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“ Efficiency in Public Sector: A Neural Network Approach ”

Francisco J. Delgado
Department of Economics
University of Oviedo (Spain)
E-mail: fdelgado@uniovi.es

Abstract
Here artificial neural networks (ANNs) are employed for efficiency purposes. First, the main features of ANNs are presented. Then, the common techniques of the efficiency literature are reviewed: parametric (deterministic and stochastic) and non-parametric (Data Envelopment Analysis [DEA] and Free Disposal Hull [FDH]). ANNs are employed for production frontier approximation. Their advantages and drawbacks in the efficiency context are examined. Finally, these various methodologies are applied to the refuse collection services using a sample of Spanish (Catalonian) municipalities. The results are compared with Pearson´s correlation and Spearman´s rank-correlation coefficients.

Keywords: neural networks, efficiency, production frontier, DEA, public services
JEL codes: C14, C45, D24, H49, H72

1. Introduction[1]

The efficiency measurement has been extensively treated in the last two decades. The interest of this research has focused in both the private and the public sectors. In the public sector, the budget restrictions are getting increasingly stronger in the framework of the deficit control and debt reduction[2]. Other reason for the interest in the efficiency of the public sector is the weight of this sector in the economy.

From the seminal work of Farrell (1957), several exhaustive revisions of the efficiency measurement topic are available (Farë, Grosskopf and Lovell, 1985; Fried, Lovell and Schmidt, 1993; Coelli, Prasada Rao and Battese, 1998; Kumbhakar and Lovell, 2000). For a view of its application to the public sector, see Fox (2002).

Parametric and non parametric approaches are widely-used in the efficiency measurement. The first include both deterministic and stochastic frontiers. The latter include Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH). In the public sector context, there are some reasons to prefer non parametric approaches: unknown technology, inexistent or non significant prices, multiple outputs,...

Artificial neural networks (ANNs) are universal approximators of functions and have been successfully used in many research areas: air traffic control, character and voice recognition, medical diagnosis and research, weather prediction,... But ANNs have also been extensively applied to economics and finance. Zhang, Patuwo and Hu (1998) and Vellido, Lisboa and Vaughan (1999) are excellent reviews on this topic.

Within the efficiency measurement literature, ANNs are still not very employed. Athnassopoulos and Curram (1996) compare ANNs and DEA. In a simulation exercise, they conclude that DEA is superior to ANNs for measurement purposes and ANNs are similar to DEA in ranking units. In an application to banking, ANNs are more similar to the constant returns to scale DEA than the variable returns to scale DEA. Costa and Markellos (1997) analyse London underground efficiency with time series data. They explain how ANNs result similar to Corrected Ordinary Least Squares (COLS) and DEA, but ANNs offer advantages at decision making, impact of constant vs variable returns to scale or congestion areas. Fleissig, Kastens and Terrell (2000) employ neural networks for cost functions estimation. They find convergence problems when the properties of simmetry and homogeneity are imposed to the ANNs. Santin, Delgado and Valiño (2004) use a neural network for a simulated non-linear production function and compare its performance with traditional alternatives like stochastic frontier and DEA in different observations number and noise scenarios[3].

The main aim of this paper is to contribute to the use of neural networks in the efficiency measurement. After reviewing different possibilities for that end, an application to the refuse collection service is presented.

[1] An extended version (in spanish) of this paper can be found at the Institute for Fiscal Studies (Spain): www.ief.es/Publicaciones/papelest/03/pt_26_03.pdf, and it was presented at the "XI Encuentro de Economía Pública", Barcelona, February 2004.

[2] Although this framework is clearer in the EMU context, with the Stability and Growth Pact, it is generally assumed today that reduced public deficit can result on more economic growth and stability.

[3] Other references are Joerding et al. (1994), a paper that explores theoretical properties imposition about technology – positivity, monotonicity, quasiconcavity- and concludes that ANNs are similar to Fourier flexible form. Curram, Athanassopoulos and Shale (1999) proposed a new method for frontier approximation by correcting the error on training process. In Guermat and Hadri (1999), a Monte Carlo simulation is carried out to compare backpropagation neural network and translog model in stochastic frontiers. They concluded that ANNs outperform translog and Cobb-Douglas when translog function is simulated, but no differences were found when Leontief or CES are simulated.

This paper is organized as follows. Section 2 briefly describes ANNs. Section 3 presents the methodologies used in efficiency measurement literature, and the neural networks approaches are explained. Results from the empirical study are summarized in Section 4, and concluding remarks are provided in Section 5.

