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Modeling the competitive market efficiency of Egyptian companies: A probabilistic neural network analysis

Mohamed M. Mostafa

Auburn University, College of Business, 415 West Magnolia Avenue, 242 Lowder Business Building, Auburn, AL 36849, USA

A R T I C L E I N F O

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A B S T R A C T

Understanding efficiency levels is crucial for understanding the competitive structure of a market and/or segments of a market. This study uses two artificial neural networks (NN) and a traditional statistical classification method to classify the relative efficiency of top listed Egyptian companies. Accuracy indices derived from the application of a non-parametric data envelopment analysis approach are used to assess the classification accuracy of the models. Results indicate that the NN models are superior to the traditional statistical methods. The study shows that the NN models have a great potential for the classification of companies' relative efficiency due to their robustness and flexibility of modeling algorithms. The implications of these results for potential efficiency programs are discussed.

1. Introduction

The competitiveness of a country derives from the efficiency of its enterprises. While competitiveness at the national level is reflected in the performance of the country, it is reflected in the size of the market share at the company level (Porter, 1998). Both notions highlight the importance of efficiency and performance evaluation. Efficiency evaluation and benchmarking are widely used methods to identify the best practices as a means to improve the performance and increase productivity (Barros, 2004). Measuring efficiency levels has become an important issue for managers and investors alike (Galagedera & Silvapulle, 2002). Consumers also benefit from efficient resource usage and allocation because this may mean lower prices and more professional service (Anderson, Fok, Zumpano, & Elder, 1998).

Gandjour, Kleinschmit, Littmann, and Lauterbach (2002) concluded that many quality and efficiency indicators used by executives are lacking in general validity. Using a recognized and valid measure of efficiency is critical for managers seeking to increase the effectiveness of their organizations. Over the past two decades, data envelopment analysis (DEA) has become a popular methodology for evaluating the relative efficiencies of decision making units (DMUs) within a relatively homogenous set (e.g. Sun & Lu, 2005). DEA is an approach to estimate the production function of organizations and organizational units and enables the assessment of their efficiency.

Although widely employed to evaluate efficiency across industries (e.g. Rickards, 2003), DEA can hardly be used to predict the performance of other DMUs (Wu, Yang, & Liang, 2006). As a result, neural network models (NN) were introduced recently to complement DEA in estimating efficiency frontiers of DMUs (Wang, 2003). Wang (2003) showed formally that neural network find data envelopes based on the entire data set, rather than some extreme data points. Athanassopoulos and Curram (1996) were first to combine NN and DEA for classifying and predicting efficiency in bank branches. A comprehensive search through several databases yielded no studies dealing with companies' efficiency using a DEA-NN approach. This confirms Santin, Delgado, and Valino (2004, p. 630) claim that NN models "have no theoretical studies in efficiency analysis and few applications have been made in this field." We, going beyond the conventional methods, have attempted to merge both methodologies to evaluate the relative efficiency of the top listed companies in Egypt. The paper also contributes methodologically through the comparison of various parametric and non-parametric techniques, which results in considerable information for business analysis. More specifically, the purpose of this research is twofold:

- To assess the market performance of the top listed companies in Egypt; and
- To benchmark the performance of NN models against traditional statistical techniques.

This paper is organized as follows. The next section summarizes the methodology used to conduct the analysis. The subsequent section presents empirical results of the efficiency levels of Egyptian companies. After a brief preliminary data analysis, this section first set out efficiency scores derived from estimating the basic DEA models; it also presents sensitivity analysis of DEA-NN derived efficiency scores as a rough validity check on the results. Next, the

E-mail address: mmm0010@auburn.edu

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paper sets out some managerial and policy implications of the analysis. The final section of the paper deals with the research limitations and explores avenues for future research.

2. Literature review

PFA, pre-eminently data envelopment analysis (DEA), has been widely used as an efficiency measurement tool in a variety of fields. For instance, in the banking industry, Miller and Noulas (1996) examined the efficiency of large U.S. banks. They found overall technical efficiency of around 97%. However, the majority of banks were found to be too large and experiencing decreasing returns to scale. A second stage regression analysis showed that pure technical efficiency is positively related to bank size and bank profitability. Bhattacharya, Lovell, and Sahay (1997) used a two-stage DEA approach to examine the impact of liberalization on the efficiency of the Indian banking industry. In the first stage a technical efficiency score was calculated, whereas in the second stage a stochastic frontier analysis was used to attribute variation in efficiency scores to three sources: temporal, ownership and noise component. Using a bootstrapping DEA technique, Casu and Molyneux (2003) investigated efficiency across European banking systems. Results suggest that there has been a slight improvement in bank efficiency levels since the implementation of the EU's Single Market Programme. Krishnasamy (2003) used both DEA and Malmquist total factor productivity index (MPI) to evaluate bank efficiency and productivity changes in Malaysia over the period 2000–2001. The results from the analysis indicated that total MPI increased in all the bans studied. The growth of productivity in these banks was attributed to technological change rather than technical efficiency change. Lo and Lu (2006) employed a two-stage DEA approach including profitability and marketability to explore the efficiency of financial holding companies (FHCs) in Taiwan. Factor-specific measures and BCC (Banker-Charnes-Cooper) model were combined together to identify the inputs/outputs that are most important and to distinguish those FHCs which can be treated as benchmarks. Results show that big-sized FHCs are generally more efficient than small-sized ones. Wu et al. (2006) integrated DEA and neural networks (NNs) to examine the relative branch efficiency of a large Canadian bank. Findings suggest that the predicted efficiency using the DEA-NN model has good correlation with that calculated by DEA, which indicates that the predicted efficiency using the DEA-NN approach is a god proxy to classical DEA approach.

