as a two-stage structure and calculated inefficiency in banks of Bangladesh. Fukuyama and Matousek [37] utilized a network model based on deficiency variable to assess bank performance considering an undesirable output. Akbari et al.[38] utilized a network DEA based on deficiency variables to appraise efficacy of Iranian banks. Kao and Liu [10] paid attention to time and evaluated commercial banks of Taiwan in multiple periods. They considered units (banks) in consecutive periods as a parallel network. They used Kao's model [39] with parallel structures to measure efficiency and obtained both overall efficiency and period efficiency, but weakness of their work was that they did not consider relationship of each unit with itself in consecutive periods. Zha et al. [29] provided a model based on deficiency variables to assess a dynamic two-stage structure for bank and used it to appraise efficiency of Chinese banks. Avkiran [11] designed a dynamic network model for commercial banks and showed that a more comprehensive analysis on efficiency estimation can be provided considering dimensions of network and time. Moreno and Lozano [30] provided a super dynamic network model. Wu et al. [31] investigated effect of revenue management on performance of banks and for this purpose, provided a dynamic network model based on deficiency variables. Fukuyama and Weber [12-13] developed dynamic network models introducing a dynamic network structure for Japanese banks. Soleymani Mal Khalifeh et al. [9] developed a dynamic network model to evaluate bank performance. However, these models are not applicable to estimate efficiency in the future and must be combined with a prediction technique [47].

2.4 Artificial Neural Network

McCulloch and Pitts [40] showed that neural network is capable to be expressed in a mathematical algorithm and provided the first artificial neural networks [41]. Neural networks provide a self-organizing method based on mathematical algorithm to resolve problems [42]. Neural networks have several applications such as echology [43], prediction [14,44], classification [42,45] and clustering [46].

Emrouznejad and Shale [48] measured efficiency of decision-making units using combination of artificial neural network and DEA. Desheng et al. [49] used a combination of artificial neural network and DEA to assess efficiency of banks in Canada. Chun Tsai et al. [50] evaluated customers to receive loan in banks of Taiwan combining artificial neural network and DEA. This paper obtained efficiency in consecutive periods and then estimated efficiency of next period via combining artificial neural network and dynamic network DEA.

3 Research Methodology

The study utilizes an analytical method that is of mathematical analysis research methods aiming to develop relationships between concepts defined by mathematical relationships [51]. The following stages have been conducted to obtain objectives of the research. First, structure of bank branches and input and output variable were specified. Then, a dynamic network model was formulated and implemented for 16 periods using past information and efficiency of internal structure of a unit's stages was evaluated. Finally, amounts of efficiency were estimated for 17 periods using neural network.

3.1 NAR Neural Network

In this paper, NAR artificial neural network has been used for prediction. The network is a regressive dynamic neural network with multiple layers to predict auto regression processes.

Fig. 1: Regressive neural network

This network is able to predict future amount of x(t) having the previous amounts of time series of x(t-1),…, x(t-d)

$$X(t)= f(x(t-1),\dots,x(t-d)) \quad (1)$$

After network training, the network was used for prediction. Fig. 3 shows the circular network used for future prediction.

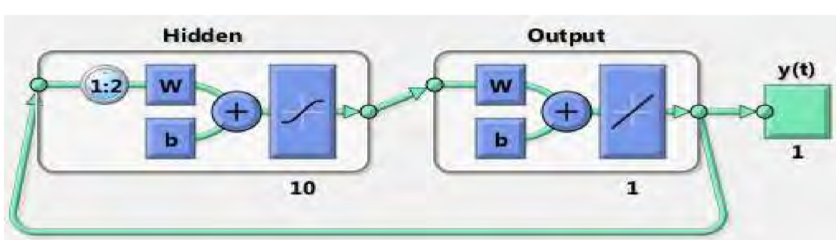

Fig. 2: Closed neural network

3.2 Structure of Dynamic Network DEA Model

A two-stage network structure for bank branches was designed according to theoretical principles and comments of experts. Fig. 3 shows the structure for two consecutive periods. In this structure, the first stage was named deposit collection and inputs of the stage included number of human forces and fixed assets. The second stage was named loaning. Inputs of this stage included output of the first stage (deposit) and delayed claims (interim variable) of the previous stage. Finally, amount of given loan was defined as output of the second stage [5,37].