2. A brief review of artificial neural networks[4]

ANNs are mathematical models that emulate the behaviour of the human brain. Its appeal comes from its capacity for extracting patterns from the observed data without assumptions about the underlying relationships. These non linear models can approximate unknown mappings and its derivatives by a three-layer structure: input, hidden and output layers (Hornik, Stinchcombe and White, 1989; 1990). The common networks are feedforward neural networks or multilayer perceptron, where connections between neurons are from input to output without feedbacks.

Architecture selection and neural learning are basic issues in neural modelling. In the architecture selection, or selection model in econometric language, the researcher must determine the number of input and hidden units and the activation function. A data pre-processing can also be applied. The lack of a general procedure results in a trial and error process[5], and the final architecture is selected according to some information criterion (AIC or SIC). A multilayer perceptron can be represented as:

$$y = f(x,q) + e = b_0 + \sum_{j=1}^{q} b_j G(\tilde{x}' g_j) + e \quad (1)$$

where $\tilde{x} = (1, x_1, x_2, ..., x_r)'$, $j = 1, ..., q$; $q = (b_0, b_1, ..., b_q, g_1', ..., g_q')$ and e represents the error, usually assumed in econometrics to be random and normally distributed with zero mean and constant variance.

[Insert Figure 1]

The transfer function is usually chosen to be monotone and nondecreasing. In this paper the output activation function is linear, and the hidden transfer function (G) is logistic or hyperbolic tangent. The logistic function maps into the [0,1] interval, whereas the tanh maps into the [-1,1] rank.

In the training phase, estimation in econometric jargon, backpropagation (Rumelhart et al., 1986) is the most used method. BP is a gradient (steepest) descent method that minimizes an error function (sum of error squares) by modifying the network parameters according to[6]:

$$q_{k+1} = q_k + h \frac{\partial E}{\partial q_k} \quad (2)$$

where k denotes iteration number, and h the learning rate between 0 and 1. An improvement

[4] More details can be found in comprehensive books like Bishop (1995), Ripley (1996) and Haykin (1999). White (1989) contains a detailed statistical analysis of the neural learning, BP included, and Warner and Misra (1996) and Cooper (1999) offer a good statistical point of view too. In Cheng and Titterington (1994) ANNs and traditional statistical models are shown together (with discussion). Kuan and White (1994) exhibit ANNs as non linear models, with an asymptotic theory of the neural learning. Beltratti, Margarita and Terna (1996) explore theoretical applications of neural networks for economic and financial modelling. Zapranis and Refenes (1999) review the model identification and selection with many examples from financial economics. They conclude with an interesting case of study totally developed. Kaashoek and van Dijk (2003) describe the neural networks as an econometric tool with several illustrations about chaotic models, nonlinear trend s in real exchange rates and a time-varying Phillips curve.

[5] For this reason ANNs could initially be conceived as a black-box method.

[6] BP or delta-rule has been re-discovered by Rumelhart et al. (1986). In essence, small random parameters are chosen and error is first calculated on the output layer. Then the error propagates back to the hidden layer to adjust the weights and finally to the input layer. However, BP can be seen as a numerical optimization technique, and quasi-Newton and conjugate-gradient methods can be used for neural training.

consists of adding a new term called momentum that depends on the last parameter value.

However, BP has been severely criticized and new alternatives were further analysed. On this topic, the Levenberg-Marquardt[7] algorithm can improve significantly the performances of BP (Hagan and Menhaj, 1994).

3. Methodologies

First, the techniques of the traditional efficiency literature are shortly reviewed: parametric (deterministic and stochastic) and non-parametric (Data Envelopment Analysis and Free Disposal Hull).

The parametric techniques assume a particular functional form for the production frontier. Cobb-Douglas is the simplest but it is widely-used, whereas translog, CES or generalized Leontief are more flexible forms. In the case of a deterministic frontier, the deviations are explained because of inefficiency, whereas in the stochastic models frontier the deviations are decomposed into noise –usually semi-normal- and inefficiency components (Aigner et al., 1977).

