Benchmarking: An International Journal

Best performance modeling using complementary DEA-ANN approach: Application to Japanese electronics manufacturing firms

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Received 4 September 2014
Revised 9 December 2014
Accepted 27 December 2014

Best performance modeling using complementary DEA-ANN approach

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Abstract

Purpose – The purpose of this paper is to design an innovative performance modeling system by jointly using data envelopment analysis (DEA) and artificial neural network (ANN). The hybrid DEA-ANN model integrates performance measurement and prediction frameworks and serves as an adaptive decision support tool in pursuit of best performance benchmarking and stepwise improvement.

Design/methodology/approach – Advantages of combining DEA and ANN methods into an optimal performance prediction model are explored. DEA is used as a preprocessor to measure relative performance of decision-making units (DMUs) and to generate test inputs for subsequent ANN prediction modules. For this sequential process, Charnes, Cooper, and Rhodes and Banker, Chames and Cooper DEA models and back propagation neural network (BPNN) are used. The proposed methodology is empirically supported using longitudinal data of Japanese electronics manufacturing firms.

Findings – The combined modeling approach proves effective through sequential processes by streamlining DEA analysis and BPNN predictions. The DEA model captures notable characteristics and efficiency trends of the Japanese electronics manufacturing industry and extends its utility as a preprocessor to neural network prediction modules. BPNN, in conjunction with DEA, demonstrates promising estimation capability in predicting efficiency scores and best performance benchmarks for DMUs under evaluation.

Research limitations/implications – Integration of adaptive prediction capacity into the measurement model is a practical necessity in the benchmarking arena. The proposed framework has the potential to recalibrate benchmarks for firms through longitudinal data analysis.

Originality/value – This research paper proposes an innovative approach of performance measurement and prediction in line with superiority-driven best performance modeling. Adaptive prediction capabilities embedded in the proposed model enhances managerial flexibilities in setting performance goals and monitoring progress during pursuit of improvement initiatives. This paper fills the research void through methodological breakthrough and the resulting model can serve as an adaptive decision support system.

Keywords Data envelopment analysis, Artificial neural network, Best performance modeling, Japanese electronic industry

Paper type Research paper

Benchmarking: An International Journal
Vol. 23 No. 3, 2016
pp. 704-721

1463-5771
DOI 10.1108/BIJ-09-2014-0083

Introduction

Performance measurement and prediction is a generic management practice and has been considered a crucial step toward performance improvement across industries and countries. In today's competitive business and economic environment, superiority-driven business excellence has become imperative for both leading and lagging firms. The initiatives have been frequently understood from the benchmarking context with its rationale focussed on "improvement to be the best" (Anand, 2008; Camp, 1995; Maire *et al.*, 2005). The pursuit of best practice, demands technical expertise in the process of identifying benchmarking targets, measuring performance gaps, setting improvement goals, and monitoring their progress status (Prašnikar *et al.*, 2005). In addition to technical proficiency, a high level of managerial expertise is also considered crucial for successful implementation of best practices. For example, during the course of setting improvement goals pursuant to performance gaps between the best player and an entity of interest, namely, a decision-making unit (DMU), managers should be capable of verifying whether set goals are viable and achievable. Furthermore, managers should possess the ability to monitor and adjust action plans through "what-if" scenarios. Therefore, intuitive prediction capability should be considered one of the most progressive performance benchmarking tools in the decision-making process for sustainable performance settings (Francis and Holloway, 2007; Hsiang-Hsi *et al.*, 2013; Pendharkar, 2011). With this practical necessity and research void taken into consideration, this paper introduces a combined data envelopment analysis (DEA) and artificial neural network (ANN) approach and proposes an adaptive performance measurement and prediction modeling in support of best performance benchmarking and stepwise improvement.

DEA has been a popular optimization tool with its theoretical basis in linear programming. As an extreme point method, DEA identifies best practice DMUs, measures relative efficiency, and projects improvement level for each inefficient DMU to become efficient. However, despite its popularity in benchmarking studies, DEA has shortcomings with respect to its prediction capabilities which limits its usage (Mostafa, 2007, 2009; Wang *et al.*, 2013). For this reason, the integration of measurement and prediction frameworks still remains a challenging task (McAdam *et al.*, 2008). Furthermore, the importance of finding balance between theoretical and practical alternatives and the lack of techniques to monitor progress make methodological advancement more than a pressing need, especially in this volatile business environment (Francis and Holloway, 2007). ANNs, modeled after human thinking paradigms, acquire knowledge through an iterative learning process and weight adjustment between interconnected neurons. In doing so, ANN achieves generalization and abstract learning from a limited set of information and provides nonlinear mapping and predictive power (Fausett, 1994; Yi and Thomas, 2009). ANNs, especially the back propagation neural network (BPNN) model used for this study, search for weight sets to form a best fit through observed data sets. Therefore, BPNNs resemble a regression type of learning and excels in predicting central tendency of observed data rather than approximating extreme data sets (Pendharkar and Rodger, 2003; Wu *et al.*, 2006). Clearly, the predictive potential of ANN and the optimization capacity of DEA exhibit complementary features, thus envisioning a prominent modeling option.

