ANN-DEA Approach of Corporate Diversification and Efficiency in Bursa Malaysia

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ABSTRACT

There is little consensus on the corporate diversification-efficiency relationship in the diversification literature. According to the corporate diversification, firms have a tendency to get more market share with diversifying in the local segment or in the international market. Theoretically, a contradictory exists between the profitable strategy and the value reducing strategy in the diversification strategy. In this paper, we measure firm's efficiency by applying Data Envelopment Analysis (DEA) in manufacturing firms listed in Bursa Malaysia for five years. Meanwhile, a feed forward multilayer perceptron neural network is applied to model the mapping function between the input and output data to the efficiency score. Back propagation (BP) learning algorithm is applied to update network's weights through minimizing the cost function, and the best topology of the network is conducted. The result of this study shows that there is a negative relationship between total product diversification and efficiency, and international diversification has a non-linear effect on the efficiency.

1. Introduction

In the fast developing world, firms have undeniable effect on the economy of their countries as well as the abroad through different methods such as corporate diversification [20]. According to the corporate diversification, firms have a tendency to get more market share with diversifying in the local segment or in the international market. The importance of the corporate diversification is up to the level that makes it as important phenomena in the modern business world [6].

Theoretically, a contradictory exists between the profitable strategy and the value reducing strategy in the diversification [39]. Researchers use a regression model to conduct this struggle. However, regression models have some limitations in dealing with this contradictory while Artificial Neural Networks (ANN) is able to handle these problems more properly. In addition, Doaei and Shavazipour [21] ap-

plied data envelopment analysis to evaluate the efficiency degree based on the corporate diversification and the financial performance factors. Then, they utilized the Malmquist index of productivity (MIP) to measure the productivity changes of Malaysian manufacturing firms. In this study, we extend their work by applying Artificial Neural Networks in order to make clear more accurately optimized impact of the total product diversification and the international diversification on the efficiency. In a recent endeavor, Wang *et al.* [49] Study the impact of corporate diversification on corporate performance of the top 100 manufacturing companies in Taiwan. They applied a dynamic data envelopment analysis model to estimate efficiency in the first stage, and adopt OLS regression analysis in the second stage from 2009 to 2013. The results show that diversification has positive impacts on dynamic efficiency.

This paper is divided into seven parts. The next section reviews the related research. Section 3 describes data envelopment analysis. Artificial Neural Networks is presented in section four. Section 5 contains research methodology. Experiments and results are summarized in section six. Further discussions and conclusion have been cited in section 7.

2. Review of Literature

Doaei *et al.* [19] reviewed some main theories that support why firms diversify. Resource-based theory [40] and market power theory [22] confirms positive and agency theory [29] and free cash flow theory [28] state negative impact of diversification on firm's financial performance. Now, related studies are presented briefly.

Sometimes firms can achieve higher performance by doing corporate diversification (product and international) [37]. In addition, the firm can enhance economies of scope from many international markets and product portfolios. Due to this cause, corporate diversification (product and international) in general matter has a positive effect on performance [8,15,34]. Thus, diversification in various kinds of product and present in an international market causes the firm to enhance its performance [26].

In the contrary of these privileges, expanding into new segments and nations may also suggest a decrease in performance. Additionally, the expanding may happen to follow the personal objectives by managers, such as reducing employment risk or getting more bonuses at sacrifice of firm's profitability and growth [33,48,43]. Therefore, more coordinating is required once the firm grows in new segment and market, otherwise it may lead many costs for a firm [8,27,30,50]. In sum, it may be expensive for firms to connect between internal corporate settings and the external environment. Further, expanding into new geographic markets where the culture, regulation and habits are different, may influence the firm's performance [8,48]. Nevertheless, high level of diversification can reduce performance [31].

