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A novel method for forecasting the Malmquist productivity index by artificial neural network: Evidence from Iranian commercial bank

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Abstract
Banks are the most important part of today's economy and society. Therefore, their performance and productivity measurement is crucial. This study attempts to calculate productivity change of one of the Iranian commercial banks for the five years' period. The Malmquist productivity index was selected as measurement tool of efficiency and technical changes. In literature mostly a static form for calculating the Malmquist productivity index was available. As few studies have been conducted in dynamic form this, in this study the forecasted progress or regress for bank branches is calculated by integrating artificial neural network and Malmquist index. The results demonstrated that more branches' productivity would progress in next sixty months.

Keywords: Malmquist productivity index; Artificial neural network; Data envelopment analysis; progress or regress.

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1. Introduction

As Commercial banks play important role in nation's economy, the efficiency related studies of financial institutions has increased enormously, such as Berger and Humphrey [1].

For surviving in today's ever-changing business environment, efficient use of resources to enhance productivity as well as achievement of planned activities is crucial for bank branches. Malmquist productivity index (MPI) is a pioneer approach in literature for analyzing productivity changes. The idea of using MPI was first introduced by Malmquist [2]. Caves et al [3] used MPI for comparing production technology of two economies.

Malmquist index has various desirable features. MPI does not need constructed inputs and outputs and could be used when prices are not available. Cost minimization or profit maximization is not necessary to be assumed, which makes it useful in situations in which producers have different objects, either are unknown or are unachieved. Also, the MPI is easy to compute, as demonstrated by Fare et al. [4], and its different decompositions can be used for analyzing productivity change. Several authors studied and developed MPI in the non-parametric framework. Such as, Fare et al [5]. There are various studies, which used MPI in banking industry. Berg et al. [6] applied the MPI to Norwegian banking sector during the deregulation of the 1980s. The efficiency and productivity growth in the Japanese banking industry have been measured by Fukuyama [7] during the 1989-1991 periods. Noulas [8] compares efficiency and productivity differences among Greek banks during the 1991-1992 periods. Productivity indices for Thai banks constructed by Leightner and Lovell [9]. For five years 1989 to 1994. Gilbert and Wilson [10], demonstrate the effects of deregulation on the productivity of Korean banks among 1991 to 1994. Mukherjee et al. [11], studied productivity growth in US commercial banks over the initial post-regulation period 1984-1990. Efficiencies and productivity changes in Portuguese banks is investigated by Canhoto and Dermine [12]. During the deregulation period 1990-1995. Productivity change in European banking during the 1994-2000, is displayed in research by Casu et al. [13]. The same study in Serbian Banks conducted by Markovic et al. [8]. Fajra Octrina et al. [14] evaluate the productivity level of Indonesian banks during 2012-2016 by MPI. Khalili-Damghani et al. [15] analyzed the productivity in the most profit-making branches of a private bank within two years by using Malmquist productivity index (MPI) and an input-oriented data envelopment analysis (DEA) in constant returns to scale (CRS) and variable returns to scale (VRS) conditions. Despite the malmquist index approach has been used in a variety of studies related to the financial economic sector [16], only a hand full of studies paid attention to forecasting the malmquist index such as, Daskovska et al. [17]. As mentioned in Wang [18] and Wu, et al [19], artificial neural network (ANN) is a useful tool for forecasting. There are few researches addressing the combination of DEA and ANN, Bose and Patel [20] overcame the regression model shortcoming of a single dependent variable by using the neural network, they described a combinatorial method for a data generation procedure and training and prediction to overcome this data-based shortcoming. Also, He-BoongKwon [21], used the CCR model and ANN for measuring performance and predicting the model of Class I railroads in the United States. In another work, Doaei, et al. [22], predicted Malaysian manufacturing firms' efficiency by applying a mixed method of Data

Envelopment Analysis (DEA) and ANN. In this paper combination of ANN and MPI is used for forecasting each bank branches' progress or regress. The combination of ANN and MPI, which used in this paper, is never used for forecasting productivity index as a dynamic way for forecasting progress or regress for bank branches. The paper is classified as follow. In Section 2, a brief description of artificial neural network and the malmquist index can be seen. Section 3 describes models and methodology used in this paper. The results are given in Section 4. At last, Section 5 includes conclusions and future works.