Literature shows encouraging but rare outcomes of the combined approach of DEA and ANN with most of the studies focussed on predicting DEA efficiency as an indirect performance measure. Researchers have extended pilot studies conducted by Athanassopoulos and Curram (1996) through comparative and complementary studies using DEA-ANN and reported promising potential of the combined approach (Emrouznejad and Shale, 2009; Hsiang-Hsi *et al.*, 2013; Kuo *et al.*, 2010). However, very limited empirical studies have been conducted in the past and more promising successes yet to be made in this research stream. Recent literature reports the possibility of extending this combined model to the application of best performance benchmarking through prediction of optimal outputs beyond efficiency scores (ES; Kwon, 2014). This paper adds empirical evidence of the effectiveness of the combined model by using a large number of companies from the Japanese electronics industry. Demonstrated capability over similar but divergent companies enhances the potential utility of the combined model as a generalized method. Moreover, this study presents practical implementation of the method as a decision support tool with the capacity to test what-if scenarios.

Exploring an innovative performance measurement and prediction framework using DEA-ANN, this study fulfills a practical need and improves benchmarking and decision-making processes. The proposed combined model utilizes DEA as a preprocessor and the subsequent ANN model conducts prediction tasks for best performance output for each DMU. In addition to methodological advancement, this paper provides an insight on Japanese electronics manufacturing firms and their operations through efficiency analysis.

In summary, the main purpose and motivations for this research paper is threefold:

(1) to present integrated performance measurement and prediction model, thus bridging the research gap through methodological advancement.

(2) to enhance managerial flexibility in selecting actionable options from theoretical and practically feasible alternatives and potential progress monitoring through adaptive decision support measures.

(3) to provide empirical support on the proposed model using a large data set through streamlining sequential processes of DEA measurement and ANN prediction.

This paper is organized as follows. Related studies are reviewed in the first section, and the innovative input-output modeling system section briefly discusses theoretical background of the integrated approach. Model building processes and variables are discussed in empirical processes followed by experiment results which are discussed in empirical analysis and results section. Concluding remarks and suggestions for future studies are presented at the end.

Related studies

A growing number of recent studies (Hsiang-Hsi *et al.*, 2013; Yi and Thomas, 2009) signify ANNs as one of the emergent performance analysis methods, particularly with respect to input-output-based performance schemes. ANNs have been shown to be a promising performance benchmarking tool. With further exploration and greater empirical successes ANNs have the potential to be a new modeling tool in the areas of clustering, classification, and prediction. ANNs, modeled after biological neurons, are characterized by adaptive learning and generalization, thus providing robust data processing capabilities in the presence of complex and nonlinear relationships between input and output variables. Most of the previous studies, therefore, have investigated the feasibility of using ANN and reported superior performance of standalone ANN models over traditional approaches. Indeed, literature shows rich applications exploring the predictive potential of ANNs in the areas of supply chain benchmarking (Kuo *et al.*, 2010; Li and Dai, 2009), quality improvement (Alolayyan *et al.*, 2011; Carlucci *et al.*, 2013), project performance (Georgy *et al.*, 2005; Li and Liu, 2012), scheduling (Alpay and Yuzugullu, 2009; Tirkel, 2013), and demand predictions (Kourentzes, 2013;

Lau *et al.*, 2013). In these applications, a three layered BPNN model has been a popular choice due to its nonlinear model building capabilities (Ülengin *et al.*, 2011). BPNN has its strength in learning general patterns and central tendency of distributions through its regression type learning, therefore, it exposes limitations in learning optimal performance patterns as a standalone method (Athanassopoulos and Curram, 1996; Pendharkar and Rodger, 2003; Ülengin *et al.*, 2011). Up to this date, rare attempts have been made to further explore the strengths of BPNN and overcome its drawbacks, especially within the context of superiority-driven benchmarking and performance prediction.

DEA has been widely used in best practice benchmarking studies as a nonparametric optimization method since its introduction in late 1970s. As a frontier method, DEA measures relative efficiency of DMUs and project improvement levels for inefficient DMUs in terms of resource utilization and output generation. DEA has been a well suited method for best practice benchmarking as evidenced by a plethora of articles and its application within a variety of organizations, business sectors, and practices such as airports (Adler *et al.*, 2013; Georges and Gillen, 2012) banking (Paradi and Zhu, 2013; Paradi *et al.*, 2011), healthcare (Ferrier and Trivitt, 2013; Gok and Sezen, 2012), hotels (Huang *et al.*, 2012; Peng *et al.*, 2013) railroad (Bhanot and Singh, 2014; Feli *et al.*, 2011), production (Chen *et al.*, 2014; Lozano, 2014), supplier selection (Mirhedayatian *et al.*, 2014; Pitchipoo *et al.*, 2012), and socially responsible operations (Lu *et al.*, 2013; Sun and Stuebs, 2013). Comprehensive review of DEA studies and potential areas for further applications are well stated in recent review papers (Liu *et al.*, 2013a, b). However, despite its proven capability, DEA lacks predictive capacity which, in contrast, is a strength of ANN. Notably enough, both ANN and DEA demonstrate complementary features that can be built into a promising combined model.