The non-parametric approach makes no assumption about the functional form of the frontier. Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) have been widely-used. In the first approach, a deterministic frontier is constructed by enveloping the available data using mathematical programming, and constant (DEAcrs) or variable (DEAvrs) returns to scale, and convexity are common assumptions (Charnes, Cooper and Rhodes, 1978; Banker, Charnes and Cooper, 1984). In FDH convexity assumption is dropped so the units marked as inefficient in FDH are also inefficient in DEA, but the opposite is not always true (Deprins, Simar and Tulkens, 1984; Tulkens, 1993). FDH uses real observed units whereas DEA also makes comparison with virtual composite units.

Finally, in the neural network approach, we may consider at least three alternatives[8]:

- From the estimated network - ANN1.

In this case the efficiency measure of a unit is established in relation to average performance. Thus, indicators will be superior to 1 or 100% when the unit behaves better than average, and inferior to 1 or 100% if the unit is “inefficient”. These measures are not directly comparable with the traditional techniques. Athnassopoulos and Curram (1996) called this option “non-standarized efficiency” E^{NE}:

$$\mathrm{E}_i^{NE} = \frac{y_i}{\hat{y}_i} \qquad (3)$$

To achieve a real production frontier there are some alternatives:

- Shift the network by the largest positive error – ANN2.

This option is similar to COLS. The correction by the largest postive error is sensitive to outliers and the frontier will be deterministic. The efficiency scores take values between 0 and 1. This maximum score is assigned to the unit used for correction. Athnassopoulos and Curram (1996) called this second measure “standarized efficiency” E^{E}:

$$\mathrm{E}_i^{E} = \frac{y_i}{\hat{y}_i + \max_i \hat{\boldsymbol{e}}_i} \qquad (4)$$

[7] L-M is designed to approach second-order training without having to compute the Hessian matrix. L-M is faster in training and can converge faster than BP.

[8] Costa and Markellos (1997) used an over-parameterized network, and Curram, Athanassopoulos and Shale (1999) proposed a new method by correcting the training process and stochastic frontier is achieved. However, this approach has not been employed yet.

In relation to DEA, non-standarized efficiency (E^{NE}) tends to overestimate the indicators, and standarized efficiency (E^{E}) tends to underestimate the meaures.

Costa and Markellos (1997) used a synthetic sample created by adding white noise to the original data for training, and the observed sample is used for cross-validation. If the "largest positive error from generated sample is used in COLS, then frontier will be stochastic".

- Shift the network by a mean of largest positive errors – ANN3.

For attenuating the effect of the largest positive error, in this work a new approach is proposed. This option consists of not considering the largest, but some percentage of the largest positive errors. After some proofs, a 5 per cent has been selected:

$$\mathrm{E}_i'^{E} = \frac{y_i}{\hat{y}_i + avg(\hat{e}_i^{5\%})} \qquad (5)$$

[Insert Figure 2]

4. Data and results

For illustrating the potential of the artificial neural networks, a comparative study is carried out in the public sector context, specifically the refuse collection services (Bosch, Pedraja and Suárez-Pandiello, 2000) from a sample of 72 spanish municipalities. The output considered is solid waste (SOW) and the inputs include containers capacity (CON), vehicles (VEH) and worked hours (WOR). The summary statistics are presented in table 1. An important positive correlation between inputs 1 and 2 was detected that may affect the results from the econometric models.

[Insert Table 1]

In the parametric context, a Cobb-Douglas function and a translog function were estimated. Nevertheless, the differences between them were negligible and we selected the Cobb-Douglas because of simplicity (table 2). As early noted, the correlation between the inputs 1 and 2 causes a non significative parameter for the latter. However, this may no affect the estimation of the efficiency scores.

[Insert Table 2]

The estimated neural network incorporates four tanh hidden units and the Levengerg-Marquardt algoritmh is employed for training (table 3).

[Insert Table 3]

The main results are summarized in table 4[9]. Several differences are clearly appreciated. First, all methodologies assign 1 to the most efficient unit appart from the stochastic Cobb-Douglas and ANN1. Stochastic Cobb-Douglas and FDH show higher mean scores, and ANNs models show the highest standard deviations. Finally, the number of efficient units is different from one approach to the other. Under FDH, most units, 45 of 72, are efficient, whereas deterministic Cobb-Douglas and ANN2 indicate only one efficient unit. In ANN3 two units are marked as efficient because of the adjusting procedure.

[Insert Table 4]

[9] Detailed results are available from the author upon request.