Doaei *et al.* [18] explore the corporate diversification-efficiency relationship in the diversification literature. They contribute to the literature by looking jointly at two dimensions of corporate diversification as product diversification and international diversification and the relationship between them. The results show negative relationship between product diversification and efficiency, international diversification and efficiency and corporate diversification and efficiency in manufacturing firms listed in Bursa Malaysia. In addition, Doaei and Shavazipour [21] found out efficiency degree based on corporate diversification and financial performance factors. Then, they utilized the Malmquist index of productivity (MIP) to measure the productivity change of Malaysian manufacturing firms. Their results indicated that Bursa Malaysian experienced on average 88% productivity loss from 2006

to 2010. With regard to diversification research in Bursa Malaysia, Doaei *et al.* [20] tried to examine the relationship between total product diversification and international diversification with financial performance in manufacturing firms listed in Bursa Malaysia. They applied two regression models by return on assets (ROA) as a dependent variable. Furthermore, the main independent variables were total product diversification (TPD), related product diversification (RPD), unrelated product diversification (UPD), international diversification (ID). The results indicated product diversification, and unrelated diversification were not significant; however, related diversification and international diversification had a negative significant impact on financial performance in their models.

The nearest work in our research is presented in Karamali *et al.* [32]. In that research, ANN is applied to Data Envelopment Analysis (DEA). In the other word, using ANN, they provide a platform for simulating the level of some parameters against the rest of the parameters for generating different scenarios, which is in demand for the managers. Each state is evaluated by maintaining the score of the efficiency. Although we follow the same methodology, the topology of the network in our work is completely different. In their network, input parameters are entered to the first layer of the network (Input Layer) while the output parameters and the efficiency are considered as the outputs of the network (Output Layer). A network with about four input parameters and six output parameters does not converge fast, and its results are not reliable. In the proposed method, the input and output parameters are considered as the inputs of the network in the first level and the proposed network has just one output parameter, which is efficiency value.

3. Background
3.1 Efficiency and Data Envelopment Analysis (DEA)

DEA was presented in 1978 by Charnes, Cooper and Rhodes for measuring efficiency in public programs [10], where this tool is used in many research areas. However, with respect to developing DEA models and its many advantages, Emrouznejad et al. [23] pointed out the number of research increased about 360 per year after 2004. Due to its successful application as well as case studies, DEA is given more consideration and is expanded by scholars [46].

Assume that there are n DMUs, $(DMU_j : j = 1, 2, \dots, n)$ which consume m inputs $(X_{ii} : i = 1, 2, \dots, m)$ to produce s outputs $(Y_r : r = 1, 2, \dots, s)$. The Charnes, Cooper, and Rhodes presented a fractional programming problem which measuring efficiency of DMU_0 which formulated as shown in Model (1):

$$M \quad \theta = \frac{\sum_{I=1}^{s} u_I y_{IU}}{\sum_{i=1}^{m} v_i x_{iU}} \text{ Such that } \frac{\sum_{I=1}^{s} u_I y_r}{\sum_{i=1}^{m} v_i x_i} \leq 1; \quad j = 1, \dots, n$$

$$v_i \geq 0 \quad i = 1, 2, \dots, m; \quad u_r \geq 0 \quad r = 1, 2, \dots, s \tag{1}$$

Where x_{ii} and y_r are the inputs and outputs (positive) of the DMU_j, v_i and u_r represent input and output weights, respectively (also referred to as multipliers). $x_{i(}$ is the inputs and y_r is the outputs of DMU_0. Besides, the fractional program is not used for actual computation of the efficiency scores due to its non-convex and nonlinear properties. Hence, by using Charnes and Cooper [9] transformation, Model (1) can be equivalently transformed into the linear program called CCR based on the name of Charnes, Cooper and Rhodes. However, we applied BCC (Banker, Charnes, and Cooper) model [2] to evaluate the efficiency of decision making units based on efficient frontier with respect to variable

return to scale (VRS). BCC envelopment model for finding the degree of efficiency in this research as noted in below:

$$M \quad y_0 = \theta \; Such \; that -\theta x_{i_i} + \sum_{j=1}^{n} \lambda_j x_i \leq 0 \; ; \quad i = 1,2,\dots,m$$
$$-\sum_{j=1}^{n} \lambda_j y_r + y_r \leq 0 \; ; \quad r = 1,2,\dots,s \quad (2)$$
$$\sum_{j=1}^{n} \lambda_j = 1 \; ; \quad j = 1,2,\dots,n \; ; \lambda_j \geq 0 \quad a \quad \theta \; is \; f \quad i \; s_i$$

Where x_{ii} (i = 1, ..., m) and y_r (r = 1, ..., s) (all non-negative) are the inputs and outputs of the DMU_j. While, x_{i_i} and y_r are the inputs and outputs of DMU_0. The BCC model must be run n times, once for each unit, to get the relative efficiency of all DMUs.