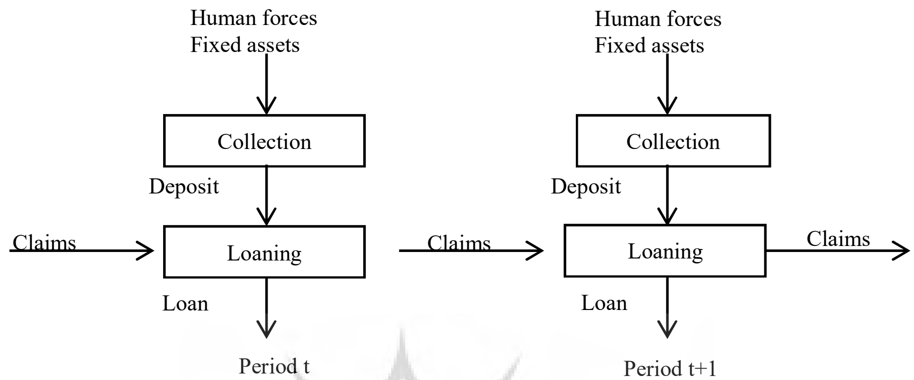

Fig. 3: Two-stage network structure for bank branches in two consecutive periods

3.3 Proposed Algorithm

First, Structure of dynamic network was designed according to the bank structure using library studies and experts' comments as shown in Fig. 4. Then, a dynamic network data envelopment analysis model was formulated and stages efficiency were obtained for 16 consecutive periods. Therefore, efficiency trend of stages was obtained during the time. Number of personnel (x_1) and amount of fixed assets (x_2) are inputs in the first stage and deposit amount (z) is output of this stage. In the second stage, in addition to inputs received from the first stage (z), there exists an input from previous period of interim variable (k) and amount of loan (y) is defined as the second stage's output variable.

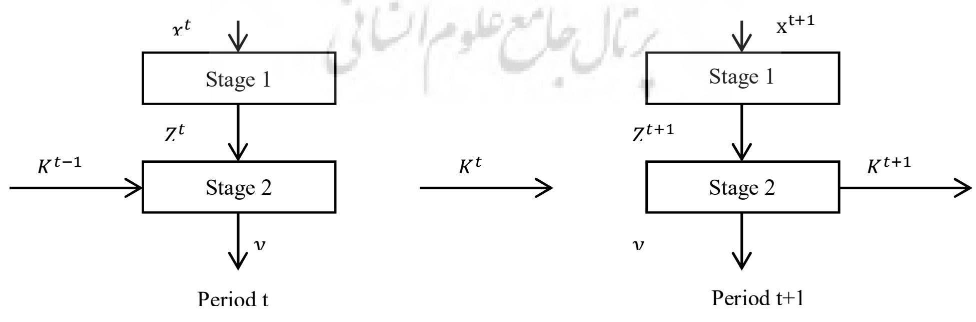

Fig. 4: Two-stage network structure for bank branches in two consecutive periods

Variable of model are defined as following:

$x_{ij}{}^{t}(i = 1, \dots, I; j = 1, \dots, n; t = 1, \dots, t)$ — *i*th input, stage 1, *j*th unit in period *t*

$Z_j{}^{t}(j = 1, \dots n; t = 1, \dots, t)$ — intermediate variable of *j*th unit in period *t*

$K_j{}^{t}(j = 1, \dots n; t = 1, \dots, t)$ — output of stage 2, *j*th unit in period *t* (interim variable)