Substantial research has been conducted on DEA applications to hospitals. For example, Sherman (1984) examined the efficiency of seven teaching hospitals in Massachusetts. The study found that two of the seven hospitals were inefficient and suggested specific input reductions for the inefficient hospitals. Using a sample of 3000 urban hospitals, Ozcan and Luke (1993) looked at the relationship between four hospital characteristics (size, membership in a multi-hospital system, ownership and payer mix) and hospital efficiencies. O'Neill (1998) applied supper-efficiency to hospitals by calculating supper-efficiency scores for a DEA model using data from 27 large, urban hospitals. Hu and Huang (2004) applied DEA to compute hospital efficiencies in Taiwan, and then used both the Mann-Whitney test and Tobit regression to explore the effects of environmental variables on these efficiency scores. The study found that public ownership adversely affects hospitals' efficiency. Laine et al. (2005) analyzed the association between quality of care and technical efficiency in hospitals' long-term care wards for the elderly in Finland. DEA was used to calculate technical efficiency while the Mann-Whitney test and correlation coefficients were used to explore the association between quality and efficiency. The results suggest that an association may exist between technical efficiency and some dimensions of quality.

Numerous studies have also been done on DEA applications in farm production. For instance, Audibert, Mathonnat, and Henry (2003) assessed the role of malaria and some social determinants on the cotton crop efficiency in Ivory Coast. The study found that high parasite density infection has a direct and indirect negative effect on efficiency in the cotton crop. Krasachat (2004) applied DEA to study efficiency of rice farms in Thailand. A Tobit regression was also used to explain the likelihood of change in efficiencies by farm-specific factors. Results indicated that the diversity of natural resources has an influence on Thai rice farms' technical efficiency. Lee (2005) compared stochastic frontier analysis (SFA) and DEA methods on measuring production efficiency of forest companies. Although the study found slight differences in the efficiency scores obtained from the two methods, the highest and lowest relative efficiency ranking for forest companies remain the same. Chauhan, Mohapatra, and Pandey (2006) applied DEA to determine the efficiencies of farmers with regard to energy use in rice production activities in India. The results reveal that a possible about 12% of the total input energy could be saved if the best practice farm was used as a benchmark.

Other application areas include Internet companies (e.g. Serrano-Cinca, Fuertes-Callen, & Mar-Molinero, 2005), audit services (e.g. Dopuch, Gupta, Simunic, & Stein, 2003), football teams (e.g. Haas, Kocher, & Sutter, 2004), retail stores (e.g. Barros & Alves, 2003), aquaculture (e.g. Cinemre, Ceyhan, Bozoglu, & Kilic, 2006), insurance industry (e.g. Cummins & Rubio-Misas, 2006), supplier evaluation (Narasimhan, Talluri, & Mendez, 2001), seaports (e.g. Cullinane, Wang, Song, & Ji, 2006), airports (e.g. Sarkis, 2000), advertising agencies (e.g. Luo & Donthu, 2005), hotels (e.g. Sigala, Jones, Lockwood, & Airey, 2005), schools (e.g. Mancebon & Mar-Molinero, 2000), universities (e.g. Flegg, Allen, Field, & Thurlow, 2004), local government (e.g. Hughes & Edwards, 2000) and nations (e.g. Ramanathan, 2006).

From this brief review we find that although numerous studies have attempted to assess efficiency in the West and other parts of the world, virtually no studies have focused on measuring efficiency in Egypt. In this investigation we aim to fill this research gap by empirically evaluating marketing efficiency of top listed companies in Egypt using intelligent modeling techniques.

3. Methodology

3.1. Data envelopment analysis

Introduced in 1978 by Charnes, Cooper, and Rhodes (1978), DEA assigns an efficiency score to each unit by comparing the efficiency score of ach unit with that of its peers. It identifies a frontier comprising best performers. The DEA frontier traces the geometrical locus of all Pareto-optimal points of the production set. Those units that lie on the frontier are recognized as efficient, and those that do not, as inefficient. DEA involves the solution of a linear programming problem to fit a non-stochastic, non-parametric production frontier-based on the actual input-output observations in the sample. In the basic DEA model (CCR), the objective is to maximize the efficiency value of a test firm k from among a reference set of s firms, by selecting the optimal weights associated with the input and output measures. The maximum efficiencies are constrained to 1. The formulation is represented by model (1).

$$\begin{aligned} &\text{maximize} \quad E_{kk} = \frac{\sum_y O_{ky} V_{ky}}{\sum_x I_{kx} U_{kx}} \\ &\text{subject to}: \ E_{ks} \leqslant 1 \quad \forall \text{ firms } s \qquad (1) \\ &u_{ks}, v_{ky} \geqslant 0, ks, \end{aligned}$$

where E_{ks} is the efficiency score of firm s, using the weights of test firm k; O_{sy} is the value of output y for firm s; I_{sx} is the value for input

x of firm s; v_{ky} is the weight assigned to firm k for output y; and u_{kx} is the weight assigned to firm k for input x.

This non-linear programming is the equivalent to the linear programming problem represented by model (2).

$$\begin{aligned} &\text{maximize} \quad E_{kk} = \sum_y O_{ky} V_{ky} \\ &\text{subject to}: E_{ks} \leqslant 1 \quad \forall \text{ firms } s \\ &\sum_x I_{kx}\, U_{kx} = 1 \\ &u_{ks}, v_{ky} \geqslant 0 \end{aligned} \tag{2}$$

The transformation is completed by constraining the efficiency ratio denominator from (1) to a value of 1, represented by the constraint $\sum_x I_{kx}\, U_{kx} = 1$.