The possibility of exploiting complementary attributes of DEA and ANN was first proposed by Athanassopoulos and Curram (1996). They investigated the feasibility of ANN's in assessing the efficiency of DMUs and determined that both DEA and ANN were comparable and potentially complementary methods in performance assessment. Since then, a few researchers extended the initial work and reported encouraging outcomes. In these previous attempts, DEA was used as a preprocessor to select "efficient" training sets and to improve computational efficiency for subsequent neural networks (Emrouznejad and Shale, 2009; Pendharkar and Rodger, 2003). Most of these studies, although rare, focussed on predicting DEA efficiency scores (ES) as a surrogate measure of performance (Hsiang-Hsi *et al.*, 2013; Kuo *et al.*, 2010; Sreekumar and Mahapatra, 2011; Wang, 2003). More recently, Kwon (2014) extended a combined model to predict best performance outputs with applications to the smartphone industry. He applied DEA-ANN in predicting ES obtained from various DEA models and demonstrated the potential of the model in predicting outputs necessary to achieve the best performance level. However, he used a small size of data which included eight major companies in the global market and ten years of their financial data.

Distinguished from previous studies, the present study employs a large size of data from a different industry and country in an attempt to build an adaptive prediction model for best performance outcomes and potential incremental outcomes as well. Therefore, the findings will be useful for generalizing our initiative modeling of DEA-ANN for other industries across different countries. It is also expected that the addition of predictive capacity to the performance framework can significantly enhance managerial decision-making processes in promoting improvement initiatives and add significant value to existing literature.

Innovative input-output modeling system

DEA

DEA has been a popular choice for the analysis of the production function of homogeneous peer entities using its nonparametric approach where a priori assumptions of relationships between input and output variables are not required. The emergence of DEA dates back to late 1970s when Charnes *et al.* (1978) first developed DEA Charnes, Cooper, and Rhodes (CCR) model as a frontier technology with its theoretical roots in Farrell's (1957) work on technical efficiency. DEA, as a linear programming-based mathematical modeling tool, envelopes extreme data points to form a frontier surface. DEA models, then, identify efficient DMUs (with a score of 1), measure relative inefficiency and potential improvement for DMUs under the envelopment surface. In assessing relative efficiency, the original DEA CCR model assumes constant returns-to-scale (CRS), where increase of input scale yields a proportionate increase of outputs. Given a set of n-DMUs with r(s) dimensional vectors of input (output), the CCR efficiency of DMU_k can be formulated by following formula:

$$\text{Maximize } h_k = \frac{\sum_{j=1}^{s} o_j y_{jk}}{\sum_{i=1}^{r} q_i x_{ik}} \tag{1}$$

Equation (1), then can be transformed into a linear programming format as in Equations (2)-(4):

$$\text{Maximize } h_k = \sum_{j=1}^{s} o_j y_{jk} \tag{2}$$

s.t.:

$$\sum_{i=1}^{r} q_i x_{ik} = 1 \tag{3}$$

$$\sum_{j=1}^{s} o_j y_{jp} - \sum_{i=1}^{r} q_i x_{ip} \leqslant 0 \quad p = 1, \ldots, n \tag{4}$$

$o_j \cdot q_i \geqslant \rho \ \forall_{\text{j,i}}$ ρ: a positive infinitesimal value where y_{jp} is the quantity of jth output of DMU_p; x_{ip} the quantity of ith input of DMU_p; o_j the weight assigned to jth output; q_i the weight assigned to ith input.

In addition to the CCR model, the Banker, Chames and Cooper (BCC) model is also used in this study. As a variation to the CCR model, the BCC model assumes variable returns-to-scale and takes into account the scale effects (Banker *et al.*, 1984). A DEA model can be either input oriented or output oriented; however, the selection is dependent on the characteristics of the problem and applications (Abate *et al.*, 2013; Afzal and Lawrey, 2012). In this study, with an emphasis on predicting best output by subsequent neural network model, an output-oriented model is used.

ANN

ANN is an artificial intelligence-based information processing system that resembles the biological nervous system of a human brain and is characterized by intelligent processing and adaptive learning in its core, as a consequence, its strength resides in the capability to capture nonlinear patterns from complicated data sets (Fausett, 1994; Haykin, 1994; Rumelhart *et al.*, 1986). ANN is composed of an array of highly interconnected processing elements, alias neurons, which process and exchange information with neurons in adjacent layers in a sequential and iterative manner according to a set of protocols, and the process continues until the network learns input patterns or meets termination conditions. The learning that takes place in ANN models can be either supervised or unsupervised and has impacts on network topology as well as weight update rules. In this research, a three layered BPNN, the most popular supervised learning model, is used for its proven strength in prediction tasks.

