

ARTICLE WITHDRAWAL

Withdrawal of article entitled **“A comparative study between parametric and artificial neural networks approaches for economical assessment of potato production in Iran”**, by M. Zangeneh, M. Omid and A. Akram (Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, School of Agriculture & Natural Resources, University of Tehran, Karaj, Iran), which appeared in volume 9 issue 3, pp: 661-671, September, 2011, of the *Spanish Journal of Agricultural Research* (accepted 20 June, 2011).

This article has been withdrawn at the request of the SJAR Managing Editors, because the same paper was published in the *African Journal of Agricultural Research* (2011) Vol. 6 No. 13, pp: 3061-3070 (accepted 19 November, 2010). This duplicity was brought to our attention by the scientific community. The article content has been removed from the online journal.

The authors claim that they originally submitted the paper to the *African Journal of Agricultural Research*, but subsequently withdrew the paper from the journal. They neither gave permission nor paid any fee for publication. The managing editors of the SJAR sent an email to the *African Journal of Agricultural Research* requesting further information but the African journal never replied.

A comparative study between parametric and artificial neural networks approaches for economical assessment of potato production in Iran

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Abstract

Potatoes are the single most important agricultural commodity in Hamadan province of Iran, where 25,503 ha of this crop were planted in 2008 under irrigated conditions. This paper compares results of the application of two different approaches, parametric model (PM) and artificial neural networks (ANNs), for assessing economical productivity (EP), total costs of production (TCP) and benefit to cost ratio (BC) of potato crop. In this comparison, Cobb-Douglas function for PM and multilayer feedforward for implementing ANN models have been used. The ANN, having 8-6-12-1 topology with $R^2=0.89$, resulted in the best-suited model for estimating EP. Similarly, optimal topologies for TCP and BC were 8-13-15-1 ($R^2=0.97$) and 8-15-13-1 ($R^2=0.94$), respectively. In validating the PM and ANN models, mean absolute percentage error (MAPE) was used as performance indicator. The ANN approach allowed to reduce the MAPE from -184% for PM to less than 7% with a +30% to -95% variability range. Since ANN outperformed PM model, it should be preferred for estimating economical indices.

Additional key words: artificial neural networks; benefit to cost ratio; Cobb-Douglas production function; economical productivity; estimation error; *Solanum tuberosum*; total cost of production.

Resumen

Estudio comparativo entre enfoques paramétricos y de redes neuronales artificiales para la evaluación económica de la producción de patata en Irán

La patata es el producto agrícola más importante en la provincia de Hamadan (Irán), donde se plantaron 25.503 ha de este cultivo en 2008 bajo condiciones de riego. Este trabajo compara los resultados de aplicar dos enfoques diferentes, un modelo paramétrico (PM) y redes neuronales artificiales (ANN), para evaluar la productividad económica (EP), los costos totales de producción (TCP) y el coeficiente beneficio/costo (BC) del cultivo de la patata. En esta comparación se han utilizado la función Cobb-Douglas como PM y el proceso “feedforward” multicapa para implementar modelos de ANN. Las ANN, con una topología 8-6-12-1 con $R^2 = 0,89$, resultaron ser el modelo más adecuado para estimar la EP. Del mismo modo, las topologías óptimas para TCP y BC fueron 8-13-15-1 ($R^2=0,97$) y 8-15-13-1 ($R^2=0,94$), respectivamente. Para validar los modelos PM y ANN, se utilizó como indicador de desempeño el error porcentual medio absoluto (MAPE). El enfoque de ANN permitió reducir el MAPE desde -184% para PM a menos del 7% con un rango de variabilidad de +30% a -95%. Dado que ANN fue mejor que el modelo PM, debe ser preferido para la estimación de los índices económicos.

Palabras clave adicionales: coeficiente beneficio/costo; costo total de producción; error de estimación; función de producción Cobb-Douglas; productividad económica; redes neuronales artificiales; *Solanum tuberosum*.

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Abbreviations used: ANN (artificial neural network); BC (benefit to cost ratio); CER (cost estimation relationship); EP (economical productivity, kg S^{-1}); MAE (mean absolute error); MAPE (mean absolute percentage error); MLP (multi layer perceptron); MSE (mean squared error); PM (parametric model); TCP (total cost of production, \$ ha^{-1}).

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 estimating costs in highly uncertain contexts.

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). Quantitative methods 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).

