African Journal of Agricultural Research Vol. 6(13), pp. 3061-3070, 4 July, 2011
Available online at http://www.academicjournals.org/AJAR
DOI: 10.5897/AJAR10.116
ISSN 1991-637X ©2011 Academic Journals

Full Length Research Paper

A comparative study between parametric and artificial neural network approaches for economical assessment of potato production

Morteza Zangeneh*, Mahmoud Omid and Asadollah Akram

Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, School of Agriculture and Natural Resources, University of Tehran, Karaj, Iran.

Accepted 19 November, 2010

This paper compares results of the application of two different approaches- parametric model (PM) and artificial neural network (ANN) for assessing economical productivity (EP), total costs of production (TCP) and benefit to cost ratio (BC) of potato crop. In this comparison, ANN model and Cobb-Douglas function as PM has been used. The ANN 8-6-12-1 topology with R2=0.89 resulted in the best-suited model for estimating EP. Similarly, optimal topologies for TCP and BC were 8-13-15-1 (R2=0.97) and 8-15-13-1 (R2=0.94). The ANN approach allowed to reduce the average estimation error from -184% for PM to less than 7% with a +30% to -95% variability range.

Key words: Economical productivity, benefit to cost ratio, total cost of production, Cobb-Douglas function, estimation error.

INTRODUCTION

The estimation of present and forecast of future production costs and economical indices are key factors in determining the overall performance of a production process and achieving ways to its development: the earlier this information is known, the better the trade-off between costs and product performances will be managed. For this reason, different techniques and approaches have been developed to cope with the problem of the estimation of costs in highly uncertain contexts.

The analysis was conducted through a real case study provided by potato production process operating in the agricultural sector. The main mission of the farms is the supply, production and sale of their potato. In the global economy, the price of a product determines the effect and share of that product in target markets. Power of competition in different markets depends on price per unit of product. The capability to do cost estimation of the production can be useful to pursue the claimed strategic objective of the farm.

In particular, this study focuses on the estimation of the costs of potato production ($ kg-1) in Hamadan province of Iran. This province is the first producer of potato in Iran and exports its potato to all nearby provinces and countries. In particular, this article shows the results of a study aimed at comparing the application of two of these techniques: the parametric approach (perhaps the most diffused in practice) and a predictive model based on the artificial neural networks (ANN) theory, which has known great diffusion in the last two decades in very different application contexts.

The objective of the research was to compare the results achieved with the application of a traditional cost estimation technique (PM) with those obtained through the design and implementation of an ANN.

Overview of cost estimation techniques

From a methodological point of view, cost estimation may be based on qualitative or quantitative approaches as schematized in Figure 1 (Foussier, 2006a). Qualitative approaches rely on expert judgment or heuristic rules and will not be dealt with in this work (as they only state whether an alternative is better or worse than the other without specifying absolute values).

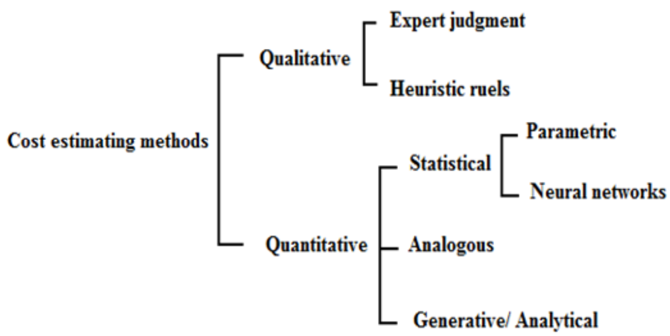

Figure 1. Classification of cost-estimating methods.

Quantitative methods instead may be further classified into statistical models, analogous models or generative-analytical models (Asiedu et al., 2000). Parametric cost models belong to the family of statistical methods, in that statistical criteria are utilized to identify the causal links and correlate costs and product characteristics, in order to obtain a parametric function with one or more variables (Foussier, 2006b). Tegene and Kuchler (1994) used a set of diagnostic tools to evaluate the forecasting performance of five farmland value models. The models were two variations of the present-value model, an ARIMA, a vector autoregression and an error-correcting model. By the Henriksson-Merton test, it was found that the error-correcting model generates superior forecasts at both forecasting horizons. Statistical methods can rely on formulas or alternative approaches to link product characteristics to costs. For example, regression analysis (Dean, 2005), but ANNs have also been employed to extend the field of statistical methods, thanks to their ability to classify, summarize and extrapolate collections of data (Bode, 2000). ANN models accept as input shape-describing and semantic product characteristics and give as output the product cost. Seo et al. (2002) also utilized ANN and statistical correlation methods in life cycle costing for use in conceptual design stages, while the same approach was adopted by Cavalieri et al. (2004) for the estimation of the manufacturing cost of mechanical components (disk brakes). Zhang and Fuh (1998) utilized ANN to estimate packaging costs based on product dimensions. This approach has known the first applications in the manufacturing sector for planning, emulation and management of production processes and plants. For example, Cavalieri and Taisch (1996) and Cavalieri et al. (1995, 1997) have developed ANNs for the design of hybrid intelligent systems and of process plants, while Zhang et al. (1996) illustrated the use of an ANN based model for the estimation of the packaging cost, based on the geometrical characteristics of the packaged product (the so-called "feature based cost").