Figure 1 shows a typical three layered BPNN model with 2 (3, 1) neurons in input (hidden, output) layer. The figure exhibits connections between neurons in the adjacent layers, and hints at massive parallelism inherent in BPNN as a connectionist model. In this layered structure, neurons in a hidden layer conduct a critical role in capturing nonlinearity between input and output variables, thus learning complex patterns. Indeed, nonlinear modeling capabilities supported by hidden neurons greatly contributed to the resurgence of ANNs since the 1980s and placed BPNN as one of the most attractive neural network models for prediction and classification problems. The number of hidden layers and neurons depends on the complexity of data patterns and desired level of accuracy, however, literature shows that one hidden layer is sufficient in most of applications with a varying number of neurons depending on applications (Azadeh *et al.*, 2011; Ciampi and Gordini, 2013; Fausett, 1994; Haykin, 1994). BPNN learning adopts a least mean squared error approach through iterative information feed forward and error back propagation processes as described below (Fausett, 1994).

Input feed forward: in this process, input neurons receive incoming signals, and hidden neurons calculate weighted net output and activate output to neurons in the output layer. Output neuron k, upon receipt of hidden output, calculates actual output (Y_k) and total error (E) between target (T_k) and actual outputs for all pairs of training input and output:

$$Y_k = f(y_{netK}) = f\left(\sum_j H_j w_{jk}\right) \tag{5}$$

$$E = 1/2\sum_k [T_k - Y_k]^2 \tag{6}$$

where f () is the activation function applied to net outputs of neuron k, y_{netK}; H_j the inputs from hidden neuron j to output neuron k; $w_{jK:}$ the weight between neurons j and k.

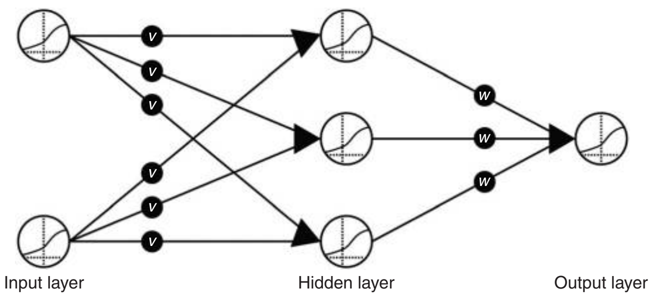


Figure 1.
BPNN Model
(2-3-1 structure)

Error back propagation: upon completion of feed forward process, error information propagates backward following a reverse path, output-hidden-input layers. Then, weight between interconnected neurons are updated in such a way to minimize E. Let $v_{i,j}(t)$ and $w_{j,k}(t)$ be weights between input and hidden neurons (i, j) and hidden and output neurons (j, k), then weight changes and new weights between associated neurons at epoch t using learning rate $\rho(t)$ can be determined by following rules (Equations (7)-(10)). This process continues until minimum error is achieved or termination conditions are met:

$$\Delta v_{i,j}(t) = -\frac{\partial E}{\partial v_{i,j}} \tag{7}$$

$$\Delta w_{j,k}(t) = -\frac{\partial E}{\partial w_{j,k}} \tag{8}$$

$$v_{i,j}(t+1) = v_{i,j}(t) + \rho(t)\Delta v_{i,j}(t) \tag{9}$$

$$w_{j,k}(t+1) = w_{j,k}(t) + \rho(t)\Delta w_{j,k}(t). \tag{10}$$

Final weight sets thus obtained through repetitive presentations of training data and weight adjustments, store abstract information and nonlinear relationships between variables. In other words, these weight sets memorize the best potential fit over presented data and enable the network to learn general patterns and central tendency of observed data (Athanassopoulos and Curram, 1996; Pendharkar, 2005; Ülengin *et al.*, 2011). In this combined DEA and ANN approach, the BPNN model is designed to learn and predict best performance outputs in addition to ES.

Empirical processes

Samples and variables

The empirical data used for the proposed model was drawn from Japanese electronic manufacturing firms (SIC 3600-3690) and the basic economic performance variables were selected from S&P Research Insight-Global Vantage. This study employs ten years of longitudinal data from 2003 to 2012 inclusive and each firm-year is treated as an individual DMU. But DMUs with negative values or extreme values (beyond 3 standard deviations in ratio variables) were excluded from the experiment to maintain the integrity of the analysis. The final sample resulted in 1,419 DMUs which were deemed sufficient for this empirical test. Table I shows the summary statistics of the variables used for this sequential modeling experiment.

