DEA Model for Measuring Operational Efficiency of Vietnam's Commercial Banks by Using Genetic Algorithms

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Abstract: Data envelopment analysis (DEA) is a nonparametric method used to evaluate the performance of organizations. In recent years, the application of the DEA method in measuring the operational efficiency of commercial banks has become more popular. This research was conducted by using genetic algorithms, whose aim was to find out appropriate variables to evaluate the performance of Vietnam's commercial banks. The result pointed out three input variables including the total amount deposit, the number of employees and leverage; and two output variables including the total revenue and net income. The model was built from the data of Vietnam's commercial banks and provides a framework to assist further researches that apply DEA in evaluating the bank's performance.

Keywords: genetic algorithms GA, operational efficiency of banks.

JEL Classification: C14 . C58 . G21 . G30.

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1. Introduction

DEA is used in many areas such as education, agriculture, sport, health,... One of the reasons that the use of DEA is widespread, is that many of its inputs and outputs are used to measure the operational performance. However, it is very difficult to select the appropriate variables. Thus, researchers are trying to find a set of common variables for one problem. There are not many studies in Vietnam's banking sector that can be used to build an appropriate DEA model. Previous studies using the DEA model were based on subjective arguments or similar studies in the world which consequently leads to inaccurate and unconvincing results. From that reality, this research was conducted to achieve two purposes: (i) to find a new approach, which is more precise for building DEA model; (ii) to select inputs and outputs variables more logically and scientifically fit for the performance evaluation of Vietnam's commercial banks. The outcome of this research study could also be used for future reference when building DEA model in different area.

2. Literature Review

2.1. An Overview of DEA Method

Data envelopment analysis or DEA is a linear programming technique developed in the work of Charnes, Cooper & Rhodes (1978). However, unlike the Stochastic Frontier which uses the econometric methods, DEA relies on mathematical linear programming to estimate the marginal production.

Charnes et al. (1978) introduced the DEA approach developed from Farrell's (1957) technical efficiency measure - from a process of single input and output relations to a multi-input, multi-output process. Since then, DEA has been used to evaluate efficiency in many areas. Färe & Grosskopf (1994) have proposed the solution for each decision-making unit (DMU) which is to use inputs at the minimum necessary level to produce a set of outputs. The input-oriented technical efficiency is a measure of the DMU's potential output from a given set of inputs. According to Lovell, Färe & Grosskopf (1993), in the case that input variables are used in a model easily controlled by an enterprise, the input orientation model shall be more appropriate and vice versa. In the banking sector, the application of the input-oriented technical efficiency shall be more appropriate.

The linear programming (LP) model measuring the input-oriented TE of any DMU is:

Min(Z), on the condition:

$$u_{jm} \leq \sum_{j=1}^{J} L_j u_{jm} \qquad (m=1,2,\ldots, M)$$

$$\sum_{j=1}^{J} L_j u_{nj} \leq Z x_{nj} \qquad (n=1,2,\ldots, N)$$

Where: $L_j \geq 0$ ($j = 1,2,\ldots, J$); Z – efficiency measure calculated for each DMU_j; ujm - output mass m produced by DMU_j; x_{nj} - input mass n produced by DMU_j; L_j - intensity variable for DMU_j.

The effect of the returns to scale can be explained by Banker, Charnes & Cooper (1984). With CRS-constant returns to scale, the condition $\Sigma L_j \leq 1$ is added, and with the variable-to-scale effect (VRS), where $\Sigma L_j = 1$ is added. Choosing between two assumptions depends on the characteristics of the DMU being considered. In general, constant returns to scale is not effective, so the article shall be conducted under the assumption of VRS.

Since the variables Z are calculated for each DMU, they are estimated from a set of observed data. The value of Z = 1 implies that the firm is efficient, while Z <1 is not efficient.