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 a 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.*, 2008). These works confirmed 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 ANN models describe the decline in the growth of consumption since the late 80s 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 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

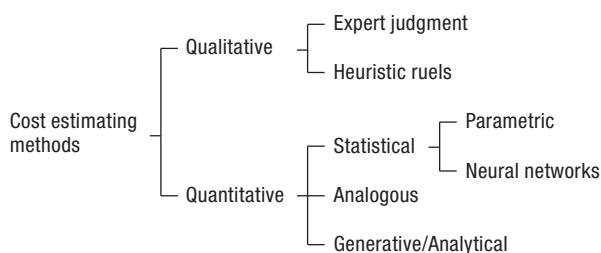


Figure 1. Classification of cost-estimating methods.

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.

In this work, the analysis was conducted through a real case study provided by a potato (*Solanum tuberosum* L.) production process operating in the agricultural sector. The main mission of the farms is the production supply and sale of their potato. In an open economy the price of a product determines the effect and share of that product in target markets. The 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. This study focuses on the estimation of the production costs of potatoes (US\$ kg⁻¹) in Hamadan province of Iran. This province is the first producer of potato in Iran and exports its potato to all of 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, the parametric model (PM) with those obtained through the design and implementation of an ANN.

Material 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 agricultural sector (Allen, 1994).

In the case of potato crop production, the first phase would be a clear definition of the production objectives and constraints. This aspect appears quite important for a farmer, which has many inherent unanticipated problems, like weather and prices. Objectives, strategies and activities to be implemented by farmers must be acceptable to government bodies associated with the agricultural sector, and specially potato producers in this province. Because of high price of a crop in one year, in the following year 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 have 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: i) technological data, related to the production processes, and ii) cost data, such as agricultural inputs costs, labor costs, etc.

The sources of information were the information based on data that were collected by questionnaire method from potato producers in Hamadan province of Iran. The data collected belonged to the production period of 2008-2009. 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.

Three indices have been used for assessing economic situation of potato production including: benefit to cost ratio (BC), economical productivity (EP) and total cost of production (TCP) presented as Eqs. [1], [2] and [3] respectively (Zangeneh *et al.*, 2010).

$$BC = \frac{\text{Total production value (\$ ha}^{-1}\text{)}}{\text{Total production costs (\$ ha}^{-1}\text{)}} \quad [1]$$

$$EP = \text{Potato yield (kg ha}^{-1}\text{)} / \text{Total production costs (\$ ha}^{-1}\text{)} \quad [2]$$

$$TCP = C_h + C_{fm} + C_{df} + C_f + C_m + C_e + C_s + C_c \quad [3]$$

where 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).

In our study, the benefit-cost ratio of the potato production was calculated by dividing the gross product value into the total production cost in order to determine economic efficiency. The EP used for assessing the ability of potato farms to convert expended cost to potato. TCP presents the sum of inputs used in potato production.

Artificial neural networks 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 (*i.e.* 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 provide the answer of the net. Another similarity between ANNs and a 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. 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, ANNs represent a powerful, non-linear and parallel computing approach that could be used to perform fast and complex computations.

Multilayer feedforward artificial neural networks

There are multitudes of ANN structures and different classification frameworks. For examples, 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 perceptron (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 (see Fig. 2). The number of hidden layers has an important role in determining the generalization

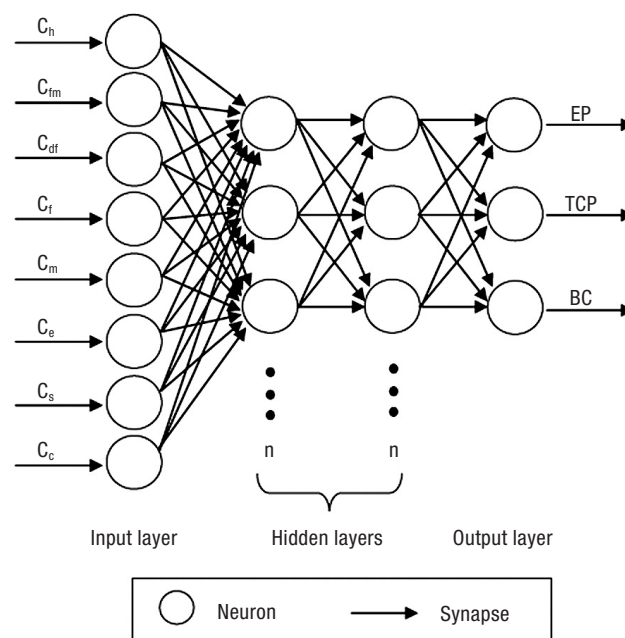


Figure 2. The structure of multilayer feedforward neural network used for modeling EP, TCP and BC.