The result of formulation (2) is an optimal simple or technical efficiency value (E^*_{kk}) that is at most equal to 1. If $E^*_{kk} = 1$, then no other firm is more efficient than firm k for its selected weights. That is, $E^*_{kk} = 1$ has firm k on the optimal frontier and is not dominated by any other firm. If $E^*_{kk} < 1$, then firm k does not lie on the optimal frontier and there is at least one other firm that is more efficient for the optimal set of weights determined by (2). Formulation (2) is executed s times (in our case 62-times) once for each firm.

The dual of the CCR model is represented by model (3):

$$\begin{aligned} &\text{minimize } \theta, \\ &\text{subject to}: \\ &\sum_s \lambda_s\, I_{sx} - \theta_{sx} \leqslant 0 \quad \forall \text{ inputs } I \\ &\sum_s \lambda_s\, O_{sy} - O_{ky} \geqslant 0 \quad \forall \text{ outputs } O \\ &\lambda_s \geqslant 0 \quad \forall \text{ firms } s, \end{aligned} \tag{3}$$

where θ is the efficiency score.

The CCR model has an assumption of constant returns to scale (CRS) for the inputs and outputs. To take into consideration variable returns to scale (VRS), a model introduced by Banker, Charnes, and Cooper (1984) (BCC) is utilized. The BCC model aids in determining the scale efficiency of a set of units (which is a technically efficient unit for the VRS model). This new model has an additional convexity constraint defined by limiting the summation of the multiplier weights (λ) equal to 1, or:

$$\sum_s \lambda_s = 1 \tag{4}$$

The BCC model evaluates whether increasing, constant, or decreasing returns to scale would boost the efficiency observed. In the case of constant returns to scale, the output changes proportionally to input, as it also does in the CCR model. But with variable returns to scale, a change in the input leads to a disproportional change in the output. The use of the CCR and BCC models together helps determine the overall technical and scale efficiencies of the firm and whether the data exhibits varying returns to scale (Sarkis, 2000).

3.2. Probabilistic neural networks

NNs have received a great deal of attention over the past few years. They are being used in the areas of prediction and classification, areas where regression models and other related statistical techniques have traditionally been used (Mostafa, 2004). The multilayer perceptron (MLP), a feed-forward back-propagation, is the most frequently used neural network technique in pattern recognition (Bishop, 1999). However, numerous researchers document the disadvantages of the MLP approach. For example, Calderon and Cheh (2002) argue that the standard MLP network is subject to problems of local minima. Swicegood and Clark (2001) claim that there is no formal method of deriving a MLP network configuration for a given classification task. Thus, there is no direct method of finding the ultimate structure for modeling process. Consequently, the refining process can be lengthy, accomplished by iterative testing of various architectural parameters and keeping only the most successful structures. Wang (1995) argues that standard MLP provides unpredictable solutions in terms of classifying statistical data.

An alternative NN architecture, the PNN is non-linear, nonparametric pattern recognition modeling technique that was originally introduced to the neural network literature by Specht (1990). PNNs require no assumptions about distributions of random variables used to classify; they even can handle multi-modal distributions. They train quickly and as well as, or better than MLP networks. They have the ability to provide mathematically sound confidence levels and are relatively insensitive to outliers (Singer & Bliss, 2003). While the MLP network requires a validation data set (i.e., wasted cases) to search for over-fitting, PNNs use all available data in model building. The PNN is based on Bayes' classification method shown in Eq. (5), where h_i and h_j are the prior probabilities, c_i and c_j are the costs of misclassification, ad $f_i(x)$ and $f_j(x)$ are the true probability density functions:

$$h_i c_i f_i(x) > h_j c_j f_j(x) \tag{5}$$

PNNs feature feed-forward architecture and supervised training algorithm similar to back propagation. The training pattern is presented to the input layer. The main role of the input layer is to map all the external signals into hidden layers by a scaling function through which each input neuron normalizes the range of external signals into a specific range that the neuron network can process. The neurons in hidden layer aim to add flexibility to the performance of the PNN so as to recording the knowledge of classification extracted from the training pattern. There must be, at least, as any neurons in the hidden layer as the number of training patterns (Tam, Tong, Lau, & Chan, 2005). The summation layer consists of one neuron for each data class and sums the outputs from all hidden neurons of each respective data class. The output layer has one neuron for each possible category. The network produces activation, a value between zero and one in the output layer corresponding to the probability density function estimated from that category. The output with the highest value represents the most probable category. Fig. 1 represents the basic structure of the PNN.

PNNs are used for classification problems where the objective is to assign cases to one of a number of discrete classes (Hunter, 2000). Theoretically, the PNN can classify an out-of-sample data with the maximum probability of success when enough training

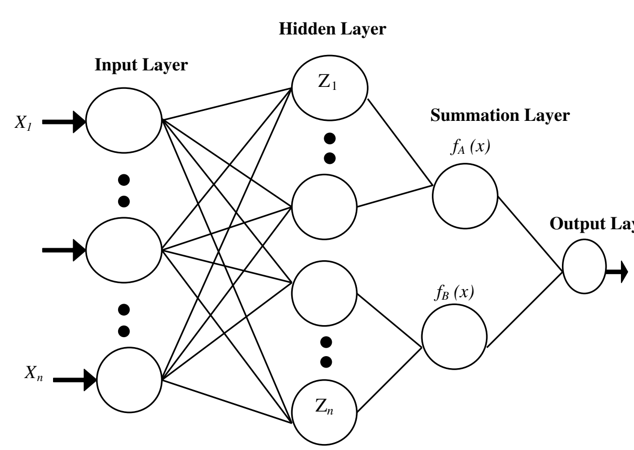

Fig. 1. Probabilistic neural network architecture.