2. Problem definition

2.1 Artificial neural network

The artificial neural networks were inspired of neural networks mainly workings of the brain. Novel structure of the information-processing system is the main part of this paradigm. In such systems large number of highly interconnected processing neurons working together to solve specific problems. Similar to people artificial neural networks (ANNs) learn by examples and trained by adjusting the weights between neurons so that an input leads to a target output.

Over the last decade various applications of ANN were introduced, one of the major applications of ANN in business application is in forecasting [16]. Many ANN models have been proposed since 1980s such as, Multi-layer perceptron (MLP), Hopfield networks, and Kohonen's self-organizing networks, which are the most influential models.

Due to inherent capability of arbitrary input – output mapping, the MLP networks are used in several problems especially in forecasting. As it shown in Fig.1, MLP networks include several layers of nodes. The input layer is the lowest layer, where the information received. The layer in which result displays is output layer.

Input layers and output layers are connected with intermediate layers, which named hidden layers. Nodes in adjacent layers are connected by acyclic arcs, which from a lower layer to a higher layer.

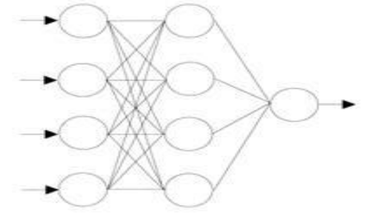

Figure 1: The structure of three layers MLP network.

Mostly multilayer network trained using the backpropagation (BP) algorithm for forecasting, which are a class of feed-forward neural networks. Bp neural networks consist of a collection of inputs and processing units named as neurons and the direction of information flow is from the input to the output layer, with supervised learning rules. In the learning process the known correct answer is compared with each network's forecast and the weights are adjusted based on minimizing the error function. For instance, for forecasting the value of *x (t+1)* in time series like *x (1) x(t), x(t-k+1) x(t)*is chosen as the inputs to multilayer network and the output will be the forecast. The network uses data that extracted from the historical time series for training and testing on large training and testing sets.

ANN must be trained to perform any task. Through the training process, arc weights, which are the key factors of an ANN, will be demonstrated.

Learned knowledge saved in arcs and nodes in the form of arc weights and node biases. The MLP training is a method of training, in which the desired response of the network (target value) for each input pattern (example) is always available.

The steps in training process are usually as following. Firstly, examples of the training set are entered into the input nodes. Secondly, the activation values of the input nodes are weighted and accumulated at each node in the first hidden layer. Lastly, activation value is obtained by an activation function, which is transforming the total into activation value. The value becomes an input into the nodes in the next layer. This process works until the output activation values are found. The training algorithm is trying to the weights that minimize the mean squared errors (MSE) or the sum of squared errors (SSE).

2.2 Malmquist productivity index

The Malmquist productivity index is a theoretical index, in which progress or regress in efficiency is shown along with frontier technology over time under the multiple inputs and outputs framework. As presented by Fare et al. (1989), the MPI is based on the distance function, which describes multi inputs and outputs production technology. Production technology at time t (s^t) for multiple-input and multiple-output is as follow:

$S^t = \{(x^t,y^t): x^t \text{ can be produce } y^t\},\ t=1,\dots T \quad (1)$

In which x^t is an (N×1) input vector and y^t is an (M×1) output vector. Then the output distance function at time *t* is described as follow:

$D^t(x^t,y^t) = \inf\{\theta : (x^t, y^t/\theta) \in S^t\},\ t=1,\dots T \quad (2)$

With given input vector, X^t, under period ***t*** technology of the output vector, y^t, the distance function in (2) is defined as the reciprocal of the maximum proportional expansion.

The distance function in (2) is defined as the reciprocal of the maximum proportional expansion of the output vector, y^t, given input vector, x^t, under period ***t*** technology.