Table I.
Descriptive statistics of variables

Variables	Mean	SD	Maximum	Minimum
Employees (000)	10.2	31	366.9	0.1
Total assets (USM$)	2,649.1	10,231.0	150,855.9	13.4
Operating expenses (USM$)	2,170.6	8,417	93,820	10.9
Revenue (USM$)	2,430.4	9,242.4	101,686.7	12.1
Market value (USM$)	1,617.5	4,850.7	50,832.6	4.50

Three variables including number of employees, total assets, and operating expenses were considered as major input variables. These variables represent, in this study setting, a firms' collective resources and efforts to generate key outputs, revenue and market value. Throughout the DEA experiments, these input variables were paired with both output variables to constitute a revenue-market value model, a base model in this study, and with a single output to form a revenue model and a market value model. These input/output pairs were further utilized in ANN experiments in a subsequent stage.

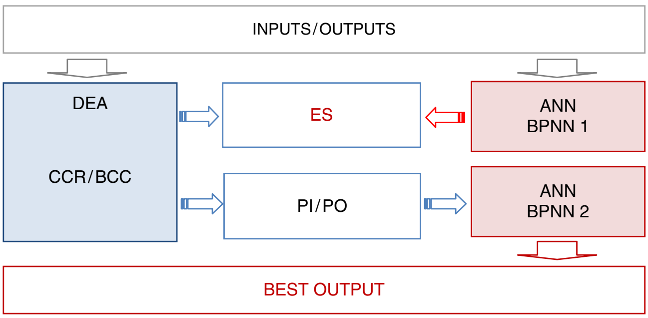
The proposed empirical model

Figure 2 visualizes the conceptual framework which shows a sequential DEA and ANN process. In this combined approach, besides being used for efficiency analysis, DEA plays a key role in generating training inputs for ANN prediction modules as a preprocessor. In DEA experiments, output-oriented versions of CCR and BCC models are used to determine the ES of each DMU by using the aforementioned input and output pairs and these DEA models to produce input and output projections (PI, PO) for each inefficient DMU to become efficient. These DEA processed outputs (ES, PI, and PO) for each DMU then become target output and noble training inputs for subsequent BPNN1 and BPNN2, respectively. As shown in the figure, BPNN1 predicts ES by utilizing original inputs and outputs as BPNN training inputs while using DEA ES as target output for BPNN1. BPNN2, in contrast, is trained to predict optimal output (PO) for each DMU using optimal inputs (PI). Once trained, the model can predict superior performance levels desired for new or hypothetical DMU inputs. In brief, BPNN1 and BPNN2 provide an effective means to estimate production functions and efficient frontiers, thus enabling prediction of relative efficiency and optimal performance in terms of output. DEA results from the revenue-market value model and the revenue model are used for BPNN1 and BPNN2, respectively.

Empirical analysis and results

DEA efficiency analysis

Table II shows DEA experiment results using CCR-output-oriented and BCC-output-oriented models. In this experiment, a revenue-market value model which utilizes revenue and market value as outputs was considered as the base model and additional experiments using single output variables were conducted for further analysis by forming a revenue model and a market value model. The DEA CCR model determines



Notes: ES, efficiency scores; PI, projected inputs; PO, projected outputs

Figure 2. DEA-ANN modeling process

overall technical efficiency (OTE) of each DMU. OTE can be decomposed into a product of pure technical efficiency (PTE) and scale efficiency (SE) by using the BCC model. While PTE assesses how efficiently a DMU transforms its inputs into outputs without considering the scale effects, SE addresses optimality of the scale of operation. The BCC model provides returns to scale information for each DMU in the form of increasing returns to scale (IRS), CRS, or decreasing returns to scale (DRS). IRS (CRS, DRS) implies that a DMU operates at a suboptimal (optimal, supra optimal) size and an increase in input scale will result in a bigger (proportional, less) increase of output, respectively.

The revenue-market value model shows slightly lower OTE when compared to PTE and identifies 16 and 58 efficient DMUs in each measure by using CCR and BCC, respectively. In this model, 1,220 DMUs (86 per cent) are operating at DRS, thus indicating supra optimal size of operations of Japanese firms in the electronics manufacturing industry in creating revenue and market value. In other words, most of the DMUs are not operating at the most productive scale size therefore reduction of excessive resources may contribute to an increase in efficiency.

To observe efficiency patterns in generating a single output, additional experiments were conducted by using a revenue model and a market value model. As shown in the Table II, the output of the revenue model shows some similarities to the revenue-market value model output in terms of average efficiency and DRS dominant operations. The market value model, in contrast, reveals much lower efficiency than the revenue model while using the same inputs. In addition, the number of DMUs at DRS reduced to less than a half with a greater increase of DMUs at CRS and IRS. The results indicate comparatively lower efficiency of Japanese firms in this specific industry in adding market value in comparison to revenue generating efficiency, thus posing potential improvement of market value. Overall, these firms do not seem to properly translate their revenue generating efficiency into creation of market value. From this perspective, financial performance indicators, such as revenue, might be used as an intermediate output variable to observe its impact on market value generation; however, this discussion is beyond the scope of this paper and can be examined in future research.