data is given (Enke & Thawornwong, 2005). The PNN has been extensively used in various pattern classification tasks in the literature due to ease of training and sound statistical foundation in Bayesian estimation theory. For example, Yang and Marjorie (1999) utilized a PNN to predict the financial crisis in oil industry companies in the USA. Jin and Srinivasan (2001) proposed a new technique for freeway incident detection using PNN. Hajmeer and Basheer (2002) used PNN to study the classification of bacterial growth. Chen, Leung, and Daouk (2003) applied PNN to stock index forecasting. Huang (2004) applied PNN to predict the class of leukaemia and colon cancer. Na et al. (2004) applied PNN to the classification of accidents in nuclear plants. Gerbec, Gasperic, Smon, and Gubina (2005) used PNN to classify consumers' electricity load profiles. Xue, Zhang, Liu, Hu, and Fan (2005) classified 102 active compounds from diverse medicinal plants with anticancer activity. Jin and Englande (2006) used PNN to classify whether a condition in a lake is safe to swim or not. Wilson (2006) successfully tested the PNN on 209 seizures obtained from an epilepsy-monitoring unit. Laskari, Meletiou, Tasoulis, and Vrahatis (2006) evaluated the performance of PNN on approximation problems related to cryptography. These applications show that while PNN has been applied to many areas, little attention has been paid to applying PNN to companies' efficiency prediction.

3.3. Data and DEA inputs–outputs

To estimate the production frontier, we used cross-sectional data obtained from one of the leading business magazines in Egypt (Business Today Egypt, 2005). This magazine publishes annually a list of the top 100 companies in Egypt. To be included in the data set used in this study, companies had to meet three conditions: first, to be listed in Cairo and Alexandria Stock Exchange (CASE). CASE has been among the five best performing stock exchanges in the world in the past two years (Business Today Egypt, 2005); second, that financial information is available; and, third, that they do not have negative financial data. DEA requires that data set to be non-negative for the outputs and strictly positive for the inputs (Sarkis & Weinrach, 2001). Unfortunately, there is no DEA model to date that can be used with negative data directly without any need to transform them (Portela, Thanassoulis, & Simpson, 2004). Due to application of DEA, which is known to be highly sensitive to erroneous data and unusual observations (Wilson, 1995), we have additionally deleted companies whose figures lie below or above 1% or 99%. Finally, as DEA requires the units analyzed to be as homogeneous as possible (Charnes et al., 1978), banks and financial service institutions were excluded from our analysis (a similar approach was used by Koh & Tan, 1999), and that left 62 companies in the final data set to be analyzed.

The first and very crucial step in conducting a DEA is the determination of inputs and outputs. The main important point in this process is that the input–output variables should be chosen in accordance with the type of efficiency being assessed (Sherman & Rupert, 2006). Efficiency in DEA is not confined to a traditional sense of operating efficiency; it can be generalized to represent relative evaluation of performance in any performance dimension if the inputs and outputs are specified according to the performance dimension considered (Manandhar & Tang, 2002). As we are interested in measuring market efficiency or market value, study variables have been determined accordingly. Following Seiford and Zhu (1999), we define a company as a firm that uses staff and assets to achieve its objectives. These are profitability, i.e., a company's ability to generate the revenue and profit in terms of its current labor and assets, and marketability, i.e., a company's market value by the revenue and profit it generates. Fig. 2 describes a company's production process based on the inputs–outputs used in the study.

It is well known that DEA is sensitive to variable selection. As the number of variables increases, the ability to discriminate between the DMUs decreases. The more variables are added the greater becomes the chance that some inefficient unit dominates in the added dimension and becomes efficient (Smith, 1997). Thus to preserve the discriminatory power of DEA the number of inputs and outputs should be kept at a reasonable level. There are no diagnostic checks for model misspecification in DEA that could result due to wrong choices in variable selection (Galagedera & Silvapulle, 2003). However, Raab and Lichty (2002) suggest a general rule of thumb – the minimum number of DMUs is greater than three times the number of inputs plus outputs. In our study with a total of two inputs and four outputs, a good minimum set is 18 data points; we have 62 data points. Another rule of thumb for selecting an appropriate sample size is to ensure that the sample size is at least three times larger than the sum of inputs and outputs (Stern, Mehrez, & Barboy, 1994). This study also satisfies this rule. A complete list of the variables used in this study appears in the Appendix.

4. Results

4.1. Preliminary data analysis

The simple DEA model is based on constant returns to scale (CRS), implying that the size of a company is not relevant when

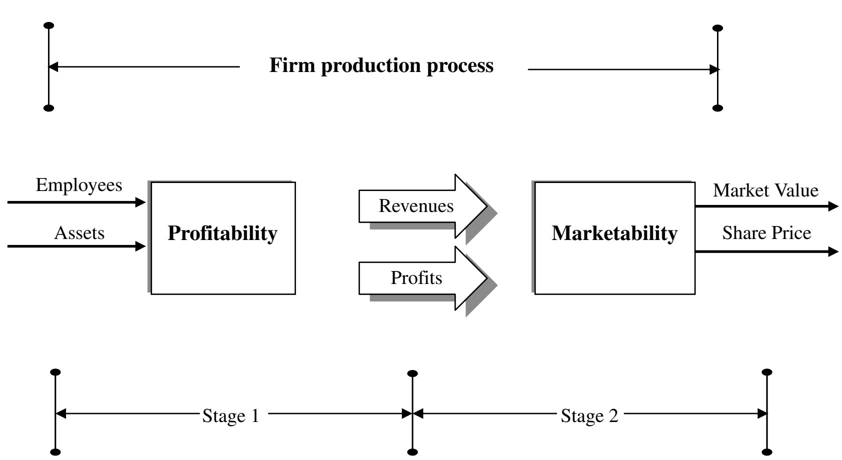

Fig. 2. Firm production process (after Seiford & Zhu, 1999).

Table 1
Product-moment correlation coefficients.