A number of papers compared the performance of ANN and parametric regression models, in a generic context (Zhang et al., 1998; Bode, 2000), in assembly industries (Shtub and Zimmermann, 1993) or for mechanical components (Cavalieri et al., 2004) and specific processing operations (Verlinden et al., 2007). These works confirm that ANN may show better performance than regression models as already pointed out by Hill et al. (1994). The relative performance of ANNs over traditional statistical methods is reported in Zhang et al. (1998). These authors provided (1) a synthesis of published research in this area, (2) insights on ANN modeling issues, and (3) the future research directions. Church and Curram (1996) made a comparison between econometric and ANN models for forecasting consumers' expenditure. They found that the ANN models, describe the decline in the growth of consumption since the late 1980s, as well as but no better than, the econometric specifications included in the exercise, and are shown to be robust when faced with a small number of data points.

Analogous methods instead identify a similar product, and reuse the cost information to estimate the future cost by analogy, adjusting the cost for the differences between the products. Analogous models thus infer a similarity in the cost structure from a functional or geometrical similarity among product features. The strength of the similarity is proportional to the correspondence of the relevant characteristics (Shields and Young, 1991), for example, measured as the distance between the points of a multidimensional features space.

Generative-analytical methods are the most accurate, in that they try to depict the actual product creation process. A detailed analysis of the production process and decomposition into the single manufacturing operations is carried out and specific models analytically estimate the cost of each processing phase, attributing a monetary value to the resources consumption, on the basis of the technical parameters characterizing the operation. A bottom-up approach is then utilized to properly aggregate the costs incurred during the process of fabrication, through summation of each cost item. A detailed model uses estimates of labor time and rates, material quantities and prices, to estimate the direct costs of a product or activity and an allocation rate is used to allow for indirect/overhead costs (Shields and Young, 1991). Therefore, a detailed costing estimate results from a generative process plan which also allows specific cost drivers to be identified, while alternatives to adjust products cost can be derived and trade-offs can be examined.

MATERIALS AND METHODS

Problem definition and data collection

Forecasts of agricultural production and prices are intended to be useful for farmers, governments, and agribusiness industries. Because of the special position of food production in a nation's security, governments have become both principal suppliers and main users of agricultural forecasts. They need internal forecasts to execute policies, that provide technical and market support for the

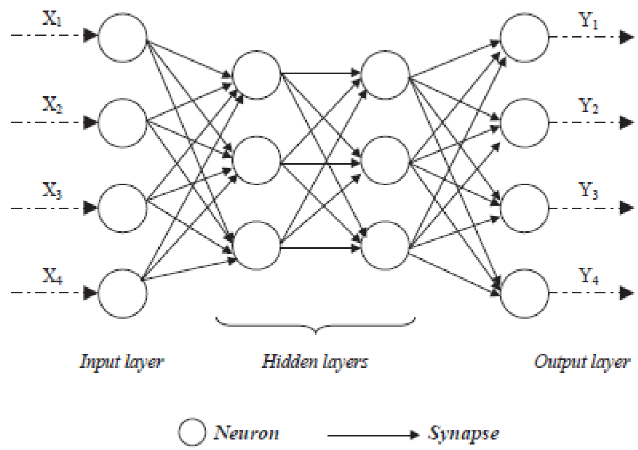

Figure 2. The structure of multilayer feedforward neural network.

agricultural sector (Geoffrey, 1994). In the case of potato crop production, the first phase would consist of a clear definition of the production objectives and constraints. This aspect appears quite important for a farmer, which has many inherent unanticipated problems. Objectives, strategies and activities to be implemented must be accepted by government, associated with agricultural sector and especially potato producers in this province. Due to high price of a crop in one year, in the following years many farmers are tempted to cultivate that crop. This phenomenon has been noticed over and over for several crops in Iran, particularly in the production of potato in the province of Hamadan. Estimation of average cost of production and pricing based on this information can reduce tensions in potato market. Government with this information can forecast the future price of potatoes, adjust its market situation and buy potatoes in excess to market requirements.

Once the problem and the methodology to be used had been defined, it is necessary to proceed to the analysis of product data, and to the identification of the information sources and of the corresponding business functions responsible for their maintenance and update. In this case, the main typologies of data are:

1. Technological data, related to the production processes.
2. Cost data, such as agricultural inputs costs, labor costs, etc.

The sources of information were the information based on data which were collected by questionnaire method from potato producers in Hamadan province of Iran. The data collected belonged to the production period of 2008 to 2009. Farms were randomly chosen from the villages in the area of study. The size of sample was determined using Cochran technique (Snedecor and Cochran, 1989). Based on this method 89 farms were interviewed.

ANN approach for cost estimation

Interest in using artificial neural networks (ANNs) for forecasting has led to a tremendous surge in research activities in the past two decades. Recent research activities in ANNs have shown that, they have powerful pattern classification and pattern recognition capabilities (Zhang et al., 1998). ANNs are inspired to the human brain functionality and structure, which can be represented as a network of densely interconnected elements called neurons. The connections between neurons are called synapses and could have different levels of electrical conductivity, which is referred to as the weight of the connection. This network of neurons and synapses stores the knowledge in a ‘‘distributed’’ manner: the information is coded as an electrical impulse in the neurons and is stored by changing the weight (that is, the conductivity) of the connections.