If the value of distance function is one, the output vector is on the boundary or frontier of technology and named efficient. Less than one means the production is technically inefficient. As can be seen in Fare et al. [23] the Malmquist total factor productivity index is displayed as the geometric mean of two Malmquist indexes and is described as:

$$M_0^t(x^{t+1}, y^{t+1}x^t, y^t) = \quad (3)$$

$$[M_0^t(x^{t+1}, y^{t+1}x^{t+1}, y^t)\ M_0^{t+1}(x^{t+1}, y^{t+1}x^t, y^t)]^{\frac{1}{2}}$$

$$= [\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)} \times \frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^{t+1}(x^t,y^t)}]$$

In which $M_0^t(x^{t+1}, y^{t+1}x^t, y^t)$ and $M_0^{t+1}(x^{t+1}, y^{t+1}x^t, y^t)$ are productivity change measurement of Malmquist indices between *t* and *t+1* period and are defined by technology at time *t* and *t+1* respectively.

Also, Fare et al. (1989) demonstrated that the Malmquist productivity index given by equation (4) is the combination of two components: first is the efficiency change (*FCH*) component in which the closeness of the operating unit to the production frontier in period *t+1*compared to period *t* is measured and referred as the catching up effect. Second is technical change (*TCH*) component, which captures the change in the production technology as a shift in the production frontier. Therefore, equation (4) is written as follows:

$$M_0^t(x^{t+1}, y^{t+1}x^t, y^t) = \quad (4)$$

$$\frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)}[\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^{t+1}(x^t,y^t)} \cdot \frac{D_0^t(x^t,y^t)}{D_0^{t+1}(x^t,y^t)}]^{1/2}$$

Where,

$$\text{FCH} = \frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)}$$

$$\text{TCH} = [\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^{t+1}(x^{t+1},y^{t+1})} \times \frac{D_0^t(x^t,y^t)}{D_0^{t+1}(x^t,y^t)}]^{1/2}$$

If M_0 $(x^{t+1}, y^{t+1}, x^t, y^t) > 1$ >1, then Productivity advances occur. In a same way, improvements in efficiency occur if *FCH*>1 and technical advances occur if *TCH*>1.

3. ANN-MPI

In this paper multilayer ANN is applied to forecast the input and outputs of each decision-making unit (DMU) in 60 months. Each bank branch is considered as a DMU. After first analyses and trial the fastest training algorithm, Levenberg–Marquardt algorithm, is chosen as training function for proposed MLP network. Training and prediction operations must be considered in MLP networks. Two data sets are used in MLP, the training set for the training of the MLP and test set for the prediction. Arbitrary values of the weights, which might be random numbers, are the beginning of training mode. In each epoch, the iteration of the complete training set, the network adjusts the weights. Adjusting the weights is based on reducing error. The prediction mode begins with information flow from inputs to outputs. The network produces an estimation of output according to the input values. The resulting error demonstrates the quality of prediction of the trained network. Fig. 2, Shows the two samples of test and train regression charts for proposed ANN.

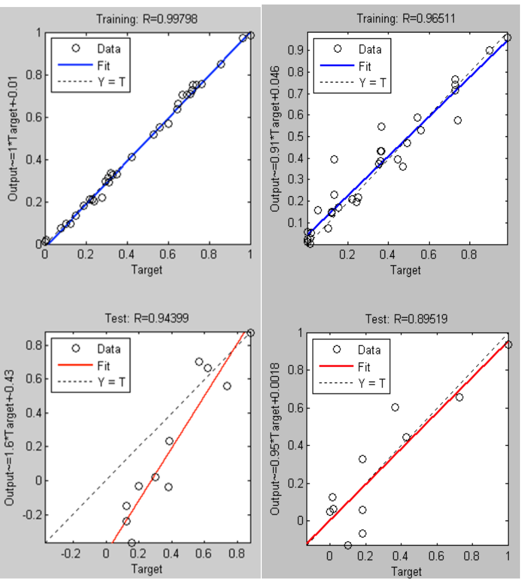

Figure2: Training and testing regression charts

Fig.2. Presents the good quality of the trained network prediction.

Table 1. Displays the parameters of the estimated artificial neural network. The estimated neural network incorporates a hidden layer and the Levenberg–Marquardt algorithm is employed for the training.