		1	2	3	4	5	6
1	Assets	1					
2	Employees	0.378**	1				
3	Revenue	0.757**	0.324*	1			
4	Profit	0.671**	0.122	0.818**	1		
5	Market cap	0.538**	0.157	0.780**	0.803**	1	
6	Share price	0.433**	0.096	0.603**	0.593**	0.440**	1

* Correlation is significant at the 0.005 level (2-tailed).
** Correlation is significant at the 0.001 level (2-tailed).

assessing efficiency. However, it is likely that the size of the company will influence its ability to produce goods and services more efficiently. As the CRS totally ignores the scale of operations and will possibly lead to an identification of very unrealistic benchmarks (Munksgaard, Pade, & Fristrup, 2005), a variable return to scale model (VRS) is used in this study. A VRS frontier allows best practice level of outputs to inputs to vary with size of company. A DEA model can be analyzed in two ways, an input-orientation or an output-orientation. An input-orientation provides information as how much proportional reduction of inputs is necessary while maintaining the current levels of outputs for an inefficient company to become DEA-efficient. On the other hand, an output-orientation analysis provides information on how much augmentation to the levels of outputs of an inefficient company is necessary while maintaining current input levels for it to become DEA-efficient. Since it is well known that, in competitive markets, the DMUs are output-oriented (Barros & Athanassiou, 2004), we use the output maximization assumption in this study.

To ensure the validity of the DEA model specification, an isotonicity test (Avkiran, 1999) was conducted. An isotonicity test involves the calculation of all inter-correlations between inputs and outputs for identifying whether increasing amounts of inputs lead to greater outputs. As positive inter-correlations were found (see Table 1), the isotonicity test was passed and the inclusion of the inputs and outputs was justified.

4.2. Efficiency scores

While standard optimization software packages can be used for estimating efficiency scores, here we used a commercial package called Frontier Analyst Professional Version 3.0 (Banxia Frontier Analyst User Guide, 2001). In this software linear programming (LP) models outlined above are solved 62-times - once for each of the companies in the data set. For each company, the software searches for a linear combination of companies in the sample that produces a greater level of output with fewer inputs. The model is searching for a comparison that identifies output slacks or excess input usage of the company under analysis. In solving the LP problem three characteristics of the model must be specified by the user: the returns to scale, the valuation system, and the orientation system. Returns to scale may be either CCR or VRS. The evaluation system refers to weights placed on the inputs and outputs in the objective function, subject to the inequality constraints. The orientation system, which defines the objective function, can be designated as input-orientation or output-orientation. In this study we use the VRS output-orientation model with the default weights suggested by the software.

The VRS scores measure pure technical efficiency (TE) only. However, for comparative purposes, we also present the CRS scores, which are composed of a non-additive combination of pure TE and scale efficiencies. A ratio of the overall efficiency scores to pure TE scores provides a scale efficiency measurement. The relative efficiency scores of the companies analyzed are presented in Table 2. The results indicate that scores range from 7 to 100 per cent for the companies in the sample, with an average of 47 percent when using the CCR model (CRS) with a standard deviation of 30.36, and from 7 to 100 per cent, with an average of 53 per cent and a standard deviation of 30.64 for the companies in the sample when using the BCC model (VRS). This means that, if the average company in the sample was to achieve the level of its most efficient counterpart then the average company could realize a 53 per cent cost saving (i.e., 1−[47/100]. A similar calculation for the most technically inefficient company reveals cost savings of 93 per cent. A Spearman's rank-order correlation coefficient between the efficiency rankings derived from CCR and BCC analyzes is 0.99. The positive and strong correlation indicates that the rank of each company derived from applying the two approaches is similar. This implies that the choice of methodology has no apparent impact on the estimated average efficiency scores.

These results are not surprising as it has been shown that DEA scores computed with the CRS assumption are less than or equal to the corresponding VRS efficiency scores (Banker et al., 1984). However, it is difficult to interpret overall companies' efficiency by comparison with other industries because of the lack of data across industries. For example, in a study of the large banks in the U.S., Miller and Noulas (1996) found 0.95 mean TE scores, which mean that companies in Egypt are less competitive and/or less efficient than the U.S. banking industry.

Bergendahl (1998) states that DEA technique is an adequate tool for benchmarking, since it allows the identification of a group of efficient companies for each non-efficient one. This identified group may be used in the definition of operational goals for their non-efficient counterpart, considering its various input and output variables. Table 2 provides the linear combination of companies on the efficiency frontier closest to a particular company. The linear combination is also referred to in the literature as the peer group or the reference set for this company and indicates to which of the efficient companies an inefficient company is closest in its combination of inputs and outputs. A company, which appears frequently in the reference set is likely to be a company which is efficient with respect to a large number of factors, and is probably a good example of an exemplary operating performer. Efficient companies that appear seldom in the reference set of other companies are likely to possess a very uncommon input/output mix and are thus not suitable examples for other inefficient companies. Fig. 3 represents the reference frequencies of the efficient companies.

It can be seen from Fig. 3 that out of the 62 companies in the data set only 10 are efficient. Of these, the one that appears more frequently as peer (i.e., benchmark) is Orascom Telecom Holdings (46 times) followed by Alexandria Pharmaceutical and Chemical Industries Company (39 times) followed by Kafr El-Zayat Pesticides company (19 times) etc. In other words, the peer count number can be considered a measure of the extent to which the performance of an efficient company can be a useful for the non-efficient ones.

4.3. DEA-NN algorithm

Following the efficiency analysis algorithm used by Wu et al. (2006), BCC method is used to calculate efficiency scores as outlined above. The results are grouped into four categories based on the efficiency scores. The efficiency score interval of $S1 \in (0.98, 1)$ is referred to as 'strong relative efficient interval'. The efficiency score interval of $S2 \in (0.80, 0.98)$ is referred to as 'relative efficient interval'. The efficiency score interval of $S3 \in (0.50, 0.80)$ is referred to as 'relative inefficient interval'. The efficiency score interval of $S4 \in (0, 0.50)$ is referred to as 'very inefficient interval'. The PNN and MLP networks are then trained with 20% of the data selected randomly. Network training is a process by which the connection weights and biases of the NN are adapted through a continuous process of simulation

Table 2
Egyptian companies' efficiency indices.