2.2. Selection of Input and Output Variables for DEA Model

In order to select the relevant variables, some methods were proposed. Jenkins & Anderson (2003) proposed a multivariate statistics method to cut down variables with low correlation. Ruggiero (2005) suggested regression analysis be an efficient method to eliminate low correlation variables, using high correlation ones if they are statistically significant. These researches build the DEA model mainly based on the correlation between variables and usage of statistical technique. The biggest disadvantage of this method is the requirement of a number of DMUs; therefore, it is very difficult to implement the method in economic sectors with small amount of DMUs, such as Vietnam's banking sector. Furthermore, how correlative the variables need to be to be accepted and put into the model is still a question left open by the scientists.

Morita & Haba (2005) proposed a method based on an experimental design and orthogonal layout in order to detect optimal variables statistically for the DEA model. Edirisinghe & Zhang (2007) built a general DEA model based on the principle of maximizing the correlation between external performance indexes. These studies tried to propose consistent method and model which are applicable in various sectors. Morita & Avkiran (2009) suggested using three-level factor design method and proved that, implementation of this method allows receiving a more suitable DEA model compared to the random selection of variables.

Overall, these researches have suggested different methods and solved out the variables for each individual sector. A similar research in Vietnam banking sector (Nguyen Quang Khai, 2016) using three-level factor design method and Mahalanobis distance suggested two input variables including the total of deposits and the number of employees, and three output variables including the revenue, net profit and leverage. However, this method depends massively on the delimitation of two groups - high efficiency and low efficiency. Nowadays, Vietnam has yet to have an official data source from this delimitation. Generally, the disadvantages of the factor design method of the above researches are randomly combined variables and unconsidered correlation between them.

Some recent researches have used the genetic algorithms GA to find out a suitable DEA model for each sector. This method is considered to be rather new and highly evaluated. Whittaker et al. (2009) used data collected from US agriculture production units in two years 1996 and 1997. The result showed that GA was a suitable DEA model building method to evaluate the operational performance in agricultural and environmental sectors. Panahi, Fard & Yarbod (2014) built a DEA model from 19 input and output variables and genetic algorithms for listed companies on the Tehran stock market. The result proved that building DEA model accordingly could help building portfolio efficiently, in other words, DEA and genetic algorithms allow effective evaluation of stock companies' performances. Another research (Aparicio, Espin, Moreno & Panser, 2014) evaluated DEA model through genetic algorithms GA and parallel python PP, which led to a conclusion that, using genetic algorithms in order to find out a suitable DEA model is a need in the future. Razavyan & Tohidi (2011) pointed out that using DEA model and genetic algorithms could evaluate and rank DMUs efficiently. Especially, Trevino & Falciani (2006), as well as Cadima, Cerderira, Silva & Minhoto, 2012), said that using genetic algorithms to find subset R for any multivariable statistic model. These authors shown specific steps in finding a suitable subset and thought that genetic algorithms are a good method in terms of selecting variable sets. According to this propose, Madhanagopal et al. (2014) used genetic algorithms GA to find a model to be considered suitable for Indian commercial banks. Therein, one input variable was amount of loan, while five output variables are total debt, other incomes, net lending incomes, investment and net profit.

Overall, researchers thought that genetic algorithms method is a good method. However, the basic disadvantage of this method is the subjective selection of output and input variables. For DEA model, this drawback may lead to a selection of low correlation variables. Due to this reason, this research was conducted with the purpose of providing a new and complete method by considering correlation from the formation of variable sets. In other words, the author shall examine the correlation between input and output variables before implementing genetic algorithms GA. With this method, the author looks forward to finding relevant input and output variables for DEA model in order to evaluate the performance of Vietnam's commercial banks. Furthermore, the author uses results from this research to verify the results of previous researches, especially those which were conducted in Vietnam, and contribute to the building of a standard DEA model for this country banking sector.