ANNs inherit the above-explained structure: they are composed of a large number of elaboration units (the neurons) linked via weighted connections (the synapses). An ANN reacts to inputs by performing the sum of the weighted impulse of the neurons: the result activates one or more specific output neurons which provides the answer of the net. Another similarity between ANNs and the brain is the learning approach. Like the human brain, an ANN needs to be trained, which means that it needs to store knowledge by means of the elaboration of a set of training data (also called patterns), which represent the experience ‘‘cumulated’’ by the ANN. This training campaign allows the network designer to ‘‘fine tune’’ the weight of the connections between neurons, by storing the specific knowledge included in the patterns.

Moreover, one of the most important characteristic of ANNs is their ability to infer from their knowledge the answer to questions (inputs) that they have never seen before. This is referred to as the generalization ability of the ANNs. This feature of ANNs reduces the amount of data needed in the training phase. To summarize, the ANNs represent a powerful, non-linear and parallel computing approach that could be used to perform fast and complex computations.

Multilayer feed forward ANN

There are multitudes of ANN structures and different classification frameworks. For example, ANN could be classified according to the learning method or to the organization of the neurons (Chester, 1993). The one that have been used in this work is called Multilayer Perception (MLP), in which neurons are organized in several layers: the first is the input layer (fed by a pattern of data), while the last is the output layer (which provides the answer to the presented pattern). Between input and output layers, there could be several other hidden layers (Figure 2). The number of hidden layers has an important role in determining the generalization ability of the MLP. MLP represents a tool, which is able to identify the relationships between different data sets, although the form of these relationships is not defined exactly. For this reason they are called ‘‘universal approximation or regression tools’’ (Hornik et al., 1989).

Parametric approach for cost estimation

In order to complete the information provided by the parametric model (PM), a cost estimation relationship (CER) has been developed. In order to find a CER, relationship between the desired outputs and inputs was estimated using Cobb-Douglas production function for the potato crop, as illustrated in Equation 1 for all EP, TCP and BC, as:

$$\ln Y_i = \alpha_0 + \alpha_1 \ln Ch_i + \alpha_2 \ln Cfm_i + \alpha_3 \ln Cdf_i + \alpha_4 \ln Cf_i + \alpha_5 \ln Cm_i + \alpha_6 \ln Ce_i + \alpha_7 \ln Cs_i + \alpha_8 \ln Cc_i + e_i \qquad (1)$$

where Yi denotes the EP, TCP and BC of the i'th farmer. The Yi was assumed to be a function of Chi, Cfmi, Cdfi, Cfi , Cmi, Cei, Csi and Cci. The meaning of the single terms of the models is reported in Tables 1, 2 and 3. In Equation (1), α_0 is a constant term, α_i represent coefficients of inputs which are estimated from the model and ei is the error term such that $\sum_{i=1}^{n} e_i = 0$.

Performance evaluation of PM and ANN models

The performance of the trained networks was measured by mean

Table 1. Description of parametric model (PM) and significance for economical productivity (EP) index.

Term	Coefficients	t-ratio	Sig
Endogenous variable:			
EP			
Exogenous variables:			
Constant term (α0)	7.593	8.054*	0.000
1. Ch	-0.015	-0.123n.s	0.217
2. Cfm	-0.074	-2.277**	0.019
3. Cdf	0.087	2.876*	0.010
4. Cf	-0.070	-1.741*	0.002
5. Cm	-0.025	-2.415**	0.047
6. Ce	0.025	0.868n.s	0.101
7. Cs	-0.559	-14.404*	0.000
8. Cc	-0.049	-1.166n.s	0.550
R2	0.76		
Durbin–Watson	2.219		
MAPE (%)	8.53		

* Significant at 1% level, **Significant at 5% level, ***Significant at 10% level.

Table 2. Description of parametric model (PM) and significance for total cost of production (TCP) index.

Term	Coefficients	t-ratio	Sig
Endogenous variable:			
TCP			
Exogenous variables			
Constant term (α0)	-0.478	-4.202*	0.000
1. Ch	-0.006	-0.391n.s	0.697
2. Cfm	0.007	1.896***	0.062
3. Cdf	-0.004	-1.145n.s	0.255
4. Cf	0.009	1.875***	0.064
5. Cm	0.002	1.640n.s	0.105
6. Ce	0.001	0.382n.s	0.704
7. Cs	0.067	14.315*	0.000
8. Cc	0.008	1.530n.s	0.130
R2	0.75		
Durbin–Watson	1.829		
MAPE (%)	32.10		

* Significant at 1% level, **Significant at 5% level, ***Significant at 10% level.

square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and coefficient of determination (R2) on another set of data (testing set), not seen by the network during training and cross-validation (CV), between the predicted values of the network and the target (or experimental) values. In validating the PM, autocorrelation was performed using Durbin–Watson (DW) test (Hatirili et al., 2005). Finally, the values of the coefficients of both ANN and PM models have been assigned in order to minimize the MAPE (defined in Equation 2) and to maximize R2:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left|\text{Actual cost}_i - \text{Estimated cost}_i\right|}{\text{Actual cost}_i}100\right) \qquad (2)$$

Basic information on input costs and economical indices of potato production were entered into Excel 2007 spreadsheets, SPSS 16.0 and Shazam 9.0 software program. NeuroSolutions 5.07 software was used for the design and testing of ANN models. To develop a statistically sound model, the networks were trained multiple times (ten) and the average values were recorded for each parameter. To avoid ‘overfitting’, the MSE of the CV set was calculated after adjusting the weights and biases. The training process continued until the minimum MSE of the CV set was reached, early-stopping scheme.