In these DEA experiments, scale size appears to impact efficiency levels in Japanese industry. The results of the revenue-market value model, illustrated in Figure 3, shows varying efficiency levels according to the size of the firm's assets. Something to note is that smaller size firms exhibit higher SE.

In addition to scale effects on efficiency, BCC efficiency trends for a ten year period were observed as seen in Table III. The revenue-market value model and market value model exhibit peak efficiency in 2005 and the revenue model in 2006. Overall efficiency of the revenue-market value model reveals gradual improvement since 2010. The revenue model, as discussed earlier, shows higher ES than the market value model throughout the observation period and exhibits consecutive improvements in the recent four years. In contrast, the market value model reveals an overall decrease since its peak in 2005 and has been reduced to half in recent years.

Table II. DEA experiment summary

	Average Efficiency			Efficient DMUs		RTS		
Measurement Model	OTE	PTE	SE	CCR	BCC	IRS	CRS	DRS
Revenue-market value	0.829	0.856	0.970	16	58	41	158	1,220
Revenue	0.828	0.853	0.972	10	33	89	116	1,214
Market value	0.211	0.260	0.879	4	20	119	698	602

Performance prediction using ANN

Efficiency prediction. The next stage of the analysis is centered on exploring predictive potential of ANNs for the development of integrated performance measurement and prediction models. For this challenging task, a three layered BPNN model was used by exploiting its adaptive learning paradigms. This experiment aimed to predict BCC ES from the Revenue-Market value model by taking both DEA input and output variables as BPNN training inputs. For this experiment, the data set was randomly partitioned into training and test data with a 7:3 ratio, therefore 993 DMUs and 426 DMUs were used for the training and test, respectively. NeuralWorks Predict software package was used for this study by utilizing built-in capabilities. The adaptive learning capability of the BPNN model can be observed by high correlations and low error rates for both training and test data sets as summarized in Table IV.

Figure 4 visualizes performance of trained BPNN in terms of error between actual and predicted ES of each DMU. In this figure, DMUs were sorted by the scale of errors. A high level of prediction accuracy can be observed from the figure, with only six DMUs beyond 10 per cent error and with the maximum error of 17 per cent, corresponding to actual error scale of 0.11. As expected and consistent with previous literature (Athanassopoulos and Curram, 1996; Ülengin *et al.*, 2011; Pendharkar and

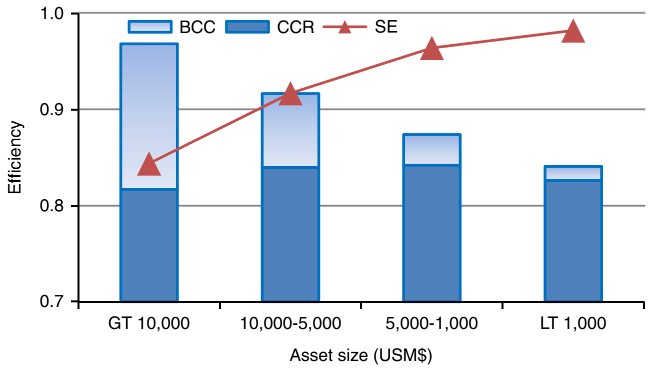


Figure 3. Efficiency variations on firm size (RM model)

Measurement model	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Revenue-market value	0.856	0.854	0.871	0.869	0.854	0.855	0.854	0.850	0.860	0.864
Revenue	0.833	0.851	0.863	0.864	0.851	0.854	0.840	0.848	0.855	0.863
Market value	0.273	0.275	0.389	0.330	0.239	0.194	0.257	0.219	0.197	0.199

Table III. BCC efficiency trends (2003-2012)

Data	*R*	AAE	MAE	DMUs
All	0.985	0.008	0.114	1,419
Train	0.985	0.008	0.102	993
Test	0.984	0.008	0.114	426

Notes: *R*, correlation between actual and predicted efficiency; AAE, Average absolute error; MAE, Maximum absolute error

Table IV. BPNN performance for efficiency prediction

Rodger, 2003), the result exhibits a regression type learning of the neural networks, which detect central tendency of a data set. In this experiment, the BPNN splits 1,419 DMUs into 772 and 647 according to the error determined by under/over predictions.

Best performance prediction. Successful implementation of the BPNN model to predict ES prompted this research to further explore its predictive potential in predicting optimal output, a direct measure of performance beyond ES. This attempt is motivated by a practical necessity of predicting target output, thus providing managers with adaptive decision support tool in setting performance goals and testing what-if scenarios within a volatile business environment. The capability to set and forecast best performance to sustain superiority is a critical necessity which significantly advances performance management paradigms and enables managers to select actionable measures. For this experiment, the revenue model was used by taking revenue as a target output to improve. As stated earlier, DEA models not only determine ES for DMUs but also project optimal input and output values for each inefficient DMU to become efficient. In this unique modeling approach, DEA-projected data are used for neural networks to learn the frontier surface and predict best output performance. As depicted in Figure 2, DEA-projected inputs (PI) and projected output (PO) vectors were used to train BPNN2 model. In this sense, DEA is functioning as a preprocessor for a subsequent prediction module. The following functional relationships hold for these input and output pairs: p_revenue $= f$ (p_employees, p_total assets, p_op.expenses), where p denotes projections made by DEA. In its core, output is a monotone increasing function of a combination of three inputs. In this scheme, the BPNN model is designed to learn patterns of the efficient frontier rather than central tendency of the original data. The developed BPNN model demonstrates high correlation and prediction accuracy of less than 10 per cent error for 95 per cent of DMUs as shown in Table V.