As a brief, DEA has many advantages, which are listed as: (a) the power to compute many inputs and outputs for each organization such as firm and not need to identify parametric assumptions of old multivariate technique, and (b) the power for benchmarking members of the efficient set and determine a relationship with inefficient units [14,44].

3.2 Artificial Neural Networks

In computer science, artificial neural networks (ANN) are computational models inspired by animals' central nervous systems that are capable of machine learning and pattern recognition. ANN is a non-parametric approach, and it does not consider any assumption about the functional form between inputs and outputs. This technique has the capability to find the relation between the variables and to correlate a set of independent variables with more than one dependent variable. Therefore, ANNs can practically correspond to DEA models when multiple inputs (parameters) are correlated to multiple outputs (parameters) [32].

In this paper, a feed forward neural network is used in order to approximate the mapping function between the input parameters and the output parameters as the inputs of the network to the efficiency score as the output parameter of the network. In addition, Back propagation (BP) learning algorithm is applied to update network's weights through minimizing the cost function.

4. Research Methodology

The sample is chosen from manufacturing firms listed in Bursa Malaysia during 2006 to 2010. 102 firms are selected due to availability of the data during this period. In this study, we used four input and six outputs for BCC model same as Doaei and Shavazipour [20].

The first key issue in any DEA application is the way of inputs and outputs selection. The outputs should reflect the business goals, and the inputs should provide the required resources for achieving those goals [38]. As Table 1 shows, return on assets (ROA), return on equity (ROE), profit margin (PM), market to book ratio (MB), Tobin's Q (TQ) and earnings per share (EPS) are chosen as outputs because these are business goals. Total product diversification (TPD), international diversification (ID), logarithm of total assets (LTS) and leverage (L) are considered as input variables because these are used for achieving the business goals.

Since for each DMU, the efficiency score is varying by alteration in the inputs and outputs, so it is necessary to consider accurate specifications in each case. In this step, the BCC model (1) is utilized. By applying input and output parameters and running the BCC model, efficiency score for each *DMU*

is obtained.[1]

Table 1: DEA Variable

1	Symbol	2	Kind of Variable	3	How measure
4	TPD	5	Input	6 7	$E = \sum_{i=1}^{n} P_i lh\,(1/P_i)$ Where, $P_i, (i = 1, ..., n)$ is the share sale of segment i in total sales of the firm and n is the number of firm's segments
8	ID	9	Input	10	The ratio of foreign sales to total sales.
11	LTS	12	Input	13	Logarithm of total assets
14	L	15	Input	16	The ratio of total assets minus total equity to total assets (total debt ratio)
17	ROA	18	Output	19	$R = \frac{N\ In}{T\ A}$
20	ROE	21	Output	22	$R = \frac{N\ In}{T\ E}$
23	PM	24	Output	25	$P = \frac{N\ In}{S}$
26	MB	27	Output	28	$M = \frac{M\ V\ p\ Sha}{B\ V\ p\ Sha}$
29	EPS	30	Output	31	$E = \frac{N\ In}{Sha\ O}$
32	TQ	33	Output	34	$T = \frac{M\ v\ o\ e + B\ v\ o\ li}{B\ v\ o\ t\ a}$

4.1 Training ANN

The critical step in using ANN is the training step. In training, the weights between different nodes in different layers of the network are set. In this step, the input parameters and the output parameters of DEA are used as input of the ANN's input layer and the efficiency score which has been obtained by DEA is utilized as the data for output layer. Therefore, by training the ANN we can find the relation of these factors. We use output parameters as the targets. In training phase ANN tries to close up the outputs to the targets. So that in the process of training this relation is estimated.

In training of the ANN, early stopping method is used. This selection is done in order to improve generality of the neural network. In the early stopping method, data records are divided to the Training set data which is used for computing the gradient and updating weights and biases of the network, Validation set, which is utilized to decrease the error of the validation set, and test set, which is used to compare performance of different networks after finalizing the training process. In addition, the transfer function for each layer, the learning algorithm, and the number of neurons in hidden layer are optimized by trial and error. These reformations are done in order to find a suitable architecture for the utilized ANN.