RESULTS AND DISCUSSION

Parametric model (PM)

In validating the PM, Durbin-Watson (DW) test revealed that DW values were 2.219, 1.829 and 2.162 for EP, TCP and BC, respectively, that is, there was no autocorrelation at the 5% significance level in the estimated models. The corresponding R2 values for EP, TCP and BC were 0.76, 0.75 and 0.74. The impact of cost inputs on desired outputs was also investigated by their coefficients. Regression results for these models are shown in Tables 1, 2 and 3. It can be seen from Table 1 that the contribution of Cs, Cf, Cdf and Cf on EP are significant at 1% level; because of using Cobb-Douglas function in the estimation, the coefficient of variables in log form can be regarded as elasticities. In the case of TCP (Table 2), only Cs has significant effect on desired

Table 3. Description of parametric model (PM) and significant for benefit to cost ratio (BC) index.

Term	Coefficients	t-ratio	Sig
Endogenous variable:			
BC			
Exogenous variables			
Constant term (α0)	3.311	6.157*	0.000
1. Ch	0.021	0.304n.s	0.762
2. Cfm	-0.053	-2.848*	0.006
3. Cdf	0.061	3.539*	0.001
4. Cf	-0.037	-1.607n.s	0.112
5. Cm	-0.013	-2.147**	0.035
6. Ce	0.026	1.585n.s	0.117
7. Cs	-0.301	-13.618*	0.000
8. Cc	-0.026	-1.098n.s	0.275
R2	0.74		
Durbin–Watson	2.162		
MAPE (%)	16.21		

* Significant at 1% level, **Significant at 5% level, ***Significant at 10% level.

output at the 1% level, while Cfm and Cf are significant at 10% level. The elasticities of Cfm, Cdf and Cs for BC (Table 3) were estimated as -0.053, 0.061 and -0.301, respectively (all significant at the 1% level). Hatirli et al. (2006) estimated an econometric model for greenhouse tomato production in Antalya province of Turkey. They concluded that among the energy inputs, human energy was the most important input that influences yield. Singh et al. (2004) concluded that in zone 2 of Punjab, the impact of human and electrical energies were significant to the productivity of wheat crop at 1% level.

In this case, each term represents a component of the cost related to the execution of the different production operations (planting, crop management and cultivation, harvesting, etc.). Some of these variables turned out to be quite independent from the morphological characteristics of the crop, and they have been assigned mean values.

ANN model

In the discussed case, ANN represents a valid tool for the identification of the transfer function of the analyzed processes, through an implicit link between the input values (various component of potato production cost) and the output values (EP, TCP and BC). With regard to the specific ANN architecture used, given the peculiar purposes of the application, the multilayer perception (MLP) has been preferred, since it usually leads to the most satisfactory results (as reported in Hornik et al., 1989). The proper structure has been selected after having tested more than 30 ANN configurations with different numbers of hidden layers (varied between one and two), different numbers of neurons for each of the hidden layers, and different inter-unit connection mechanisms. A summary of main results for EP, TCP and BC are illustrated in Table 4. For each output, the best ANN is highlighted in the Table.

The learning algorithm adopted is a typical one for this type of ANN: the back propagation algorithm with momentum and a flat spot elimination term. The set of patterns has been divided into three subsets: 60% has been used as a training set (in order to adjust the weight of the connections and store the knowledge), 15% has been used as a cross validation set and the remaining 25% has been used as a testing set to evaluate the responses of the net to unseen patterns (in order to evaluate the degree of generalization). The results of this testing phase are reported by the MAPE, as performance indicator. It is quite evident that the two-layer configuration shows better performances than the one layer one. This result is a further confirmation of some theoretical assumptions reported in literature (Chester, 1993), where the superiority of a two-layer solution is put in relationship with its shorter training times (given the same number of connections) and the better rate of output prediction.

Comparison of the results of the two approaches

The PM and ANN models have been tested and validated by comparing the results provided by these models with the actual costs of 23 of all relevant components (cost of each input, divided for test set) produced by the farms. Overall comparison of estimating errors is shown in Table 5. According to the results obtained from Table 5, the

Table 4. Alternative configurations of ANN for the economical productivity (EP), total production costs (TCP) and benefit to cost ratio (BC) of potato crop (optimal networks are highlighted).