ability of ANNs. 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 Eq. [4] for all EP, TCP and BC, as:

$$\ln Y_i = \alpha_0 + \alpha_1 \ln C_{hi} + \alpha_2 \ln C_{fmi} + \alpha_3 \ln C_{dfi} + \alpha_4 \ln C_{fi} + \alpha_5 \ln C_{mi} + \alpha_6 \ln C_{ei} + \alpha_7 \ln C_{si} + \alpha_8 \ln C_{ci} + e_i \quad [4]$$

where Y_i denotes the EP, TCP and BC of the i^{th} farmer. The Y_i was assumed to be a function of C_{hi} , C_{fmi} , C_{dfi} , C_{fi} , C_{mi} , C_{ei} , C_{si} and C_{ci} . The meaning of the single terms of the models is reported in Table 1. In Eq. [4], α_0 is a constant term, α_i represents coefficients of inputs which are estimated from the model and e_i is

the error term such that $\sum_{i=0}^n e_i = 0$.

Table 1. Description of parametric model (PM) for the economical productivity (EP), total production costs (TCP) and benefit to cost ratio (BC)

Endogenous variable	Exogenous variables	Coefficients	t-ratio	Significance	R ²	Durbin-Watson	MAPE (%)
EP					0.76	2.219	8.53
	Constant term (α_0)	7.593	8.054*	0.000			
	1. C_h	-0.015	-0.123 ^{n.s}	0.217			
	2. C_{fm}	-0.074	-2.277**	0.019			
	3. C_{df}	0.087	2.876*	0.010			
	4. C_f	-0.070	-1.741*	0.002			
	5. C_m	-0.025	-2.415**	0.047			
	6. C_e	0.025	0.868 ^{n.s}	0.101			
	7. C_s	-0.559	-14.404*	0.000			
	8. C_c	-0.049	-1.166 ^{n.s}	0.550			
TCP					0.75	1.829	32.10
	Constant term (α_0)	-0.478	-4.202*	0.000			
	1. C_h	-0.006	-0.391 ^{n.s}	0.697			
	2. C_{fm}	0.007	1.896***	0.062			
	3. C_{df}	-0.004	-1.145 ^{n.s}	0.255			
	4. C_f	0.009	1.875***	0.064			
	5. C_m	0.002	1.640 ^{n.s}	0.105			
	6. C_e	0.001	0.382 ^{n.s}	0.704			
	7. C_s	0.067	14.315*	0.000			
	8. C_c	0.008	1.530 ^{n.s}	0.130			
BC					0.74	2.162	16.21
	Constant term (α_0)	3.311	6.157*	0.000			
	1. C_h	0.021	0.304 ^{n.s}	0.762			
	2. C_{fm}	-0.053	-2.848*	0.006			
	3. C_{df}	0.061	3.539*	0.001			
	4. C_f	-0.037	-1.607 ^{n.s}	0.112			
	5. C_m	-0.013	-2.147**	0.035			
	6. C_e	0.026	1.585 ^{n.s}	0.117			
	7. C_s	-0.301	-13.618*	0.000			
	8. C_c	-0.026	-1.098 ^{n.s}	0.275			

***, **, *. significant at 1%, 5% and 10% level, respectively.

Performance evaluation of PM and ANN models

The performance of the trained networks was measured by mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and coefficient of determination (R^2) 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 (Hatirli *et al.*, 2005). Finally, the values of the coefficients of both ANN and PM models that have been assigned in order to minimize the MAPE (defined in Eq. [5]) and to maximize R^2 :

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left(\frac{|Actual\ cost_i - Estimated\ cost_i|}{Actual\ cost_i} \times 100 \right) \quad [5]$$

The 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 programs (Zangeneh *et al.*, 2010). Neuro-Solutions 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 of 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, DW test revealed that DW value was as 2.219, 1.829 and 2.162 for EP, TCP and BC, respectively, *i.e.* there was no autocorrelation at the 5% significant level in the estimated models. The corresponding R^2 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 Table 1. It can be seen from Table 1 that the contribution of C_s , C_f , C_{df} and C_r 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 elasticity. In the case of TCP (Table 1) only C_s has significant effect on desired output at the

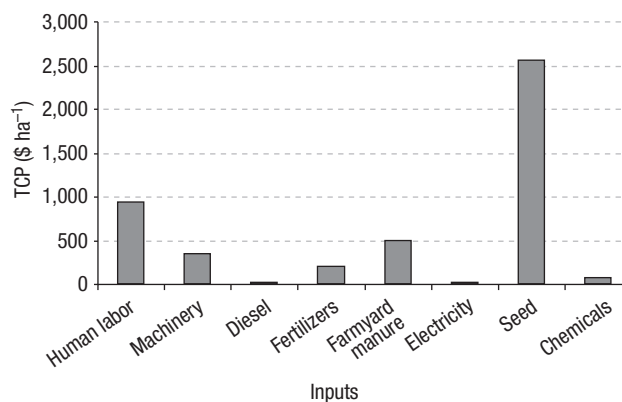


Figure 3. Share of inputs in TCP (total cost of production).