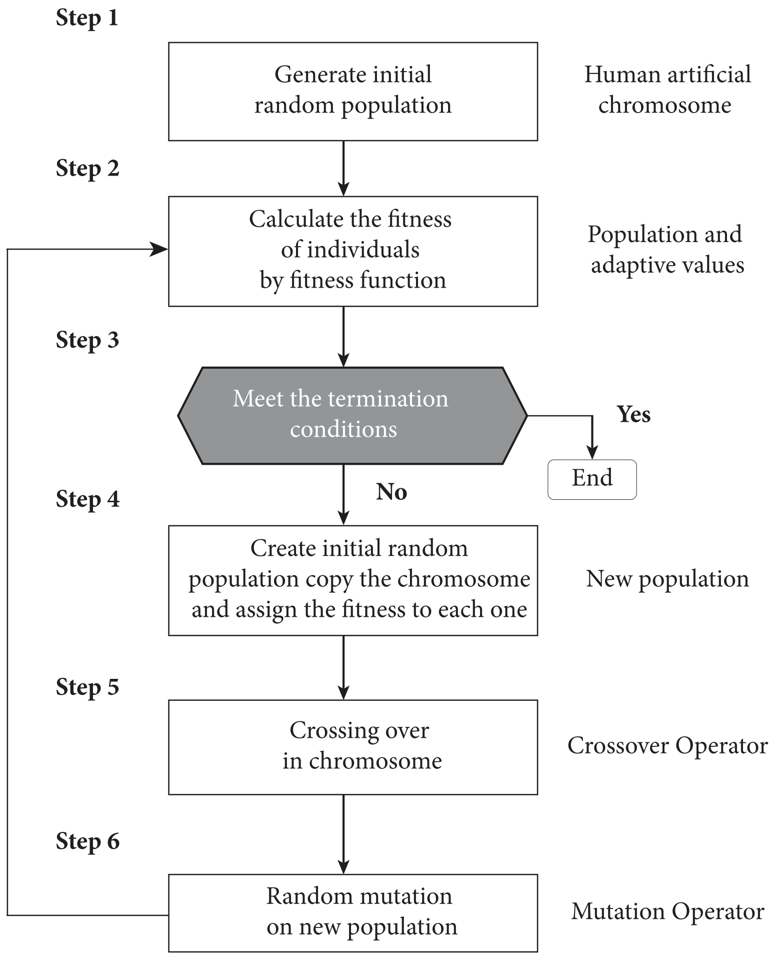
3. Methodology and Data

3.1. Genetic Algorithms and Building DEA Model

The concept of GA was first introduced by professors John Holland and De Jong in 1975. It was a thorough process of finding variables based on the basic principle of natural selection and genetic mechanisms, which means crossing over, mutation and survival of the fittest for optimization and analysis of machine learning. The steps for performing genetic algorithms are shown in Figure 1.

Based on the principle of the selection of R-set by Cadima et al. (2012), the best combination of variables for the study and the nature of the searching procedures for GA are summarized as follows:

For any subgroup of variables (called r), a subset of variables r is randomly chosen from the set of variables k as an initial population (N), where ($r \leq k$). In each iteration, the number of breeding pairs established accounts for half of the population (ie N/2) and each pair produces one (a new subgroup of r) and the child must receive all attributes from parent. Each father selected from the population in direct proportional to his or her value based on the original criteria. For each father F, an M mother is chosen with equal probability among the members of the population, of which at least two variables are independent of F. A child born by a pair (F, M) includes all variables from its parents. The remaining variables were selected with equal probability from the difference in parental symmetry with the limitation that at least one variable from M / F and one from F/M would be selected. Parent and child pairs are ranked in order of standard value and the best group of



Source: Trevino et al. (2006).

Figure 1. Genetic algorithms flow chart

subsets of r will create the next generation which will be used as the population for next time. Standards stop at generations satisfying subgroup's terms of quality g (g> gmax).

In order to measure the quality of each subgroup, this study uses the RM coefficients of Cadima, Cerdeira & Minhoto (2004) and McCabe (1984). This coefficient is the weighted average of the principal components of the data set and r - the subset variables. Furthermore, RM principal were also introduced by Cadima

& Jollife (2001), Cadima et al. (2012). The value of the RM coefficient ranges between 0 and 1.