$Y_j{}^{t}(j = 1, \dots n; t = 1, \dots, t)$ — output of stage 2, *j*th unit in period *t*

$K_j{}^{t-1}(j = 1, \dots n; t = 1, \dots, t)$ — output of stage 2, *j*th unit in period *t-1* (interim variable)

Dynamic network structure DEA model for stages efficiency assessment in a decision-making unit was formulated according to the model proposed by Tone and Tsutsui [26] as follows.

$$Min\ \frac{\sum_{t=1}^{P} w^t \left[1 - \frac{1}{4}\left(\sum_{i=1}^{2} \frac{s_i^{(t)[1]-}}{x_{i0}^{(t)[1]}} + \frac{\hat{s}^{(t)-}}{Z_0^t} + \frac{\hat{s}_0^{(t)+}}{K_0^t}\right)\right]}{\sum_{t=1}^{P} w^t \left[1 + \frac{1}{3}\left(\frac{s^{(t)+}}{y_0^{(t)}} + \frac{\hat{s}^{(t)+}}{Z_0^t} + \frac{\hat{s}_0^{(t-1)-}}{K_0^{t-1}}\right)\right]}$$

$$\sum_{j=1}^{n} \lambda_j{}^{(t)[1]}\, x_{ij}{}^{(t)[1]} + S_i{}^{(t)[1]-} = x_{i0}{}^{(t)[1]}, i = 1,2, t = 1, \dots, P$$
$$\sum_{j=1}^{n} \lambda_j{}^{(t)[2]}\, y_j{}^{(t)} - S^{(t)+} = y_0{}^{(t)}, t = 1, \dots, P$$
$$\sum_{j=1}^{n} \lambda_j{}^{(t)[1]}\, Z_j{}^{(t)} - \hat{S}^{(t)+} = Z_0{}^{(t)}, t = 1, \dots, P$$
$$\sum_{j=1}^{n} \lambda_j{}^{(t)[2]}\, Z_j{}^{(t)} + \hat{S}^{(t)-} = Z_0{}^{(t)}, t = 1, \dots, P$$
$$\sum_{j=1}^{n} \lambda_j{}^{(t)[2]}\, K_j{}^{(t-1)} - \hat{S}^{(t-1)-} = K_0{}^{(t-1)}, t = 1, \dots, P$$
$$\sum_{j=1}^{n} \lambda_j{}^{(t)[2]}\, K_j{}^{(t)} + \hat{S}^{(t)+} = K_0{}^{(t)}, t = 1, \dots, P$$
$$\lambda, S > 0$$

In the following, efficiency of various stages of branches were estimated using artificial neural network.

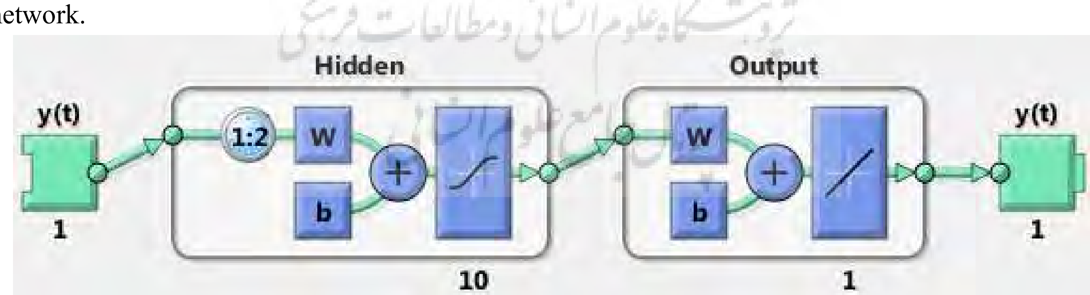

Fig. 5: Architecture of neural network

The neural network that is used in this research and showed in Fig. 5, has 10 neurons in intermediate layer and time delay of 1:2. Number of neurons and time delays obtained by trial and error. Levenberg Marquardt (LM) algorithm was used for network training. In this network, 70% of data has been used for training, 15% for validation, and 15% for prediction. Fig. 2. Shows network architecture of the study.