Network output	Number of neurons		MSE	MAE	MAPE	R2
	NH1	NH2				
EP	4	-	0.0656	0.2158	8.38	0.77
	3	9	0.0942	0.2329	7.92	0.84
	4	4	0.0544	0.1999	7.13	0.84
	5	6	0.0939	0.2155	6.30	0.89
	6	4	0.0689	0.2361	9.54	0.69
	6	13	0.1334	0.2989	8.47	0.81
	6	12	0.1027	0.2450	5.82	0.89
	10	6	0.0560	0.1967	7.59	0.82
TCP	4	-	0.0007	0.0216	9.88	0.95
	4	4	0.0010	0.0246	10.61	0.96
	8	3	0.0013	0.0268	9.18	0.96
	10	5	0.0016	0.0308	20.30	0.87
	13	15	0.0009	0.0224	9.08	0.97
	16	7	0.0013	0.0264	17.23	0.86
	17	19	0.0011	0.0248	14.75	0.90
	20	10	0.0012	0.0254	18.35	0.85
BC	4	4	0.0188	0.1168	11.73	0.90
	7	7	0.0396	0.1462	9.15	0.92
	10	10	0.0275	0.1279	11.93	0.89
	15	9	0.0370	0.1505	13.91	0.88
	15	10	0.0228	0.1276	14.30	0.82
	15	13	0.0309	0.1338	10.17	0.94
	16	23	0.0244	0.1250	14.08	0.86
	18	20	0.0224	0.1208	13.91	0.87

Table 5. Overall comparison of estimating errors of parametric model (PM) and ANN model for the economical productivity (EP), total production costs (TCP) and benefit to cost ratio (BC) indices.

Output	Method of estimation	Training data set		Test data set		Entire data set	
		MAPE (%)	Range (%)	MAPE (%)	Range (%)	MAPE (%)	Range (%)
EP	PM	8.53	+23.39/-23.11	7.92	+16.42/-25.22	8.33	+23.39/-25.22
	ANN model	5.89	+17.37/-17.89	7.30	+11.38/-20.07	6.30	+17.37/-20.07
TCP	PM	32.10	+51.31/-184.36	23.12	+39.84/-79.28	28.98	+51.31/-184.36
	ANN model	7.94	+23.53/-59.70	13.55	+30.59/-32.63	9.51	+30.59/-59.70
BC	PM	16.21	+43.18/-80.51	24.65	+34.01/-95.86	18.64	+43.18/-95.86
	ANN model	6.90	+26.37/-31.70	20.53	+30.09/-95.68	10.17	+30.09/-95.68

superiority of ANN models over the Cobb-Douglas model as parametric approach is evident: the average MAPE of EP fell from 8.28 to about 7.66%. In the case of the other desired outputs, similar trends can be seen: the average MAPE of TCP and BC fell from 24.22 and 25.78% to 14.34 and 21.82%, respectively. This outcome can be easily seen in Figure 3, which shows the average MAPE of the EP, TCP and BC. The maximum value of MAPE is about -95.87% for the PM in the case of BC. In the case of PM, the average estimation error was computed as 8.53, 32.10 and 16.21% for EP, TCP and BC, respectively, with a maximum variability range about

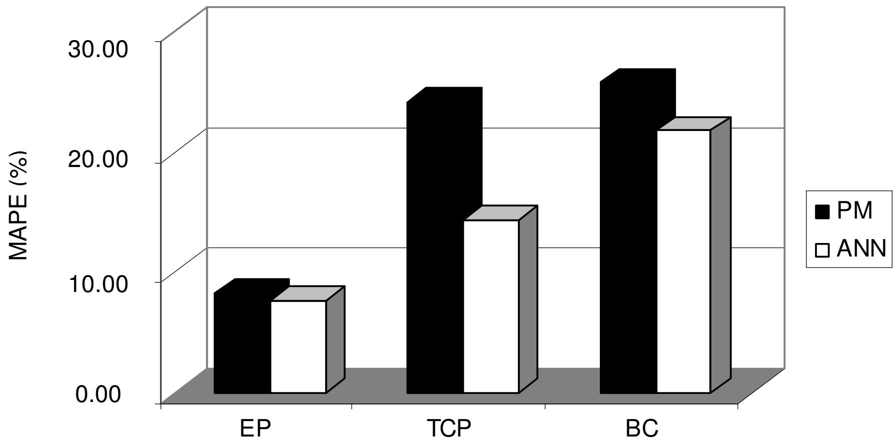

Figure 3. MAPE Comparison of economical productivity (EP), total cost of production (TCP) and benefit to cost ration (BC) for parametric and ANN models.

+51.31 to -184.36% for TCP. Overall, the parametric and ANN models, MAPE computed over the entire data set was at maximum 28.98% for PM of TCP and at minimum 6.3% for ANN model of EP. Of course, the superiority of the ANN could derive from a poor design of the PM (although this seems not to be the case here). But, apart from absolute superiority judgments, what emerges is thesuperiority of ANN models over the Cobb-Douglas model as parametric approach is evident: the average MAPE of EP fell from 8.28 to about 7.66%. In the case of the other desired outputs, similar trends can be seen: the average MAPE of TCP and BC fell from 24.22 and 25.78% to 14.34 and 21.82%, respectively. This outcome can be easily seen in Figure 3, which shows the average MAPE of the EP, TCP and BC.