In this analysis a key objective consists of showing if there exist clear differences in efficiency rankings. A correlation study is carried out and the Pearson´s coefficient (table 5) and the Spearman´s rank coefficient (table 6) are shown.
From table 5, ANN1 results are highly correlated with those obtained in parametric (0.8) and DEAcrs (0.7) techniques. ANN2 and ANN3 show correlations about 0.5 with the same methods. Non parametric models present similar results. The same conclusions can be reached from the results reported in table 6. Again, the neural models 2 and 3 performance is different and provide alternative results from the traditional approaches.
Finally, all methodologies agree with the most efficient units and those municipalities with the lowest scores, so these results are more robust.

[Insert Table 5]

[Insert Table 6]

5. Concluding remarks

Today, several approaches for the efficiency measurement are available. Parametric techniques, both deterministic and stochastic, and non parametric approaches, like DEA and FDH, are the most widely-used. In this paper we have used artificial neural networks to measure and rank decision-making units efficiency. Neural networks are universal aproximators of functions and its derivates. These models are non linear and highly flexible, and hence they provide a good instrument for these purposes. Several alternatives from neural networks were explained.

The application to refuse collection services shows that the neural networks offer new insights into efficiency analysis. Although several differences in quantitative measures are evidenced, it is important to note that there exist common trends as shown by the correlation and rank-correlation analysis. The most efficient units were correctly identified by practically all the approaches, and also the lowest efficient units, so these results are more robust.
Finally, new theoretical and empirical research is needed for justifying the use of the neural networks in efficiency analysis. Considering non-controllable inputs like in DEA can be a further extension in the framework of the neural nets. As a final remark, we believe it is useful to view the neural networks as a complementary, rather than alternative, tool for efficiency analysis.

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Figure 1. A three-layer neural network

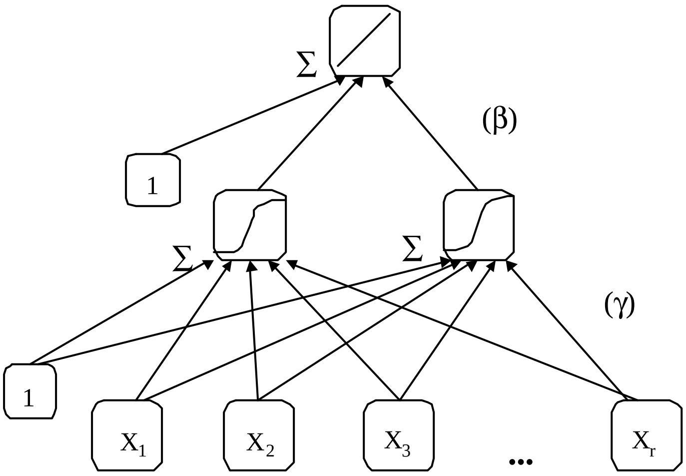

Figure 2. Production function and frontier function from neural network

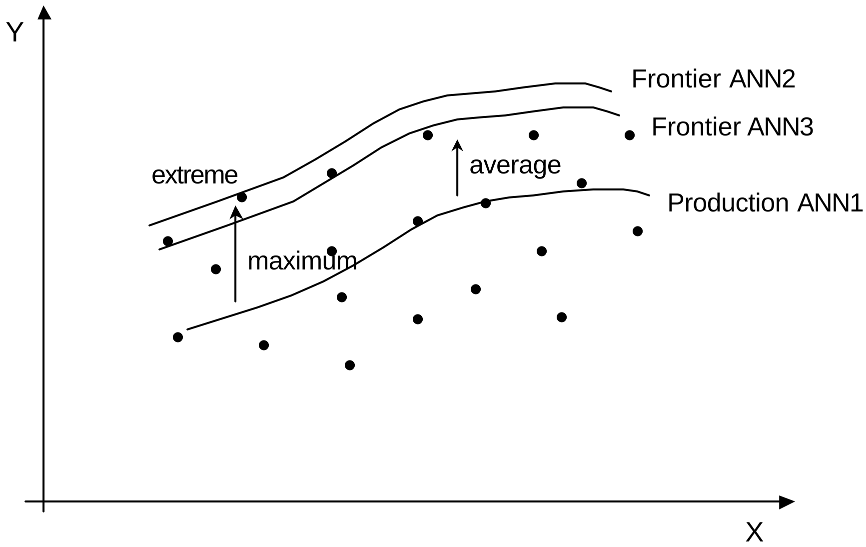

Table 1. Summary statistics

	Output SOW	Input 1 CON	Input 2 VEH	Input 3 WOR
Minimum	1506.20	67.20	4.00	480.00
Maximum	88309.00	5279.15	329.00	420480.00
Mean	13321.62	655.47	49.53	24088.50
Standard deviation	18015.36	970.33	61.82	52709.46
Coef. variation	1.35	1.48	1.25	2.19
1st quartile	3799.39	181.16	18.88	5515.00
Median	7389.00	360.15	26.50	8845.50
3rd quartile	13167.70	642.83	50.00	19514.70
Correlation				
Output RES	1.000			
Input 1 CON	0.931	1.000		
Input 2 VEH	0.929	0.817	1.000	
Input 3 WOR	0.487	0.419	0.504	1.000