4 Case Study

4.1 Data Information

Amounts of these variables collected from bank branches for six-month periods between 2011 and 2017 (16 periods in total). Odd and even periods represent the first and the second half of year, respectively. Table 1 shows collected information for three last periods.

Table 1: Amounts of model variables for periods 14, 15 and 16.

Period 14					Period 15					Period 16					
Loan	Claims	Deposit	Fixed assets	Human forces	Loan	Claims	Deposit	Fixed assets	Human forces	Loan	Claims	Deposit	Fixed assets	Human forces	Bank branch
185	9	173	15.9	8	73	12	98	17	8	146	6	195	17	8	1
233	10	133	26.7	10	121	19	74	28.5	10	242	10	148	28.5	10	2
225	8	107	13.6	11	107	23	66	14.5	11	214	12	132	14.5	11	3
127	6	120	11.4	8	65	15	73	12.1	8	130	8	145	12.1	8	4
222	8	101	12.1	8	105	27	54	12.9	8	211	13	109	12.9	8	5
161	11	93	9	8	98	23	63	9.6	8	197	11	126	9.6	8	6
234	12	125	7.3	10	110	25	85	7.8	10	220	12	170	7.8	10	7
213	8	136	23.9	10	105	23	77	25.5	10	210	11	155	25.5	10	8
224	9	107	22.8	9	118	21	63	24.3	9	236	10	125	24.3	9	9
121	4	109	22.5	7	55	7	67	24	7	111	3	134	24	7	10
28	14	105	9	7	130	24	60	9.6	7	261	12	119	9.6	7	11
145	10	91	9	8	96	18	62	9.6	8	192	9	114	9.6	8	12
238	14	118	7	9	122	29	64	7.4	9	243	14	127	7.4	9	13
108	3	128	6.8	9	65	13	71	7.2	9	130	6	142	7.2	9	14
139	7	133	10.9	9	67	13	74	11.6	9	133	7	148	11.6	9	15
141	6	153	13.6	7	69	13	82	14.5	7	138	6	163	14.5	7	16
266	12	115	28.5	7	138	30	70	30.4	7	275	15	141	13.4	7	17
212	11	161	11.9	10	113	33	88	12.7	10	226	16	175	12.7	10	18
260	8	113	26.3	8	129	25	64	28.1	8	257	13	127	28.1	8	19
155	8	137	7.9	6	82	25	84	8.4	8	164	12	167	8.4	8	20
197	11	129	5.6	8	96	22	73	5.9	8	191	11	146	5.9	8	21
108	3	177	12	12	66	16	97	12.8	12	132	8	193	12.8	12	22
152	5	159	19.3	8	81	16	100	20.6	8	163	8	200	20.6	8	23
235	8	110	11.5	7	118	25	65	12.3	7	237	12	131	12.3	7	24

4.2 Results and Analysis

Efficiency of branches formulated using the proposed model for 16 periods and implemented via Lingo software. Table 2 presents the results including efficiency of stage 1, efficiency of stage 2 and overall efficiency. In addition, Table 2 presents performance of each period and each year compared to other branches and share of each stage and each year in efficiency and inefficiency.

Table 2: Amounts of calculated efficiency using dynamic network model for four last periods