Table 1: Estimated neural network parameters

Concept	Result
Data	Input 6000 past data/output predicted data
Network architecture	2-3-1
Algorithm	Levenberg–Marquardt
Epochs (max)	10000
R^2	0.99
Learning rate	0.7
Mean square error	0.001

After forecasting inputs and outputs by ANN, the MPI model, which is applied by a number of researchers in bank efficiency studies, must be selected for calculating the productivity change of each branch. The whole process is presented in Fig. 3.

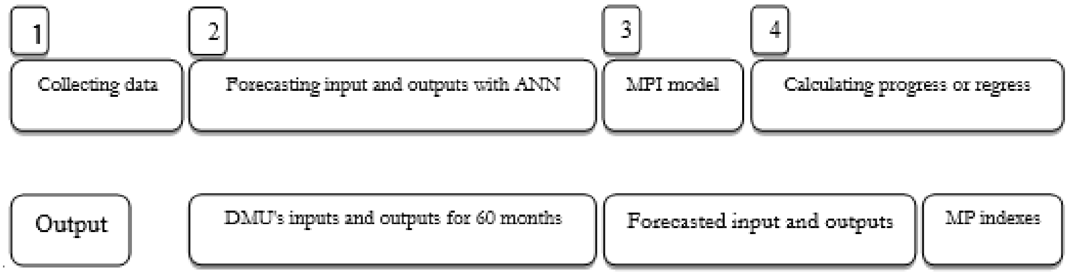

Figure 3: The steps of ANN-MPI

4. Computational results

100 branch of one of Iranian commercial banks were selected and the related data were collected. The data cover the period of March to February in year 2006 to 2011. Each branch demonstrates a decision-making unit (DMU) and uses two inputs to produce seven outputs as it shown in Table 2.

As there are two inputs, seven outputs and 60 months' time horizon 540 observations used in the analysis. The Panel data was used to arrive to MPI estimates, with a total of 100 bank branches in next 60 months.

After forecasting inputs and outputs with ANN, MPI used for calculating the productivity change, which each DMU will have. Table 3 Shows the results.

As mentioned before, MPI >1 means Productivity advances occurred. According to Table 2. More than half of the branches will progress in five years. Four different branches selected for analysis as it shown in Fig 4, 25th branch have regress between second and third years (MPI=0.9) but finally with MPI=1.01, the productivity advances achieved. 68th branch have progress (MPI=1.3) in forth year but in fifth year the regress will be forecasted. 36th does not have progress at all. 11th branch and 98th branch always have progress.

Table 2: Inputs and outputs of branches

Inputs	Outputs
1- Deposit's paid profit (X_1)	1- Income condominium (Y_1)
	2- Fee (Commission) (Y_2)
2- Expenses (personnel & official) (X_2)	3- Other income (Y_3)
	4- Main deposits (Y_4)
	5- Other deposits (Y_5)
	6- Current deposit (Y_6)
	7- Loan granted account (Y_7)