As stated earlier, the BPNN model was trained by using DEA-projected optimal input/output pairs which form hypothetical DMUs. However, DEA projections reveal slacks in a number of employees across most of the inefficient DMUs. These DMUs are required not only to improve output but also to reduce their employees in order to achieve superior performance in practice. This may pose a potential dilemma between theory and practice

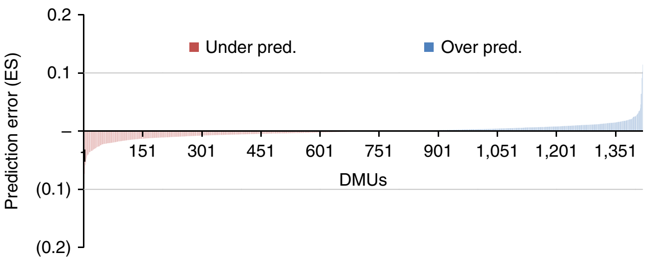


Figure 4.
BPNN learning and prediction error

Table V.
BPNN performance for best performance prediction

Data	R	AAE	MAE	DMUs	Accuracy				
All	0.994	168.3	27,782.4	1,419	Error	10%	20%	30%	BT 30%
Train	0.993	170.8	27,782.4	993	DMUs	1,343	43	11	22
Test	0.996	162.6	11,991.0	426		(94.6%)	(3%)	(0.8%)	(1.6%)

in real applications, therefore the following questions are raised: are mathematical or theoretical solutions always feasible options for managers? In this research setting, how much additional revenue should be generated to tradeoff employee reduction? With this dilemma taken into consideration, additional tests have been conducted for the validation of ANNs and further exploration of trained BPNN models.

For the experiments, DMUs with slacks of up to 50 per cent in the number of employees were considered as new test inputs for the BPNN prediction module and these DMUs were categorized into five groups depending on their slack levels in 10 per cent intervals. Be reminded that the BPNN was trained by using a slack-adjusted optimal set of data; therefore, these original test inputs with no slack adjustment form new and unseen test cases for the trained BPNN model. Due to inclusion of slacks in test inputs, the BPNN is expected to estimate higher output for each DMU than DEA-projected optimal output. Consequently, the BPNN output represents target performance and the gap between these two outputs indicates additional improvement to be made at the cost of maintaining input slacks. Test results are summarized in Table VI.

The table shows average input slacks of DMUs and expected performance improvement in each category. For example, in order to save 50 per cent of employees, those DMUs, on average, need to achieve additional improvement of 4.58 per cent in the sense of optimal performance. The test results hint at a need for managerial flexibility in selecting practically feasible options through what-if analysis by trading off input reductions and output increases. Figure 5 visualizes these test results and shows an increasing trend of expected output according to the increase of input level.

	Slack level (number of employees)				
Upper limit	10%	20%	30%	40%	50%
Number of DMUs	109	142	146	123	141
Average slack	5.06%	15.01%	24.98%	35.08%	44.69%
Average improvement	0.37%	1.16%	2.18%	3.25%	4.58%