Period 16			Period 15			Period 14			Period 13			Bank
Overall	2nd half	1st half	Overall	2nd half	1st half	Overall	2nd half	1st half	Overall	2nd half	1st half	Branch
0.37	0.12	0.72	0.15	0.10	0.72	0.25	0.20	0.78	0.09	0.08	0.78	1
0.16	0.15	0.39	0.17	0.16	0.39	0.38	0.44	0.43	0.21	0.20	0.43	2
0.64	0.84	0.44	0.53	0.65	0.44	0.67	1.00	0.43	0.57	0.71	0.44	3
0.53	0.64	0.43	0.48	0.55	0.44	0.60	0.77	0.44	0.38	0.41	0.43	4
0.71	1.00	0.45	0.54	0.66	0.45	0.75	1.00	0.51	0.65	0.80	0.50	5
0.75	0.90	0.61	0.67	0.76	0.60	0.65	0.78	0.55	0.59	0.66	0.55	6
0.82	0.81	0.87	0.75	0.70	0.87	0.81	0.85	0.82	0.61	0.53	0.81	7
0.63	0.83	0.43	0.50	0.60	0.42	0.62	0.80	0.46	0.57	0.69	0.45	8
0.65	1.00	0.37	0.60	0.83	0.37	0.64	0.91	0.39	0.44	0.52	0.38	9
0.74	1.00	0.48	0.73	1.00	0.48	0.73	1.00	0.48	0.27	0.26	0.47	10
0.80	1.00	0.61	0.80	1.00	0.61	0.83	1.00	0.66	0.83	1.00	0.66	11
0.72	0.85	0.60	0.71	0.83	0.59	0.63	0.75	0.54	0.50	0.53	0.53	12
0.83	0.98	0.68	0.76	0.85	0.68	0.79	0.85	0.77	0.70	0.65	0.76	13
0.79	0.84	0.77	0.48	0.40	0.77	0.92	1.00	0.84	0.59	0.55	0.84	14
0.62	0.66	0.61	0.63	0.67	0.61	0.62	0.64	0.67	0.47	0.43	0.66	15
0.75	0.82	0.70	0.63	0.61	0.70	0.74	0.73	0.80	0.48	0.40	0.80	16
0.71	0.95	0.47	0.62	0.78	0.47	0.70	0.92	0.47	0.73	1.00	0.47	17
0.70	0.78	0.66	0.56	0.58	0.66	0.69	0.72	0.74	0.60	0.57	0.73	18
0.64	0.91	0.39	0.51	0.64	0.39	0.69	0.97	0.43	0.65	0.89	0.42	19
0.88	0.79	1.00	0.68	0.45	1.00	0.81	0.65	1.00	0.73	0.50	1.00	20
0.57	0.68	0.70	0.55	0.37	0.69	0.63	0.82	0.79	0.60	0.57	0.73	21
0.61	0.60	0.68	0.37	0.31	0.68	0.80	0.86	0.76	0.61	0.54	0.75	22
0.35	0.67	0.69	0.52	0.47	0.68	0.64	0.64	0.67	0.47	0.44	0.56	23
0.79	0.96	0.60	0.61	0.66	0.59	0.76	0.90	0.61	0.73	0.83	0.61	24

Fig. 6 shows efficiencies of stage 1 (deposit collection) and stage 2 (loaning) independently for branches 11 and 12. As it is visible in Fig. 6, the first stage of Branch 12 until period 6 is more efficient than Branch 12, but in the following, Branch 11 obtained higher efficiency. In addition, efficiency of the second stage of Branch 11 is almost fixed until period 6, but since period 7 the amount is increasing and reaches full efficiency in period 9.