The maximum value of MAPE is about -95.87% for the PM in the case of BC. In the case of PM, the average estimation error was computed as 8.53, 32.10 and 16.21% for EP, TCP and BC, respectively, with a maximum variability range about +51.31 to -184.36% for TCP. Overall, the parametric and ANN models, MAPE computed over the entire data set was at maximum 28.98% for PM of TCP and at minimum 6.3% for ANN model of EP. Of course, the superiority of the ANN could derive from a poor design of the PM (although this seems not to be the case here). But, apart from absolute superiority judgments, what emerges is the robustness of the ANN when faced with a small number of data points, which leads to excellent results on all of the validation samples. Thus contradicting those who say that this methodology, thanks to its many free parameters, allows the error on data used for its construction to go to zero, while the overall performance (the mean error on the population in general) can be far less satisfactory (Mason and Smith, 1997). In addition to reduction of MAPE in ANN model in comparison to MP, growth of R2 also occurred that can be easily understood from Figure 4. Percentage error values for the ANN models of EP, TCP and BC are shown in Figures 5, 6 and 7, respectively. Again, the superiority of ANN models to PM can be seen. Our results proved the work by Mason and Smith (1997), where the performances of regression and ANN approaches for cost estimation purposes were compared. Their results indicated that the ANN-based models are characterized by higher precision, especially when the analytical expression that links input and output variables is not known, or when it cannot be expressed in polynomial form.

It is also interesting to extend the present analysis beyond the quantitative data to include also some qualitative considerations. The most relevant point concerns the inherent logic of the two approaches: while the use of a PM requires the specification of the analytical expression of the relationship that links input and output to start with, this is not necessary with ANN approach. Hence, the ANN is characterized by the possibility to determine autonomously the most appropriate form of the relationship. This can be seen both as strength and weakness; Indeed:

1. The extant analysis of the problem is much leaner and faster, and in the case of very complex or innovative problems, the outcome is not dependent on the ability of the analysts, to find the key independent variables and the most appropriate kind of analytical expression;
2. At the same time, the impossibility to know the kind of mathematical relationship can be seen as a limit of the ANN approach, since it is not clear how the results are achieved. In other terms, in the ANN approach the object of analysis is treated as a “black box”; hence, it is impossible to give a theoretical interpretation to the results provided by the tool, especially in the case of unpredicted or (at least intuitively) unjustified values. This fact has often led some skepticism about this

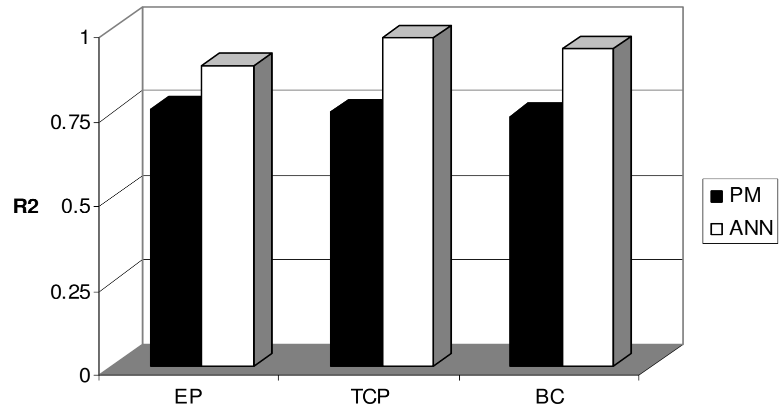

Figure 4. Growth of R2 of ANN model comparison to parametric model (PM).

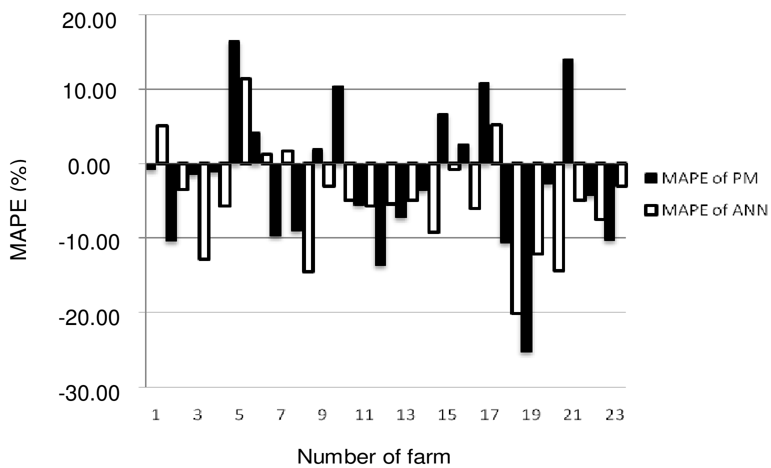

Figure 5. MAPE in the estimation of economical productivity (EP) of potato production over the validating data set (ANN model vs. parametric model).

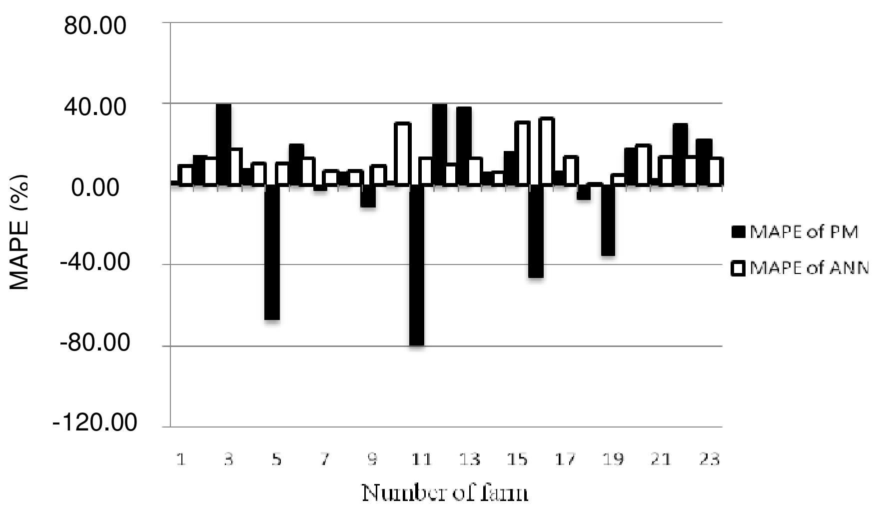

Figure 6. MAPE in the estimation of total cost of production (TCP) of potato production over the validating data set (ANN model vs. parametric model).