The RM coefficient:

$$RM = corr(A, K_r, A) = \sqrt{\frac{tr(A^t K_r A)}{tr(X^t X)}}$$

$$= \sqrt{\frac{\Sigma_{i=1}^{k} \Upsilon_i (C_m)^2{}_i}{\Sigma_{j=1}^{k} \Upsilon_i}} = \sqrt{\frac{tr[S^2]_R S_R^{-1}}{tr(S)}}$$

With:

$$S = \frac{1}{n} A^t A$$

Where: A - full matrix; K_r - the orthogonal projection matrix on the open subspace created by a subset of variables r; S - correlation matrix K*K of the whole data; R - the set of variables r in the set of variables; S_R - the sub-matrix r x rof S, derived from keeping rows and columns with index R; $[S^2]$ R - the sub-matrix Rx of S^2 obtained by retaining the rows and columns associated with R; γ_i - the ith eigenvalue of the covariance matrix (or correlation) is defined by A; Corr - Correlation matrix; tr - matrices.

3.2. Data

According to Sealey & Lindley (1977), in the big picture of all studies in the banking sector, there are two approaches to the selection process of input and output for the DEA model. It is a "production" and "intermediation" approach. Under the "production" approach, the banking sector is a service sector which uses inputs such as labor and capital to provide deposits and loan accounts. An intermediation approach regards banks as financial intermediary funds between savings and investment spending. Banks collect deposits, use labor and capital, then transfer these sources of fund to lender to create assets and other income. However, all previous studies used only correlative analysis. Taking into consideration these two approaches, Morita et al. (2005), Morita et al. (2009) argued that using random methods for selecting variables requires a combination of both approaches. Results from previous authors have proved that such combinations will help to build a better model. For the above reasons, with the GA method, the writer believes that combining the two way of approach is necessary and appropriate, in which all the input and output variables are considered as a whole. The initial variables were only selected after previous studies in the world, as well as in Vietnam, were carefully examined.

Table 1. Initial selected variable

Input		Output	
Variable name	**Label**	**Variable name**	**Label**
Total capital	VON	Total of loans	TCV
Total deposit	TTG	Other income	TNK
Number of branches	TCN	Financial income	DTC
Labor	TLD	Total revenue	TDT
Interest rate	TLV	Investment	DTF
Other expenses	CPK	Net profit	LNR
Total expenses	TCP	Gross profit	LNG
Cash	TTM	Revenue/profit ratio	DLN
Fixed assets	TCD		
Leverage ratio	RDB		

The data is taken from financial reports, annual reports and other information published in the media of 34 commercial banks in Vietnam in 2015. The commercial banks appeared in the research are those with information widely published and meet the criteria of the research.

4. Results and Discussion

The table 2 below shows the descriptive statistics for the research data.

First of all, sets of optimal input and output variables were selected by using GA. As mentioned, the research applied the principle of the subset R by Cadima et al. (2012) with random selection of the best subsets. The number of inputs and outputs selected were 10 and 8 accordingly. In DEA model, Cooper, Seiford & Tone (2007) provided two thumb rules for sample selection. First of all, $n > \max(S * P)$, meaning sample size has to be greater than or equal to multiplication of numbers of input and output factors. Secondly, $n \geq 3(S + P)$, meaning numbers of observations in data should have at least 3 times the total of inputs and outputs, in which n is the sample size (number of DMU), S is the number of inputs and P is the number of outputs. According to these conditions, research proceeded on selecting 5 or 6 outputs and inputs of any kinds, since the number of commercial banks (DMU) are 34, less than $(10*8) = 80$ and $3(S + P) = 3(10 + 8) = 54$. The selection is based on identification of correlation between variables principle. Variables