	Company	CCR efficiency	BCC efficiency	RTS	Reference set	Scale efficiency
1	Misr beni suef cement	100	100	0		1
2	Misr qena cement	100	100	0		1
3	Kafr El-Zayat pesticides	100	100	0		1
4	Alexandria pharma and chem indus	100	100	0		1
5	Egyptian company for mobile serv	100	100	0		1
6	Orascom construction industries	100	100	0		1
7	Orascom telecom holdings	100	100	0		1
8	Vodafone Egypt	100	100	0		1
9	Amereya cement	95.96	100	0		0.96
10	Sinai cement co	94.26	100	0		0.94
11	Misr free shops co	92.21	96.02	1	8,5,2,1,6	0.96
12	Oriental weavers	83.01	92.67	−1	8,9,6,4	0.9
13	Arab drugs and chem industries	76.51	90.73	1	8,9,10	0.84
14	Egyptian satellite co	76.51	84.2	1	8,10	0.91
15	Suez cement	71.23	83.02	−1	8,9,7,6,4	0.86
16	Egypt gas	70.79	81.63	−1	9,7,1	0.87
17	Paints & chem industries co	70.45	77.09	1	2,6	0.91
18	Alexandria national iron and ste	69.15	75.92	1	9,7,5,6	0.91
19	Memphis pharma	67.88	71.13	−1	8,9,5,6,4	0.95
20	Abu qir fert & chem industries	57.22	71.02	−1	8,2,4	0.81
21	Central & west delta flour mills	53.69	69.93	1	7,5,2,6	0.77
22	Upper Egypt flour mills	53.15	65.27	1	8,6	0.81
23	Media production city	45.8	63.27	1	8,7,5,10,6	0.72
24	South cairo and giza mills & bak	45.19	62.83	1	8,10,6	0.72
25	Nasr co for civil works	44.7	62.17	1	9,6	0.72
26	Tourah Portland cement	44.54	59.66	1	8,10,6	0.75
27	Nile pharma and chem industries	44.36	52.2	1	8,6	0.85
28	North Cairo flour mills	44.07	51.61	1	8,6	0.85
29	East delta flour mills	43.66	51.04	1	8,10,6	0.86
30	Delta industries	40.08	49.99	−1	8,5,3,4	0.8
31	Medical union pharma	39.75	49.62	1	8,6	0.8
32	Mohandes insurance	39.04	48.32	−1	8,5,3	0.81
33	Egyptian starch & glucose	38.78	47.09	1	8,10	0.82
34	Egyptian financial and industria	37.39	45	1	8,9,5,10,6	0.83
35	Cairo pharma and chem industries	35.27	45	−1	8,9,6,4	0.78
36	Misr oils and soaps	33.87	43.44	−1	8,9,2	0.78
37	Egyptian int'l pharma industries	32.13	40.27	−1	8,6,4	0.8
38	Eastern tobacco company	29.92	39.56	−1	8,5,6,4	0.76
39	Alexandia flour mills	29.14	39.07	−1	7,2,6,4	0.75
40	Giza general contracting	26.01	38.04	1	8,6	0.68
41	Central egypt flour mills	25.77	34.8	−1	8,5,4	0.74
42	Bisco misr	25.68	34.72	−1	8,5,3,4	0.74
43	Egypt aluminum	25.21	31.82	−1	8,6,4	0.79
44	Arab cotton ginning co	25.03	30.86	1	8,6	0.81
45	Canal shipping agencies	24.77	27.26	1	8,5,10,6	0.91
46	Amoun pharma company	24.32	26.81	1	8,6	0.91
47	Egyptian chemical industries	22.39	26.31	1	8,6	0.85
48	El-Nasr transformers	21.92	23.02	−1	8,6,4	0.95
49	Extracted oils and derivatives	20.47	22.16	1	8,6	0.92
50	Egyptian contracting	20.02	21.44	−1	8,5,4	0.93
51	Misr chem industries	19.82	20.04	1	8,6	0.99
52	Cairo poultry processing company	19.58	19.81	1	8,6	0.99
53	Rakta paper manufacturing	18.32	18.51	−1	8,2,4	0.99
54	National cement	17.37	18.45	−1	8,6,4	0.94
55	General silos and storage co	16.63	18.42	−1	8,3,4	0.9
56	Egyptian electrical cables	15.84	17.56	1	8,9	0.9
57	Alexandria spinning and weaving	13.07	16.88	1	8,6	0.77
58	Arab polvara spinning and weaving	10.11	14.53	1	8,10,6	0.7
59	Industrial & engineering enterpr	8.74	10.75	1	8,6	0.81
60	El-Nasr clothes and textiles	8.53	9.57	1	8,10,6	0.89
61	Egyptian iron & steel company	7.22	8.99	−1	8,6,4	0.8
62	Orascom hotel holdings	6.6	6.7	−1	8,9,6,4	0.99

Note: RTS = Return to scale; 0 = constant; −1 = decreasing; 1 = increasing.

by the environment in which the network is embedded. The primary purpose of training is to minimize an error function by searching for a set of connections strengths and biases that causes the NN to produce outputs that are equal or close to targets. A number of training algorithms can be used. In practice, the Levenberg-Marquardt routine often finds better optima for a variety of problems than do the other optimization techniques (Shavlik, Mooney, & Towell, 1991). After the training phase the NN model is applied to the data set to classify each company into one of the four categories. Following Athanassopoulos and Curram (1996), inputs to the PNN represent the same inputs to the DEA plus performance targets and efficiency measures. The latter two measures can easily be obtained by solving the DEA model.