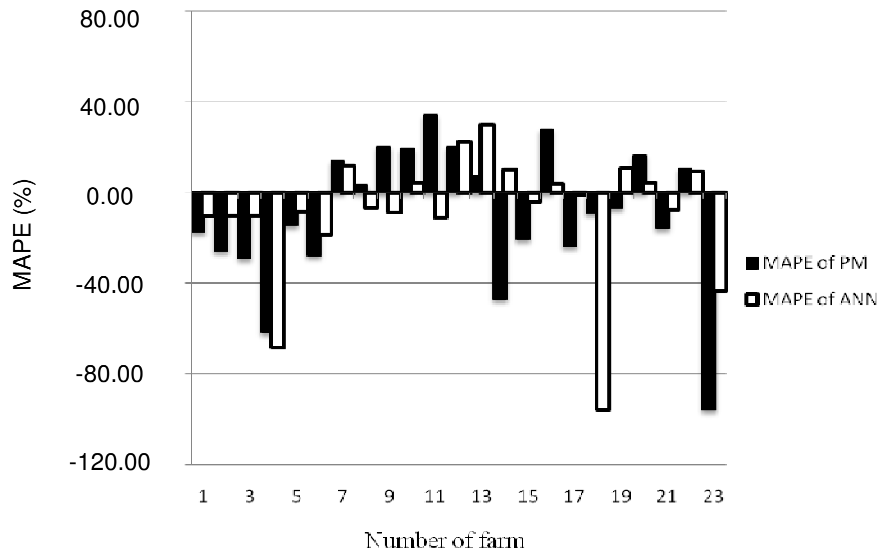

Figure 7. MAPE in the estimation of benefit to cost ration (BC) of potato production on the validating data set (ANN model vs. parametric model).

methodology in several application contexts, due also to the difficulty that its "sponsors" face, when they are asked to prove the quality of the outcome in case of counter-intuitive or questionable results. Moreover, it could be objected that if the knowledge of the form of the relationship is not needed to implement an ANN approach, it is nevertheless necessary to pre-determine the structure of the network. The answers that can be given to this critical consideration are the following:

1. The application contexts of the various supervised and unsupervised neural network structures that have been developed so far (MLP, RBF, ART, SOM, etc.) are quite well known, and the identification of the most appropriate structure is then facilitated;
2. The software packages for the design of ANNs are generally provided with tools aimed at evaluating the "learning attitude" of the network, and, in case of negative response, at implementing the appropriate modifications.

Another point that is often cited by the users of PMs is the excellent (or at least satisfactory) quality/cost ratio. But the implementation cost of ANN models is generally quite similar to that of the PM (the lower costs of preliminary analyses being balanced by the higher costs of developing and testing the ANN). Instead, the higher robustness of the methodology, and the consequent higher propensity to deal with redundant or wrong information enable the elimination or consistent reduction of the activities of data analysis, which are generally very time consuming (and, hence, quite expensive). Strength of ANNs is related to their flexibility to changes made in the structure of the analyzed system once the development of the model has been already completed. For example, if the production process of the firm is modified through the implementation of new technologies, while the PM must be completely revised and retested, using a ANN it will be sufficient to conduct a new training program with a new set of data (the structure of the network may not even be modified).

On the other hand, ANNs are completely data-driven: an adequate set of construction data is then required, while a cost estimation relationship for the PM model can be deduced from technical considerations on the production process and on the kind of resources used (as for the typical engineering estimating approach), provided that it can be subsequently validated.

Conclusions

This paper aimed at illustrating the compared results of the application of two different approaches-respectively PM and ANN-for forecasting economical productivities (EP, TCP and BC) of potato crop produced in Hamadan province of Iran. The procedure used for developing the two estimating methods was fully described and the obtained performances were evaluated in comparison with each other. We also discussed the merits and limitations of the analyzed approaches. The choice of the predictive model is generally based on the classical cost/ benefit ratio: in this sense, the regression models have often been preferred. But the more recently developed ANN models seem to represent a valid and attractive alternative, especially when the cost estimation relationship form is not known, and cannot be logically argued (since in this case psychological barriers deriving from the impossibility to check the relationship with common sense can be overcome more easily).

In the case study illustrated in this paper, with respect to the Cobb-Douglas production function as parametric model, the ANN has shown better results in all the validation samples, and no significant variance problems (that is, the dependence of the model on the data set used to construct it) have emerged. The ANN approach allowed to reduce the MAPE from over -184 for PM to less than 7% with a +30 to 95% variability range.