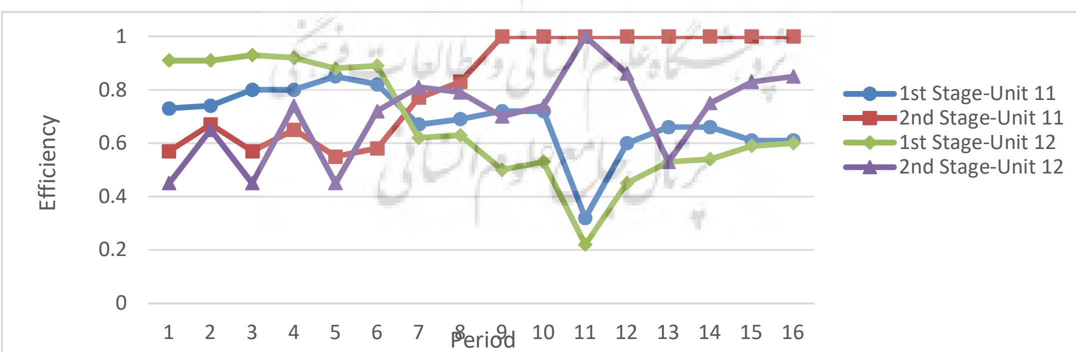

Fig. 6: Efficiency of stages of units 11 and 12 in 16 periods

However, efficiency of the second stage for Branch 12 has experienced high fluctuation in various periods. In general, Branch 11 has been more efficient than Branch 12 in both stages. In general, efficiency of the second stage in odd periods (related to the first half of year) are lower than those of even periods and this can be attributed to lack of ability of clients to pay installments in the first half of year. Then, efficiency estimation in the next period was performed using artificial neural network. This prediction was done using data of 24 bank branches in 16 periods using MATLAB software. After calculating MSE (amounts of Table 2), amounts of efficiency for period 17 has been predicted and presented in Table 3. Since training of any model of neural networks follows a probabilistic process and inputs are selected randomly, therefore errors obtained for each run of model will be different. Therefore, a mean error is obtained after several runs of model. In this study, seven repetitions were implemented and the results are presented in Table 4. This table shows prediction accuracy of each variable for periods for each of bank branches. The least amount of MSE in the first stage is related to Unit 21 (0.0001) and the least amount in the second stage was obtained for Unit 3 (0.0055).

Table 3: Predicted values for period 17

EFFICIENCY			DMU	EFFICIENCY			DMU
Overall	Stage2	Stage1		Overall	Stage2	Stage1	
0.64	0.88	0.58	13	0.63	0.21	0.78	1
0.65	0.39	0.60	14	0.74	0.11	0.51	2
0.63	0.11	0.50	15	0.60	0.61	0.57	3
0.63	0.84	0.58	16	0.69	0.07	0.57	4
0.66	1.00	0.51	17	0.74	0.59	0.52	5
0.73	0.42	0.74	18	0.60	0.68	0.48	6
0.55	0.82	0.4	19	0.74	0.76	0.72	7
0.58	0.88	0.99	20	0.56	0.57	0.59	8
0.46	1.00	0.67	21	0.55	0.24	0.31	9
0.49	0.85	0.61	22	0.62	0.22	0.43	10
0.46	0.76	0.55	23	0.67	1.00	0.62	11
0.56	0.75	0.61	24	0.65	0.75	0.71	12

Table 4: Values of MSE

MSE			DMU	MSE			DMU
Overall	Stage2	Stage1		Overall	Stage2	Stage1	
0.0301	0.0202	0.0800	13	0.0561	0.0470	0.0357	1
0.0341	0.0066	0.0241	14	0.0355	0.0631	0.0155	2
0.0084	0.0141	0.0404	15	0.0065	**0.0055**	0.0064	3
0.0486	0.0071	0.0181	16	0.0123	0.0471	0.0711	4
0.0042	0.0622	0.0487	17	0.0096	0.0201	0.0291	5
0.0097	0.0073	0.0205	18	0.0160	0.0864	0.0327	6
0.0189	0.0128	0.0248	19	0.0164	0.0497	0.1032	7
0.0510	0.0922	0.0067	20	0.0053	0.0203	0.0091	8
0.0125	0.0456	**0.0001**	21	0.0134	0.0420	0.0037	9
0.0945	0.0279	0.0804	22	0.0272	0.0369	0.0069	10
0.0305	0.0368	0.0209	23	0.0090	0.1830	0.0163	11
0.0131	0.0288	0.0126	24	0.0217	0.0470	0.0357	12