1% level, while C_{fm} and C_r are significant at 10% level. Finally, the elasticity of C_{fm} , C_{df} and C_s for BC (Table 1) 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 our 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. For example electricity is independent from morphological shape of potato, while chemicals directly dependent to it. The comparison of input importance is illustrated in Figure 3. As can be seen, seed has the most importance in TCP, followed by human labor and farmyard manure, respectively.

Artificial neural networks 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. The proper structure is an ANN model which indicates good results for predicting desired outputs. Robustness of proper structure in estimating results can be determined by several indices such as MAPE, R^2 and MAE. All ANN models for prediction of each output (economical indices) have been presented in Table 2. Only one model has been selected as proper structure for each output based on its characteristics and the remaining structures are rejected. A summary of main results for EP, TCP and BC are illustrated in Table 1. For each output, the best ANN is highlighted in Table 2.

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

Table 2. Alternative configurations of ANN for the economical productivity (EP), total production costs (TCP) and benefit to cost ratio (BC) of potato crop (in bold, optimal networks)

Network output	Number of neurons		MSE ¹	MAE ²	MAPE ³	R^2
	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

¹ MS: mean square error. ² MAE: mean absolute error. ³ MAPE: mean absolute percentage error.

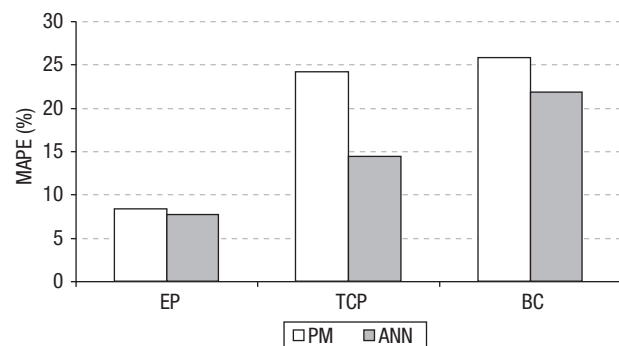
Table 3. Overall comparison of estimating errors of parametric model (PM) and ANN model for the economical productivity (EP), total production costs (TCP) and benefit to cost ratio (BC) indices

Output	Method of estimation	Training data set		Test data set		Entire data set	
		MAPE ¹	Range (%)	MAPE ¹	Range (%)	MAPE ¹	Range (%)
EP	PM	8.53	+23.39/-23.11	7.92	+16.42/-25.22	8.33	+23.39/-25.22
	ANN	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	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	6.90	+26.37/-31.70	20.53	+30.09/-95.68	10.17	+30.09/-95.68

¹ MAPE: mean absolute percentage error.

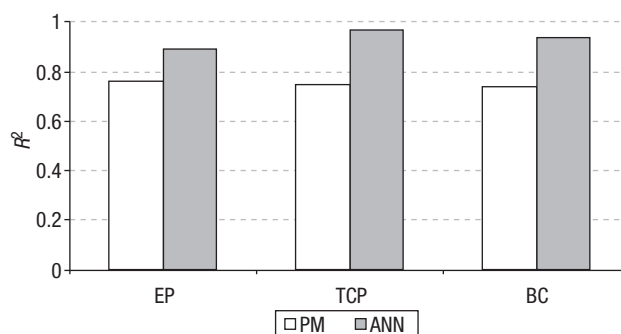
models with the actual costs of 23 of all relevant components (cost of each input, divided for test set) produced by the farms. Overall comparison of estimating errors is shown in Table 3.

According to the results obtained from Table 3, the superiority of ANN models over the Cobb-Douglas model as PM approach is evident: the average MAPE of EP fell from 8.28% to about 7.66%. In the case of 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 4, 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

**Figure 4.** MAPE (mean absolute percentage error) comparison of economical productivity (EP), total cost of production (TCP) and benefit to cost ratio (BC) for parametric and ANN models.

of the ANN could derive from a poor design of the PM (although this seems not to be the case here).