5. Experiments and Results

In order to evaluate the proposed method, after training the network and determining one of the relations between the input data and the output data as input of the network and the efficiency as the output of network, two experiments are conducted. In the first experiment, the trained ANN is run using test data in order to investigate its sensitivity. And in the second experiment, the network is simulated

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[1] Refer to Doaei and Shavazipour (2014) for more details about the results of DEA model.

for the altered input data. In this experiment, by altering each input parameter, sensitivity of the system is evaluated.

5.1. Training ANN by different architectures to estimate relations between inputs-outputs and the efficiency

Sometimes from managers' point of view, it is important to investigate, if fixed efficiency is used by some special inputs and outputs, how much efficiencies should be produced. So, in order to learn this relation, we use the input and output parameters as the inputs of the ANN and the efficiency as the outputs of ANN. Therefore, in the architecture of ANN, the input vector by the input parameters and output parameters has ten elements, and output layer has only one neuron. A topology of the network is illustrated in Figure 1.
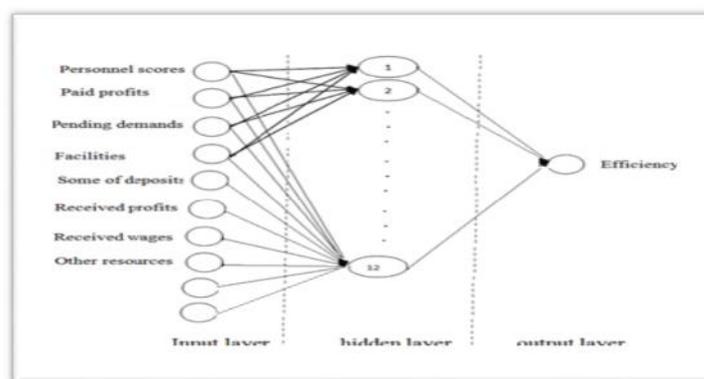
Figure 1: Topology of the Proposed Network

5.2. Simulating the outputs by running ANN

Now it is possible to estimate the efficiency scores by preferred alteration in the input and output parameters using obtained ANN from previous step. This method helps managers to decide if input sources are consumed according to desired efficiencies, how much efficiency could be obtained.

In this study, 80 percent of data is used for training, 10 percent for validation and 10 percent for test. The used neural network in this study is a two-layer neural network with a single hidden layer. Among different examined ANNs, we used ANN by the architecture that is composed:

- ﴾ Early stopping method for improving the generalization
- ﴾ Tan-sig transfer function in both layers
- ﴾ Resilient Back-propagation (Rprop) training algorithm
- ﴾ 12 neurons in hidden layer
- ﴾ Msereg1 perform function with perform ratio equal to 0.5 in order to compute the error in training process and to improve the generalization of the network.

Error! Reference source not found. illustrates the error in training, validation and test data sets. Mean Squared Error is used as the error index, and it is calculated for all three datasets: Train, Validation, and Test datasets. As it is clear in the figure, the charts converge to zero after a small number of iterations. **Error! Reference source not found.** shows the correlation between the outputs and the targets. The correlation is calculated separately for training, validation and test data sets. All the sub-

images illustrate that the output and the target values follow a similar pattern and the smaller values are corresponded to the smaller values and the bigger values are matched to the bigger ones. It means the model could simulate behavior of the system properly.
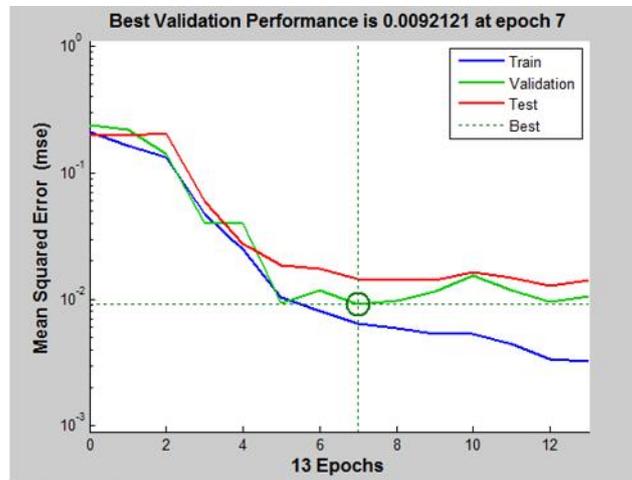