Efficiency estimation of the next period can provide useful information to design a plan to make inefficient units efficient. For example, efficiency of the second stage (loaning) for Branch 12 in Period 12 is equal to 0.85, and this means that if the branch wants to make only the second stage efficient independently from stage 1, it should increase its loans by 1.17 times (1 divided to 0.85) according to historical data. However, efficiency prediction of this stage shows that its efficiency in the next period will be 0.75. Therefore, if the unit wants to increase its loans by 1.17 times, it will be inefficient in the next period and should increase the amount by 1.33 times (1 divided to 0.75). As it can be seen in Table 3, efficiency of Stage 1 (loaning) of Branch 12 in period 16 is equal to 0.60 and this means that if the unit wants to make only stage 1 efficient independently from stage 2, according to historical information it should give 1.66 times (1 divided to 0.60) more loans. While the predicted value for efficiency in period 17 is 0.71, therefore this stage will reach full efficiency by increasing to 1.40. This can be considered as a plan for stages of Branch 12 in period 17. Therefore, by estimating the efficiency of next period, a more accurate targeting can be provided for stage of deposit collection and loaning and thereby inefficiency can be prevented in the future.

5 Conclusion

Efficiency of various stages of bank branches including deposit collection and loaning during the time through designing and resolving DNDEA model. The results showed that loaning stage compared to deposit collection stage has obtained more full efficiency records but it has experienced higher fluctuations in various periods while efficiency trend in the first stage had more stability in the branches. Efficiencies off all units in Period 11 for deposit collection stage have experienced a decrease drastically and this can be attributed to environmental factors. Efficiency in some of branches e.g. Branch 3 in deposit collection stage, has been almost fixed during the study time and in some branches e.g. Branch 12 in the second stage, there been existed much fluctuations. Investigating the reason of severe fluctuations can be studied in the future works. As it is specified in the assessment, some of branches have descending trend in efficiency, therefore a plan can be developed to prevent the decrease in their efficacy and occurrence of inefficiency in the future (e.g. Stage 1 of Branch 18 in the last three periods). In addition, some of branches have experienced ascending trend in efficiency. In these cases, required controls can be performed to robust and reach full efficiency (e.g. Stage 2 of Branch 6 in the last four periods). Some of branches are efficient in various periods (e.g. efficiency in deposit collection for Branch 20).

This issue can be investigated in the future works to study reasons of continuous efficiency in various periods. In some of branches such as Branch 20 which have high efficiency in the first stage, efficiency of the second stage in low. This can be attributed to conflict between departments in the branch. Reaching to high efficiency for a branch as a whole, not for each department of the branch is the case than can be investigated in the future research. In this research, a new approach has been provided to predict efficiency in the future via combining DEA models with prediction techniques. This enhances the role of managers from evaluator to planner. Predicting the values of efficiency, we can control efficiency in the future. Efficiency control for a decision-making unit and its stages, maintaining the efficiency of efficient units, and preventing the inefficiency of stages of a decision-making unit before their occurrence are of necessities of the present work. Since neural network model has several applications in prediction, values of efficiency for next period was obtained by combining these models and DNDEA. According to the results, managers can calculate efficiency of stages of future for a branch and plan to increase efficiency. For example, if the future efficiency has decreased compared to the previous periods, efficiency decrement can be prevented by providing an appropriate plan. This case can be seen in Stage 2 of Branch 12 in which it has been predicted that efficiency will be decreased in period 17. In addition, efficiency of Stage 2 for units 9 and 10 that are calculated equal to 100% according to the values of model, and it is predicted that these units will be inefficient in period 17. Therefore, at the current time, managers can decide about required actions to prevent this inefficiency in loaning. In addition, in case of branches that prediction shows an efficient future about them, they should attempt to maintain the current situation and avoid change in order to keep their way. Calculating a range of input and output variables in which efficiency will be maintained and considering these values as a target for efficient units is a subject for future works. In addition, a better plan can be provided according to historical data in order to increase efficiency of inefficient units by using the values.

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