Table 3: The MPI results

Branch No.	MPI	Progress/Regress	Branch No.	MPI	Progress/Regress
1	0.10	Regress	51	0.12	Regress
2	1.16	Progress	52	1.50	Progress
3	0.35	Regress	53	1.55	Progress
4	0.37	Regress	54	2.27	Progress
5	0.30	Regress	55	3.67	Progress
6	2.33	Progress	56	0.34	Regress
7	0.33	Regress	57	1.45	Progress
8	1.29	Progress	58	7.34	Progress
9	0.52	Regress	59	0.37	Regress
10	2.01	Progress	60	0.29	Regress
11	2.44	Progress	61	1.05	Progress
12	1.78	Progress	62	1.41	Progress
13	2.28	Progress	63	0.87	Regress
14	3.11	Progress	64	7.19	Progress
15	1.50	Progress	65	1.37	Progress
16	2.88	Progress	66	4.62	Progress
17	1.82	Progress	67	1.33	Progress
18	1.85	Progress	68	0.95	Regress
19	2.48	Progress	69	0.66	Regress
20	0.24	Regress	70	7.55	Progress
21	0.94	Regress	71	16.19	Progress
22	0.92	Regress	72	1.49	Progress
23	1.70	Progress	73	8.06	Progress
24	0.48	Regress	74	0.32	Regress
25	1.01	Progress	75	1.52	Progress
26	0.30	Regress	76	1.75	Progress
27	1	progress/No regress	77	0.20	Regress
28	2.92	Progress	78	1.71	Progress
29	7.82	Progress	79	9.23	Progress
30	2.34	Progress	80	0.11	Regress
31	1.45	Progress	81	9.77	Progress
32	1.14	Progress	82	0.44	Regress
33	0.81	Regress	83	3.45	Progress
34	1.05	Progress	84	0.21	Regress
35	0.61	Regress	85	1.93	Progress
36	0.06	Regress	86	3.24	Progress
37	0.53	Regress	87	0.66	Regress
38	2.66	Progress	88	0.01	Regress
39	0.07	Regress	89	0.06	Regress
40	2.20	Progress	90	1.45	Progress
41	2.77	Progress	91	0.41	Regress
42	0.50	Regress	92	57.38	Progress
43	0.29	Regress	93	1.18	Progress
44	2.32	Progress	94	0.34	Regress
45	3.05	Progress	95	1.50	Regress
46	0.42	Regress	96	1.55	Progress
47	2.09	Progress	97	2.27	Progress
48	10.78	Progress	98	3.67	Progress
49	0.90	Regress	99	0.34	Progress
50	2.007	Progress	100	1.01	Progress

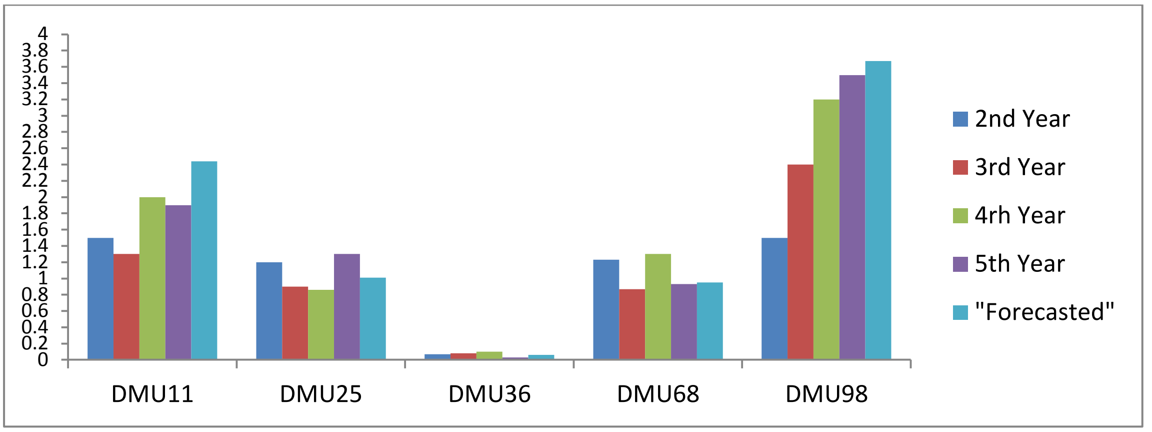

Figure 4: MPI for 4 previous years VS forecasted MPI

As the prediction error is less than 0.001, the predicted MPI is following the previous trend.

5. Conclusions and future works

This paper presents an ANN-MPI study to the branches in one of Iranian commercial banks. The result helps DMUs to know if they could have progress or regress through the five years' horizon. Malmquist productivity index used in many studies to show if each DMU shows progress or regress. In this study, artificial neural network used to enrich MPI to forecast the productivity change over sixty months. Results show that 59 percent of branches will have improvements in efficiencies. We also consider dynamic model for panel data with GMM estimator. As, the relation between independent variables and dependent variables are unknown, the results are not reliable. Compared with dynamic panel data, ANN is much more reliable in our case. In addition, we can list the following directions for future research: First, Ranking DMUs can be considered for future work. Second, other algorithms for forecasting can be used instead of artificial neural networks. Third, other versions of ANN can be used for estimation.

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