Figure 2: Error in the training, validation and test process

In **Error! Reference source not found.**, dependency degree between the efficiency value as the output of the system and its target is shown. In average, a correlation equal to 0.8906 shows that the system is simulated correctly.
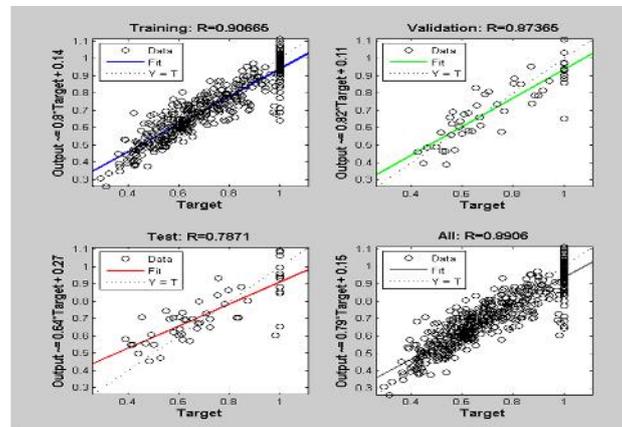

Figure 3: The R-value in training, validation and test set

## 5.3. Altering Input Variables and Simulating the Outputs

In this step by altering the input variables and considering ideal efficiency, the output variables are estimated. Considering this variation and ideal efficiency, preferred ANN estimates the outputs. The variation of inputs in each input parameter is from 0.2 time of the primary value up to 2 time of this value. This means that in each experiment while the other parameters are fix, value of a specific

parameter is changed from 0.2 time of its real value to 2 time of that parameter. Figure 5 shows by increasing the scale of TPD parameter, the efficiency decreases with a rather unique trend. It means
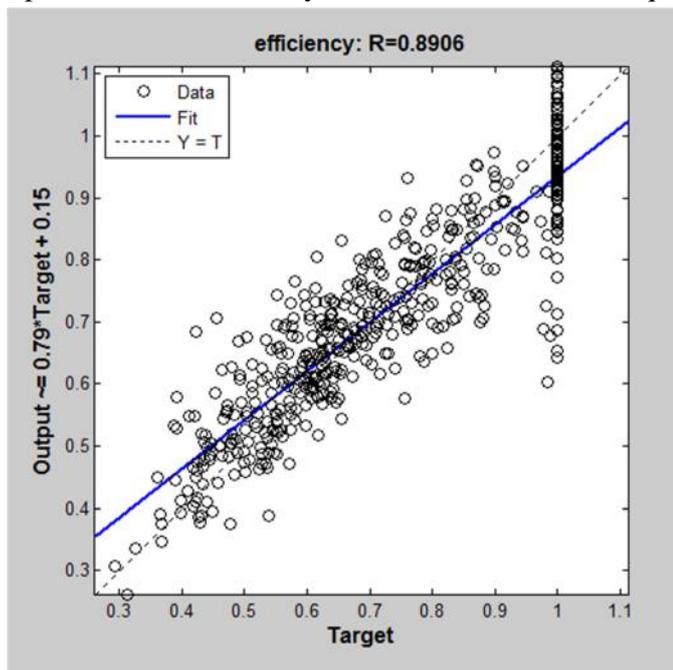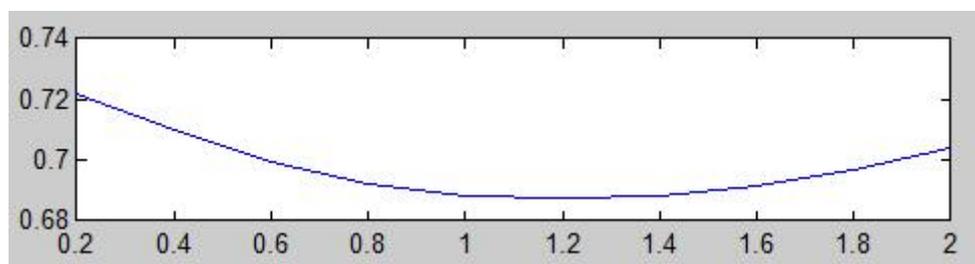