There are many computer software packages available for building and analyzing NNs. Because of its extensive capabilities for building networks based on a variety of training and learning

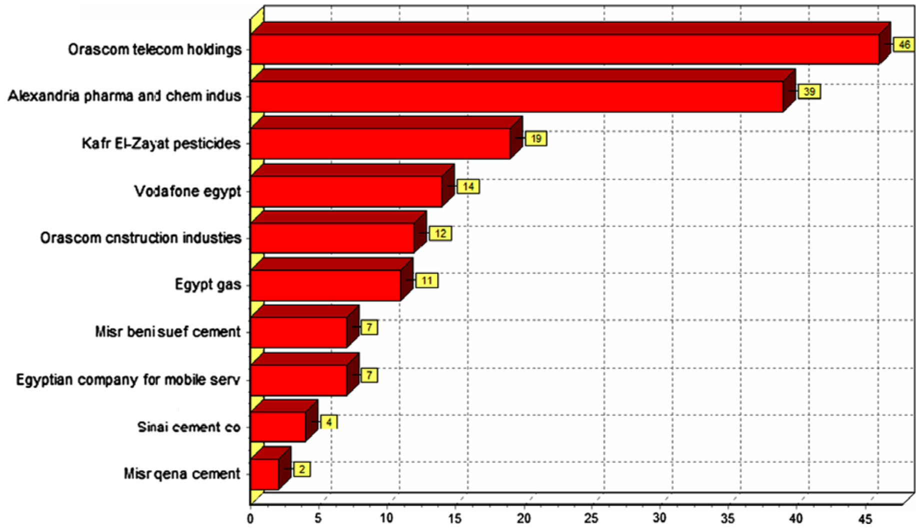

Fig. 3. Efficient companies' reference set frequencies.

methods, Neural Tools Professional package (Palisade Corporation, 2005) was chosen in this study. This software automatically scales all input data. Scaling involves mapping each variable to a range with minimum and maximum values of 0 and 1. Neural Tools Professional software uses a non-linear scaling function known as the 'tanh', which scales inputs to a $(-1, 1)$ range. This function tends to squeeze data together at the low and high ends of the original data range. It may thus be helpful in reducing the effects of outliers (Tam et al., 2005).

4.4. PNN-based classification

To study the effectiveness of the PNN-based classification of relative efficiency, the results of PNN were compared with both MLP network and the traditional multiple discriminant analysis (MDA). MDA is frequently used supervised pattern recognition technique. A linear function of the variables is sought, which maximizes the ratio of between-class variance and minimizes the ratio of within-class variance. MDA is an extremely simple and efficient method of classification. Indeed, it cannot be outperformed if the two distributions are normal and have the same dispersion matrix (i.e., Bayes limit). A common measure of predictive models is the percentage of observation correctly classified or the hit ratio. Table 3 reports the predictive accuracy of the three models. As can be observed in Panel (a), the PNN classifier predicted the training sample with 94% accuracy and the test sample with 83.7% accuracy after 153 trials (runs). In Panel (b), the MLP classifier had an accuracy rate of 100% for the training sample and 83.7 accuracy rates for the test sample, while the MDA model had an accuracy rate of 75.8% as reported in Panel (c).

Our results confirm the theoretical work by Hecht-Nielson (1989) who has shown that NNs can learn input–output relationships to the point of making perfect forecasts with the data on which the network is trained. However, perfect forecasts with the training data do not guarantee optimal forecasts with the testing data due to differences in the two data sets. The superior performance of the PNN can be traced to its inherent non-linearity. This makes an NN ideal for dealing with non-linear relations that may exist in the data. Our results also corroborate the findings of other researchers who have investigated the performance of 0NN compared to other traditional statistical techniques, such as regression analysis, discriminant analysis, and logistic regression analysis. For example, in a study of clinical diagnosis of cancers, Shan, Zhao, Xu, Liebich, and Zhang (2002) found a hit ratio of 85% for the PNN model compared to 80% for the MDA model. In a study of credit-scoring models used in commercial and consumer lending decisions, Bensic, Sarlija, and Zekic-Susac (2005) compared the performance of logistic regression, neural networks and decision trees. The PNN model produced the highest hit rate and the lowest type I error. Similar findings have been reported in a study examining the performance of NN in predicting bankruptcy (Anandarajan, Lee, & Anandarajan, 2001).

4.5. Sensitivity analysis

Despite the satisfactory classification performance of the PNN in this study, such models are often criticized as black boxes that do not allow decision-makers to make inferences on how the input variables affect the models' results. One way to address this issue is to conduct sensitivity analysis. Sensitivity analysis in this study was performed using the variable impact option in Neural Tools software. The purpose of variable impact analysis is to measure the sensitivity of net predictions to changes in independent variables. This analysis is only done on training data. Fig. 4 shows that the most important input variable for the PNN is revenue followed by share price. The lower the percent value for a given variable, the less that variable affects the predictions. The results of the analysis can help in the selection of a new set of independent variables, one that will allow more accurate predictions. For example, a variable with a low impact value can be eliminated in favor of some new variables.

5. Implications

Systematic benchmarking through efficiency measurement is one method managers can use to ensure the efficiency of their companies. In contrast with piecemeal examination of single performance indicators, global efficiency techniques used in this study can offer Egyptian managers a rounded assessment of their companies' performance. Unlike targets that are based on individual performance measures, global efficiency measures can offer local managers the freedom to set their own priorities, and to seek out improvements along dimensions of performance where they believe that gains are most readily secured. DEA results can also be used by Egyptian managers to support other objectives, such as allocating finance or identifying the priorities for inspection and improvement of performance. One of the important implications

Table 3
Predictive accuracy of classification models.