Table 2. Cobb-Douglas results

	Cobb-Douglas det.	Cobb-Douglas stoc.
Constant	2.2188 (7.17)	2.3240 (3.21)
Ln CON	0.8002 (13.20)	0.8004 (12.77)
Ln VEH	-0.0483 (-0.67)	-0.0494 (-0.73)
Ln WOR	0.2311 (4.58)	0.2321 (3.965)
$\lambda=\sigma_u/\sigma_v$ (u semi-normal)		0.5286 (0.17)
$\sigma=(\sigma^2_u+\sigma^2_v)^{1/2}$		0.2996 (1.26)
Adjusted R^2	0.9176	
Scale returns Wald´s test Hypot: $\beta_1+\beta_2+\beta_3=1$	F=0.1797 p=0.673	

Table 3. Estimated neural network

Concept	Result
Data pre-processing	[-1,1]
Network architecture	3-4-1
Activation function: hidden / output	tanh / linear
Algorithm	Levenberg-Marquardt
Epochs (max.)	1000
R^2	0,9854

Table 4. Efficiency main results

	C-Ddet	C-Dsto	DEAcrs	DEAvrs	FDH	ANN1	ANN2	ANN3
Mean	0.5227	0.8946	0.6049	0.7268	0.9145	1.0118	0.5221	0.5569
Mínimum	0.2698	0.8318	0.2796	0.3277	0.4672	0.5092	0.1671	0.1903
Maximum	1.0000	0.9374	1.0000	1.0000	1.0000	1.8640	1.0000	1.0000
Rank	0.7302	0.1056	0.7204	0.6723	0.5328	1.3548	0.8329	0.8097
1st quartile	0.4339	0.8847	0.4987	0.5979	0.8534	0.8751	0.3101	0.3383
Median	0.5103	0.8986	0.5651	0.6957	1.0000	1.0000	0.4944	0.5374
3rd quartile	0.5959	0.9100	0.7285	0.8901	1.0000	1.1173	0.7004	0.7391
Stand deviat	0.1483	0.0232	0.1882	0.1918	0.1367	0.2698	0.2365	0.2360
Coef. Variat.	0.2837	0.0260	0.3111	0.2639	0.1495	0.2666	0.4530	0.4238
Effic. units	1	0	7	15	45	35	1	2

Table 5. Pearson´s correlation coefficient

	C-Ddet	C-Dsto	DEAcrs	DEAvrs	FDH	ANN1	ANN2	ANN3
C-Ddet	1							
C-Dsto	0.9373	1						
DEAcrs	0.7716	0.7617	1					
DEAvrs	0.6413	0.6550	0.7861	1				
FDH	0.5099	0.6025	0.5871	0.7411	1			
ANN1	0.8221	0.7829	0.7015	0.5962	0.5638	1		
ANN2	0.5269	0.4694	0.4380	0.3750	0.2628*	0.4173	1	
ANN3	0.5478	0.4917	0.4576	0.3764	0.2751*	0.4437	0.9986	1

All coefficients are significative at 1% level, except * , at 5%

Table 6. Spearman´s rank-correlation coefficient

	C-Ddet	C-Dsto	DEAcrs	DEAvrs	FDH	ANN1	ANN2	ANN3
C-Ddet	1							
C-Dsto	0.9999	1						
DEAcrs	0.8326	0.8343	1					
DEAvrs	0.6368	0.6385	0.7626	1				
FDH	0.5359	0.5359	0.6451	0.7964	1			
ANN1	0.7841	0.7846	0.7812	0.5996	0.6041	1		
ANN2	0.4694	0.4689	0.4877	0.3076	0.2281**	0.3940	1	
ANN3	0.4909	0.4904	0.5094	0.3229	0.2485*	0.4208	0.9986	1

All coefficients are significative at 1% level, except * , at 5%, and **, at 10%