Figure 4: The R-value between efficiency and target

efficiency of the participant firms has a reverse relationship with Total Product Diversification (TPD) parameter.
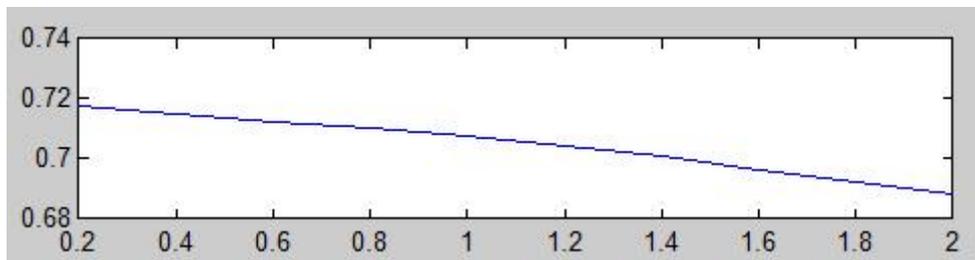
Figure 5 : The Efficiency when the TPD parameter scales from 0.2 to 2

Figure 6 : The Efficiency when the ID parameter scales from 0.2 to 2

Figure 6 illustrates variation of the efficiency when the ID parameter is scaled. This figure shows that the International Diversification parameter has a non-linear effect on the efficiency of the firms so that by decreasing this parameter's value to a value less than real value the efficiency experiences a better situation and it increases. In the other side by increasing the ID's value, the efficiency of the efficiency grow up albeit after a small gap between 1 to 1.3 that the efficiency decreases.

6. Discussion and Conclusion

In this study, firms' efficiency is measured by BCC (Banker, Charnes, and Cooper) envelopment model. For this purpose, four inputs and six outputs from 102 manufacturing firms listed in Bursa Malaysia for five years during 2006-2010 are collected and evaluated. Then, ANN is applied. Relying on the generated model, the following section discusses the key determinant of efficiency and corporate diversification of Malaysian manufacturing firms listed in Bursa Malaysia. The determinant variables are, total product diversification (TPD), international diversification (ID), logarithm of total assets (LTS), leverage (L), return on assets (ROA), return on equity (ROE), profit margin (PM), market to book ratio (MB), Tobin's Q (TQ) and earnings per share (EPS). However, there are two important variables as TPD and ID; so, we discuss on that variables.

The result of this study shows that there is a negative relationship between TPD and efficiency. These findings are supported by a number of studies such as Rumelt [41], Montgomery [36], Berger and Ofek [3], Comment and Jarrell [13], Servaes [42], Denis et al.[17], Clasessens et al.[12], Anderson et al.[1], Clasessens et al.[11], Tongli et al.[47], and Chakrabarti et al.[7]. They found out negative association between product diversification and financial performance. Our findings have signified that firms with high level of product diversification have a low level of efficiency. In addition, most of related studies about international diversification like Brewer [4], Michel and Shaked [35], Geringer et al. [25] and Denis et al. [6] found out international diversification results in a negative impact on financial performance. However, the results show the ID has a non-linear effect on the efficiency. Moreover, a U-shaped relationship between international diversification and firm performance has been found in some studies as Gaur and Kumar [24], Thomas [45] and Caper and Kotabe [5].

For future studies, researchers should consider big sample in Bursa Malaysia or other developing countries. Also, they should utilize other methods instead of applying data envelopment analysis (DEA) for measuring firms' efficiency. Finally, some practical consideration can be investigated by the authors. For example, all the input data do not deserves to be applied on the model; providing they are affected by some unseen factors, they are not match with the others and the model; these kinds of data should be detected, enhanced or neglected using some machine learning methods. It seems ANN can get substituted with a more conceptual model. Using evolutionary algorithms such as Genetic Algorithm can model the system more conceptual.

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