Table VI. Target improvement for additional inputs

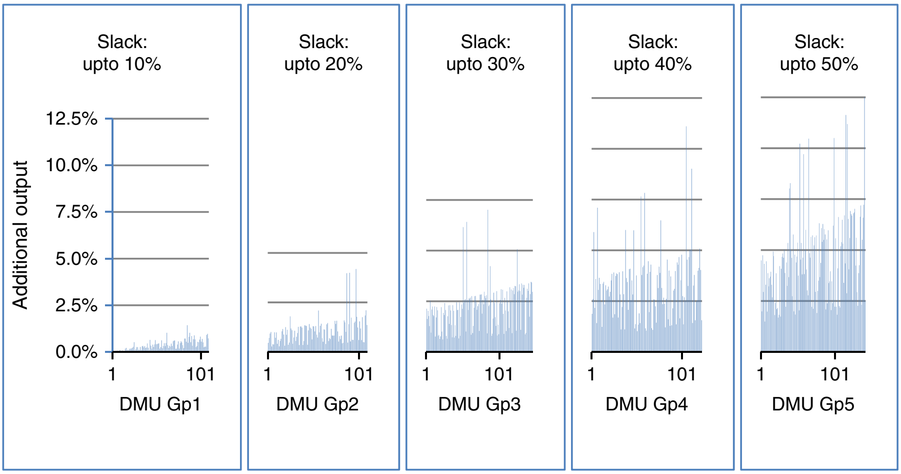


Figure 5. Prediction results without slack adjustment

As observed from the experiment, the BPNN model, especially in combination with DEA, demonstrates its potential usage as an adaptive decision support system in pursuit of improvement initiatives within the benchmarking context. According to current literature, benchmarking processes can be broadly categorized into planning, analysis, and implementation phases (Anand, 2008; Prašnikar *et al.*, 2005). During these phases, adaptive prediction capabilities are very useful in supporting managers, especially in assessing performance gaps within DMUs in advance of launching improvement initiatives. In addition, the capability to generate and test what-if scenarios in the middle of the process is a crucial aspect required for monitoring and corrective actions. Despite being a practical necessity in this rapidly changing business environment, predictive capacity has rarely been built into the measurement framework to form an integrated performance model (Francis and Holloway, 2007; Kwon, 2014).

In utilizing traditional DEA optimizations, despite being mathematically sound, managerial intuitions are highly required to determine whether projections are viable and actionable options. As Mostafa (2007, 2009) points out, it might be practically impossible to achieve DEA targets and DEA does not consider operational environment and company-specific situations. Indeed, discernible decision making rests with managerial intuition and expertise. From this perspective, the proposed combined model can support managers to opt for a practical solution through adaptive prediction support mechanisms. In brief, managers can benefit from this innovative model to measure relative efficiency of DMUs; select target peers to benchmark; identify and set improvement goal in terms of output; adjust target goals through what-if scenarios and trade off options between input reductions and output increases.

Concluding remarks

This study presents an adaptive performance metric that integrates measurement and prediction functions by jointly using DEA and ANN to take advantage of complementarities of the two methods. The innovative methodology introduced in this paper provides a salient modeling approach to support superiority-driven best performance benchmarking and performance modeling.

DEA quantifies performance of DMUs with multidimensional input/output vectors into a scalar value, ES, which is commonly treated as a surrogate measure of relative performance of a DMU. In addition to efficiency, subsequent projection for improvement of inefficient DMUs has placed DEA as a popular measurement tool in best practice benchmarking applications. Nonetheless, lack of predictive power has been considered a serious shortfall of using DEA despite its well-known strengths. In this sense, joint use of ANNs while exploiting its predictive potential complements standalone DEA and adds meaningful value to this research avenue. The proposed combined model is empirically supported through its application to the Japanese electronics manufacturing firms, and by utilizing a large data set, this paper generalizes the proposed approach as a generic and advanced methodology.

Both theoretical and practical contributions have been made in this research. First, the presented model incorporates measurement and prediction to form an integrated performance modeling framework. Furthermore, distinguished from previous studies, the proposed approach approximates frontier patterns and predicts best performance output in addition to ES. In so doing, this paper fills the research gap and advances a research in best performance benchmarking and modeling. Second, the proposed model can solve a traditional theory-practice dilemma and help managers as a useful decision support tool. In reality, managers cannot solely rely on mathematical modeling such as DEA projections; rather they try to tradeoff between theoretical suggestions and managerial intuition. For example, as in this experiment, managers might consider alternatives to reducing 50 per cent of employees in pursuit of best practice, by balancing levels of input reduction and output increase. In essence, adaptive prediction capability to test hypothetical scenarios is a critical business necessity. Using empirical data and test cases of employee slacks, the proposed model proves effective in this endeavor, therefore can serve as a valuable decision support tool not only in planning but also in implementation stages for progress monitoring. Third, this study generalizes proposed methods of using industry data from Japanese electronics manufacturing companies. Japanese firms like Sony face steep decline in their competitive edge and struggle to reclaim their former global dominance. The proposed methodology can be a valuable support tool for those improvement conscious firms to set performance goals in their path toward superior performance.

As discussed, main focus of this paper is centered on developing two stage empirical model to integrate measurement and prediction frameworks. As a pilot application of the proposed model, the Japanese electronics industry carries rich context to be further explored. For example, comparative analysis between subgroups in the industry will result in interesting outcomes. Indeed, high efficiency may not be the most pressing objective for some companies depending on their strategic motives to enhance innovative potential and growth by preserving employee slack (Thore *et al.*, 1996). From this perspective, this study can be extended to capture efficiency patterns of subgroups in the electronics industry by identifying determinants of inefficiency and innovative potential. In this attempt, strategic performance models can be explored by using industry-specific variables to address knowledge creation, innovation, and other relevant strategic initiatives while considering technology-oriented industry characteristics. Industry level comparison between different countries (e.g. Japan vs USA) will be a promising extension of this research stream. Another fruitful research stream will be on investigating a linkage between different performance dimensions. For example, financial performance can be used as an intermediate output and the impact to terminal output (i.e. market value) can be investigated as hinted by differing DEA results presented in this paper. On the same analogy, knowledge outputs such as patents and new products may be used as a key intermediate output measure to assess a firm's innovation performance.

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