Nomenclature

ANN, Artificial neural network; BC, Benefit to cost ratio; $C_{h,}$ Cost of human labor (\$ ha^{-1}); $C_{fm,}$ Cost of farm machinery (\$ ha^{-1}); $C_{df,}$ Cost of diesel fuel (\$ ha^{-1}); C_f ,Cost of fertilizers (\$ ha^{-1}); $C_{m,}$ Cost of farmyard manure (\$ ha^{-1}); $C_{e,}$ Cost of electricity (\$ ha^{-1}); C_s ,Cost of seed (\$ ha^{-1}); $C_{c,}$ Cost of chemicals (\$ ha^{-1}); CER, Cost estimation relationship; EP, Economical productivity (\$ kg-1); GF, Generalization factor; MLP, Multi layer perception; MAPE, Mean absolute percentage error; MSE, Mean squared error; MAE, Mean absolute error; PM, Parametric model; TCP, Total cost of production (\$ kg-1).

REFERENCES

Asiedu Y, Besant RW, Gu P (2000). Simulation-based cost estimation under economic uncertainty using kernel estimators. Int. J. Prod. Res., 38(9): 2023-2035.

Bode J (2000): Neural networks for cost estimation: Simulation and pilot applications. Int. J. Prod. Res., 38(6): 1231-1254.

Cavalieri S, Maccarrone P, Pinto R (2004): Parametric vs. neural network models for the estimation of production costs: A case study in the automotive industry. Int. J. Prod. Econ., 91: 165-177.

Cavalieri S, Garetti M, Taisch M (1995). A predictive neural network modeling system for process plants, Proceedings of the 13th International Conference on Production Research 6th-10th August, Jerusalem, pp. 571-573.

Cavalieri S, Taisch M (1996). Neural networks in hybrid intelligent manufacturing systems, Proceedings of the APMS, 96th International Conference on Advances in Production Systems. 4th–6th November, Kyoto.

Cavalieri S, Rabe M, Taisch M (1997). A neural network approach to the plant design problem, Proceedings of the First International Conference on Engineering Design and Automation. 18th-21st March, Bangkok.

Chester J (1993). Neural Networks, A Tutorial, Prentice Hall, New York.

Dean EP (2005): Parametric cost deployment. Proceedings of the 7th Symposium on Quality Function Deployment. June, USA, pp. 27-34.

Church KB Curram SP (1996): Forecasting consumers' expenditure: A comparison between econometric and neural network models. Int. J. Forecasting, 12(2): 255-267.

Foussier PMM (2006a). From Product Description to Cost: A Practical Approach, vol. 1: The Parametric Approach. Springer, Berlin.

Foussier PMM (2006b). From Product Description to Cost: A Practical Approach, vol. 2: Building a Specific Model. Springer, Berlin.

Geoffrey Allen P (1994). Economic forecasting in agriculture. Int. J. Forecasting, 10(1): 81-135.

Hatirli SA, Ozkan B, Fert C (2005): An econometric analysis of energy input-output in Turkish agriculture. Renewable and Sustainable Energy Reviews, 9: 608-623.

Hatirli SA, Ozkan B, Fert C (2006): Energy inputs and crop yield relationship in greenhouse tomato production. Renewable Energy, 31: 427-438.

Hill T, Marquez L, Oconnor M, Remus W (1994). Artificial neural network models for forecasting and decision making. Int. J. Forecasting, 10(1): 5-15.

Hornik K, Stinchcombe M, White H (1989). Multilayer feedforward networks are universal approximators. Neural Networks, 2: 359-366.

Mason AK, Smith AE (1997). Cost estimation predictive modeling: Regression versus neural network. Eng. Economist, 42(2): 137-162.

Seo KK, Park JH, Jang DS, Wallace D (2002). Prediction of the life cycle cost using statistical and artificial neural network methods in conceptual product design. Int. J. Com. Int. Manuf., 15(6): 541-554.

Shields MD, Young SM (1991). Managing product life cycle cost of an organizational model. Cost Manage. Autumn, pp. 39-52.

Shtub A, Zimmermann Y (1993). A neural network based approach for estimating the cost of assembly systems. Int. J. Prod. Econ., 32(2): 189-207.

Singh G, Singh S, Singh J (2004). Optimization of energy inputs for wheat crop in Punjab. Energy Conversion Management, 45: 453-465.

Snedecor GW, Cochran WG (1989): Statistical Methods. 8th Ed. Iowa State Press, USA.

Tegene A, Kuchler F (1994). Evaluating forecasting models of farmland prices. Int. J. Fore., 10(1): 65-80.

Verlinden B, Duflou JR, Collin P, Cattrysse D (2007). Cost estimation for sheet metal parts using multiple regression and artificial neural networks: A case study. Int. J. Prod. Econ., 111: 484-492.

Zhang YF, Fuh JY, Chan WT (1996): Feature-based cost estimation for packaging products using neural networks. Comput. Ind., 32: 95-113.

Zhang G, Eddy Patuwo B, Hu MY (1998): Forecasting with artificial neural networks: The state of the art. Int. J. Fore., 14(1): 35-62.

Zhang YF, Fuh JY (1998): A neural network approach for early cost estimation of packaging products. Comput. Ind. Eng., 34(2): 433-450.