Table 2. Research data statistics

Indicator	Mean	Min	Max	Std
Number of banks	34			
Total of capital (millions VND)	343,267,215	3,368,727	720,362,607	264,125,142
Total of deposits (millions VND)	224,123,564	18,325,682	461,366,024	221,864,226
Number of branches	63	14	152	53
Labor (people)	8,436	1,902	20,406	6,584
Interest expense (millions VND)	14,235,765	1,294,133	23,563,821	10,654,780
Other expenses (millions VND)	345,439	548,620	10,261,977	1,547,286
Total of expenses (millions VND)	8,767,747	921,377	16,912,899	9,126,579
Cash (millions VND)	4,326,491	1,737,412	8,421,360	3,276,548
Assets (millions VND)	3,246,065	1,003,764	8,780,285	2,546,435
Leverage ratio	31%	24%	46%	15%
Total of loans (millions VND)	218,285,763	14,735,077	484,516,322	187,475,226
Other incomes (millions VND)	192,065	20,820	392,6120	87,248
Financial income (millions VND)	28,095,184	2,102,271	41,914,371	23,365,478
Total revenue (millions VND	29,043,564	2,132,890	48,224,665	29,265,431
Investment (millions VND)	1,083,986	465,011	2,570,122	987,832
Net profit (millions VND)	2,182,657	170,574	5,705,402	1,835,964
Gross profit (millions VND)	2,018,765	808,139	8,350,551	3,347,287
Revenue/ Profit ratio	2.1	1.8	3.5	0.9

with correlation level as 0.6 are kept, while variables with lower correlation are eliminated from the process of implementing genetic algorithms GA. After the correlation examination process, 6 inputs and 5 outputs with highest correlation were found. Six inputs were total of deposits (TTG), number of employees (TLD), numbers of branches (TCN), total expenses (TCP), leverage ratio (RDB) and cash (TTM). Five outputs are revenue (TDT), net profit (LNR), revenue/ profit ratio (DLN) , total of loans (TCV) and investments (DTF).

Table 3. Result of subsets and their highest values accordingly

	Inputs		Outputs	
r	Subset	Highest value	Subset	Highest value
1	TTG	0.8675	LNR	0.9014
2	TTG, TCN	0.9116	TDT, LNR	0.9216
3	TCN, TTM, TLD	0.9540	TDT, TCV, DTF	0.9864
4	TLD, TCP, TCN, TTM	0.9753	TDT, LNR, TCV, DTF	0.9906
5	TLV, TCN, TCP, RDB, TTM	0.9857	TDT, LNR, DLN, TCV, DTF	0.9937
6	TTG, TLD, TCN, TCP, RDB, TTM	0.9942		

Table 3 shows that subsets of inputs, outputs and highest values generated from the genetic algorithms GA give different values of r. With the 6th r for inputs and 5th r for outputs, the highest values are relatively 0.9942 and 0.9937. Therefore, the numbers of maximum output and input variables would be 5 and 6.

By applying DEA (input orientation - VRS), the operational efficiency of banks was calculated for different combination of inputs and outputs subsets. Analysis started with r = 1 for input and output, meaning one input variable and one output variable (input variables of number of employees and output variables of total revenue were randomly chosen). This Model was named M11. Next, the calculation was executed by keeping the same input variable and alternately increasing value of r (2, 3, 4 and 5) for output variables, and those models were named M12, M13, M14 and M15. Similar methods were followed in the other subsets of both inputs and outputs. There were a total of 30 models built during the process of this research.

Table 4 illustrated variables used in different models, effectiveness quantity, mean efficiency score and percentage of mean efficiency score change. In detail, the effectiveness quantity is DMU with TE value as 1,while the mean efficiency score is the mean TE value from DEA model. The selection process was as follows: Firstly, the author calculated the percentage difference between mean efficiency score for model M11 and M12. Results show the difference is only at the rate of 4,6% less than 10%. Therefore, model M11 was kept in order to calculate the mean value score of model M13. However, the difference in mean efficiency score between model M11 and M13 was at a degree of 8,6%, so model M11 was kept as the base model. This process was continued until one model holding a difference rate above

Table 4. Individual DEA models results

		M11	M12	M13	M14	M15	M21	M22	M23	M24	M25	M31	M32	M33	M34	M35
Inputs	TTG											*	*		*	*
	TLD	*	*	*	*	*	*	*	*			*	*	*	*	*
	TCN									*	*			*		
	TCP						*	*		*	*	*			*	*
	TTM															
	RDB								*				*	*		
Outputs	TDT	*	*	*	*	*		*	*	*	*		*	*	*	*
	LNR				*	*					*	*	*	*	*	*
	DLN		*	*	*	*	*	*		*	*				*	*
	TCV					*			*	*	*					*
	DTF			*	*	*			*	*	*			*	*	*
Number of efficient banks		4	6	10	9	11	11	9	12	13	8	11	16	13	11	13
Mean efficiency score		0.547	0.572	0.621	0.635	0.664	0,671	0.694	0.722	0.775	0.723	0.786	0.852	0.876	0.824	0.876
% change			4.570	8.570	11.010	4.570	5,670	9.290	13.700	7.340	0.140	8.860	18.010	2.820	3.290	2.820

Source: Author's calculation.