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 comparison to PM, growth of R^2 also occurred that can be easily understood from Figure 5. Percentage error values for the ANN models of EP, TCP and BC are shown in Figures 6a, b y c, 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

**Figure 5.** Growth of R^2 of ANN model compared to parametric model (PM).

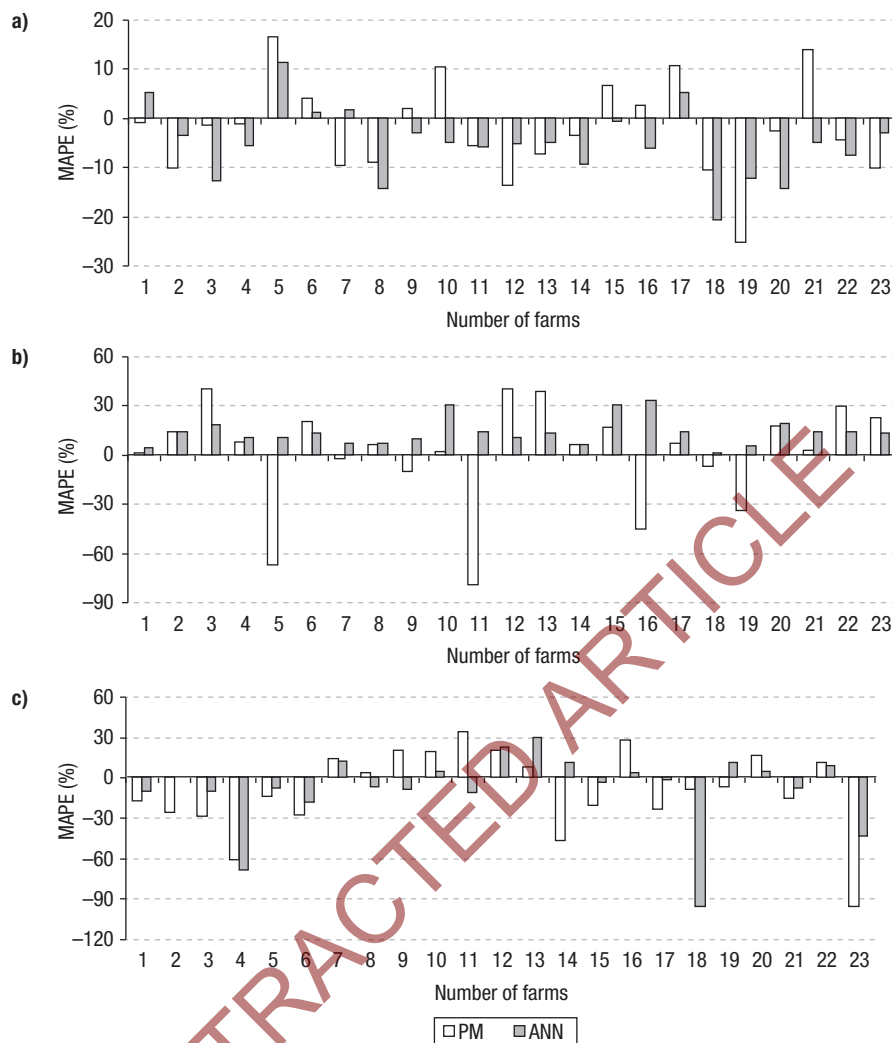


Figure 6. MAPE (mean absolute percentage error) in the estimation of a) economical productivity (EP), b) total cost of production (TCP) and c) benefit to cost ratio (BC) of potato production on the validating data set (ANN model vs. parametric model).

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 as both strength and weakness: i) the exact 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; ii) 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. The results of the ANN model can be used for both farmers and government bodies, but in different ways. Farmers can use the model for predicting their economic benefits with changing their inputs (such as elec-

tricity, chemicals, fertilizers, etc.). On the other hand, government bodies with the model can regulate the price of inputs to keep reasonable benefits for potato production in farms and improve their compatibility. The aim of developing such models is creating prediction capability for agricultural society (farmers and government bodies) to manage their economical status and regulate their situation in agricultural markets. This fact has often led to some skepticism about this methodology in several application contexts, due also to the difficulty that it's "sponsors" face when they are asked to prove the quality of the outcome in case of counterintuitive 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:

- 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;

- 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 re-tested, 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 also 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 (*i.e.* 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 than -184% for PM to less than 7% with a +30% to 95% variability range.

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