	1	2	3	4	Bad (%)
Panel (a): PNN					
Training cases					
1	9	0	0	0	0.0
2	1	3	0	0	25
3	0	0	10	2	16.7
4	0	0	0	25	0.0
Testing cases					
1	1	0	0	0	0.0
2	0	0	1	1	100
3	0	0	1	0	0.0
4	0	0	0	8	0.0
PNN summary					
Training					
Number of cases: 50					
Training time (h:m:s): 00:00:00					
Number of trials: 153					
Reason stopped: Auto-stopped					
% Bad predictions: 6.00%					
Mean incorrect prob.: 19.13%					
SD of incorrect prob.: 23.28%					
Testing					
Number of cases: 12					
% Bad predictions: 16.67%					
Mean incorrect prob.: 37.24%					
SD of incorrect prob.: 35.75%					
Panel (b): MLP					
Training cases					
1	6	0	0	0	0.0
2	0	6	0	0	0.0
3	0	0	12	0	0.0
4	0	0	0	26	0.0
Testing cases					
1	2	0	2	0	50
2	0	0	0	0	0.0
3	0	0	1	0	0.0
4	0	0	0	7	0.0
MLP summary					
Training					
Number of cases: 50					
Training time (h:m:s): 02:0:0					
Number of trials: 29807516					
Reason stopped: Auto-stopped					
% Bad predictions: 0.00%					
Testing					
Number of cases: 12					
% Bad predictions: 16.67%					
*Panel (c): MDA**					
Class count					
					Total
1	8	2	0	0	10
2	1	4	1	0	6
3	1	0	9	3	13
4	0	0	7	26	33
Class per cent					
1	80.0	20.0	0.0	0.0	100.00
2	16.7	66.7	16.7	0.0	100.00
3	7.7	0.0	69.2	23.1	100.00
4	0.0	0.0	21.2	78.8	100.00

* 75.8% of original grouped cases correctly classified.

of this study is that efficiency measures facilitate the publication of 'league tables' or rankings of entire Egyptian companies. Some authors believe that such rankings nurture public interests in the performance of organizations, promote accountability and stimulate a search for improvement (Hibbard, Stockard, & Tusler, 2003). Finally, it is hoped that Egyptian managers have the possibility to analyze organizational practices of the peer groups and that they are able to improve their future efficiency by adapting these practices for their inefficient companies.

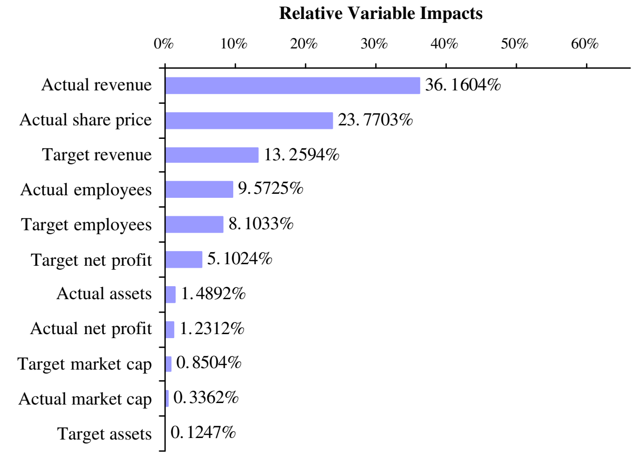

Fig. 4. Relative variable impact analysis of the variables used in the study.

6. Limitations and future research

Like any other study, the present study has several limitations that warrant more research. First, it may not always be possible for a company to ever become efficient because several of the inputs may not be under the full control of management. Therefore, it must be clear that some DEA targets might be impossible to be achieved in practice. DEA results are obtained from the application of a mathematical algorithm, without considering specific conditions and restrictions of a company. It is in the hands of managers to skillfully use these results as a support for decision making. Second, the selected variables in the present study might not be exhaustive, and the data set is short. Staat (2001) has showed formally how DEA efficiency scores are affected by sample size. Future studies may use larger sample size and panel data with different sets of inputs and outputs to test the robustness of the results. Third, this study used a cross-sectional data set to evaluate the efficiency of the top listed Egyptian companies. However, Sengupta (1995) suggests that competitiveness or efficiency can better be evaluated through analysis of average efficiencies across time. Future studies may use longitudinal designs to assess time-varying efficiency. Fourth, we followed Seiford and Zhu (1999) approach in using profitability and marketability to characterize the performance of a company. Other approaches might be used as well. For example, in an application in the health insurance companies in Canada, Wu et al. (2006) found that production and investment are good predictors of companies' efficiencies. Finally, as suggested by Bauer, Berger, Ferrier, and Humphrey (1998), for the frontier-based efficiency scores to be useful, the estimated scores should be positively correlated with traditional non-frontier-based measures of performance. Future studies should test the existence of positive rank-order correlations between efficiency scores obtained from DEA analysis and traditional efficiency measures such as financial ratios. This test would give assurance that frontier measures are not simply artificial products of the assumptions made regarding the underlying optimization techniques used.

Appendix

Inputs

Assets. Any item of economic value owned by a company and could be converted to cash.

Employees. Full-time workforce during the year of the study.

Outputs

Revenue. This is the audited figures provided by the individual companies to the CASE. Revenue is the entire amount of income (including interests earned, receipts from sales, services provided, rents and royalties) before any deductions are made.

Net profit. A profit is achieved after taxes, expenses, and extraordinary credits or charges that appear on a company's income statement are deducted.

Market capitalization. The market price of an entire company, calculated by multiplying the number of shares outstanding by the price per share.

Share price. The cost per share in Egyptian pounds for the company's stock as of December 31, 2003.

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