Table 4. Individual DEA models results (continue)

		M41	M42	M43	M44	M45	M51	M52	M53	M54	M55	M61	M62	M63	M64	M65
Inputs	TTG	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
	TLD	*		*	*	*	*	*	*	*	*	*	*	*	*	*
	TCN	*	*	*	*		*	*	*	*	*	*	*	*	*	*
	TCP		*	*	*	*	*			*	*	*	*	*	*	*
	TTM		*			*		*	*		*	*	*	*	*	*
	RDB	*				*	*	*	*	*		*	*	*	*	*
Outputs	TDT	*	*	*	*	*	*	*	*	*	*		*	*	*	*
	LNR			*	*	*			*	*	*			*		*
	DLN			*		*				*	*				*	*
	TCV				*	*		*			*	*		*	*	*
	DTF		*		*	*			*	*	*		*		*	*
Number of efficient banks		9	10	8	12	13	11	12	10	10	12	11	9	11	12	9
Mean efficiency score		0.784	0.806	0.862	0.795	0.827	0.834	0.835	0.798	0.801	0.823	0.807	0.785	0.864	0.843	0.798
% change		8.670	5.710	1.190	7.170	3.020	2.160	2.040	6.770	6.370	3.520	5.580	8.540	1.390	1.070	6.770

Source: Author's calculation.

10%, and a model based on a new basis was found. Thus, the result in table 4, model M14 would be chosen to be the next base model due to the difference rate was 11%. This process was continued until the end of model M65 and discovered that one model, which was M32, reached the final difference rate greater than 10%, the latter models' rates were less than 10%. Thus, model M32 was selected to be the base model in order to measure performance of commercial banks.

The result specified 5 variables for DEA model with three input variables and two output variables. Three input variables are: total of deposit, number of employees and leverage ratio, in which, total of deposit, number of employees are already used by other researches (Sathye, 2001; Morita et al., 2009; Soteriou & Zenios, 1999); while leverage ratio was used by Morita et al. (2009), Lauterback & Vanisky (1999). Two output variables are total revenue and net profit. These variables were selected as output variables by Yildirim, 1999; Lauterbach et al., 1999.

Generally, the result is rather consistent with previous researches. Thanks to the DEA model with five specified variables, the number of variables for DEA model has significantly decreased. The model becomes more precise and assures the validity of data from Vietnam's commercial banks. In addition, that high correlation between model variables helps increase the value of the model.

5. Conclusion

In order to evaluate the bank's operational performance, the DEA technique is used as a nonparametric method and does not require any hypothesis as in parametric method. The main advantage of DEA compared to other performance measuring methods, is that it uses a lot of inputs, outputs, and this allows the researchers to find out appropriate input and output variables for each sector. Researchers suggested that different input and output variables and the lack of any variables can affect notably on the efficiency measurement. Thus, selecting the best establishment of input and output variables in order to measure the performance of commercial banks becomes essential.

In Vietnam as well as in the whole world, many researches about building DEA model have been published. In this research, the author offered a new approach. It was to use the GA search engine, at the same time consider the correlation between variables. The result showed that, the model consisting of three input variables and two output variables is suitable for evaluating the performance of Vietnam's commercial banks. Three input variables are the total of deposits, number of employees and leverage ratio while two output variables include the total revenue and net profit. The research result is consistent to the usage of DEA model in previous researches. It can be said that, variables which are selected in the model are relevant and have high correlation. Researches in the future can utilize the result as well as method of this research in order to build up a suitable DEA model for other sectors.

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