

# Predicting operational and environmental efficiency of primary sectors of EU countries, by implementing Artificial Neural Networks

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**Abstract.** One of the most important policy reforms for the European Union (EU) agriculture was the implementation of the Agenda 2000, which establishes a new framework for subsidies management, decoupled from both crop and animal production for the vast majority of products. One of the main goals of this new policy framework is the improvement of its environmental impact. Additionally, there is a need for the implementation of new efficiency assessment and prognostication tools for the evaluation of EU farming, because the influence of market forces has been increased substantially. Regarding prognostication of crop and animal output, as well as Green House Gas (GHG) emissions, the application of Artificial Neural Networks (ANNs) is being proposed, succeeding satisfactory quality characteristics for the models being proposed for operational and environmental predictions in EU agriculture.

**Keywords:** Artificial Neural Networks, Agriculture, Efficiency, Common Agricultural Policy, Environment, Energy

## 1 Introduction

It is a continuous goal of the European Union (EU) Common Agricultural Policy (CAP) to improve both operational and environmental efficiency of agricultural holdings, aiming by this way to increase the competitiveness of EU primary sectors as a whole in a globalized production and trading framework. The quantification of this approach is being expressed by the 20-20-20 strategy which focuses on increasing the energy efficiency by 20%, reducing the CO<sub>2</sub> emissions by 20% and produce 20% of overall energy consumed by renewable energy resources (European Commission, 2011). One of the most important policy reforms for the EU agriculture was the implementation of the Agenda 2000, with the establishment of a totally new framework for subsidies management, decoupled from both crop and animal production. Since the year 2005 the new subsidy scheme has come into force, providing by this way the ability to the EU to fully comply with the last World Trade Organization (WTO) agreement of the Uruguay Round (European Commission, 2013). Under this new framework, the subsidy scheme has a pure supportive role on the producers' income, increasing by this way the impact of their managerial

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decisions on the improvement of efficiency of their holdings.

Quite important is the ability of policy makers to assess the level of success of policies being planned, before their implementation. Throughout the years it has been proven that this is not an easy task, due to the fact that this level of success is heavily depended on the assumptions being made as well as the suitability of the models being used for such estimations. Regarding agriculture, there are models focusing on the impact of policies on agricultural trade and development, as well as other tasks like biophysical and environmental ones. All these widely recognized models are based on various mathematical methodologies, providing useful information for significant issues of agriculture, like land management, agricultural trade and agricultural income. There are though other prognostication methodologies, being already used in many scientific fields with significant success, like the Artificial Neural Networks (ANNs). In this paper ANNs are being used as a tool to estimate future performance of EU countries primary sectors in both operational and environmental terms.

## 2 Background

A very important and promising methodology for both performance assessment and prognostication is the Artificial Neural Network (ANN). ANNs have been used for predicting purposes for various economic activities. In agriculture quite important is to establish models for predicting yields, turnovers, and recently undesirable outputs like GHG emissions. A recent study presented an ANN model for predicting wheat yield and GHG emissions having a 11-3-2 structure, with  $R^2$  0.99 and 0.998 for yield and GHG emissions respectively (Khoshevisan *et al*, 2013). On the same trend, ANNs were used to build models for prognostication of environmental parameters in potato production. ANN model having 11-10-6 structure achieved the best performance for this purpose (Khoshevisan *et al*, 2013). Another case study of ANNs for predicting greenhouse basil production determined satisfactory results, having a 7-20-20-1 structure and  $R^2$  of 0.976 (Pahlavan *et al*, 2012). A more policy oriented use of ANNs was applied for cropland change in Romania. This application allows land-change scientists to identify the spatial determinants based on the observed changes and to manage complex factional relationships coexisting in agricultural production process (Lakes *et al*, 2009).

Especially for CAP, prognostication of the impact of various reforms being planned was and is a continuous goal. For this reason the Global Trade Analysis Project (GTAP) applied general equilibrium model has been used taking into consideration the GTAP global data base (Hertel, 1997; McDougall, 1998). In the case of the EU enlargement towards central and eastern European countries the model implementation projected increased agricultural production for these countries and significant financial transfers from EU taxpayers to the central and eastern European farmers. The macroeconomic costs for the EU were found to be limited (Bach *et al*, 2000). Focusing on agricultural land management issues, the combined implementation of GTAP and the biophysical (IMAGE) model for the EU after the

enforcement of the 2003 CAP reform showed that there will be no drastic decrease on agricultural land use will occur in the next 30 years due to increased demand for food globally. On the contrary, significant changes on land use are expected in developing areas like Africa (Meijl *et al*, 2006). Another modelling approach is the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) model. It has been developed by the international food policy research institute focusing on connecting food supply chain and water supply and demand (Rosegrant *et al*, 2008). More recent attempts to simulate farm operation in regards of policy recommendations lead to the Farm System Simulator (FSSIM). This is a bio-economic farm model linking micro and macro analysis of farming systems in specific regions (Louhichi *et al*, 2010).

A new forecasting methodology is being proposed to predict outputs on both operational and environmental level, by the implementation of ANNs. It will be applied separately on an operational and environmental basis, attempting by this way to identify which methodological approach is simpler, regarding ANN structure, and which model performs better for prognostication purposes.

### 3 Methodological approach

For everyone who participates in a direct or indirect way in agricultural production process, it is very important to have the ability to foresee the impact of the implementation of specific policies and interventions in general in the near future. As it was presented in the literature review section, up to now there have developed models for this purpose, taking into consideration parameters affected by the CAP. The recent radical changes though towards a liberalized and more market oriented policy approach, provide the framework for the implementation of reliable models for prognostication purposes, being used for a long period of time for both economic and engineering activities (Chinchuluum *et al*, 2008; Zopounidis and Pardalos, 2010). Such models are the ANNs. The implementation of ANNs is being used to predict crop and animal production, as well as GHGs emissions, by using available data sets, in order to examine the suitability of both of them for prediction purposes (Table 1,2). ANNs time series problem definition requires the arrangement of input vectors and target vectors as well. The type series problem being used aims to predict future values of a time series  $y(t)$  based on past values of that time series and from past values of a second time series  $x(t)$ . This prediction form is called Nonlinear Autoregressive with Exogenous input (NARX), with the formula describing it to be the following:

$$y(t)=f(y(t-1), \dots, y(t-d), x(t-1), \dots, (t-d)) \quad (1)$$

The input and target vectors are randomly divided into three sets, the training, validation and generalization ones. The ration among them is 70%, 15% and 15% respectively. NARX is a two-layer feedforward network consisted of a sigmoid function in the hidden layer and a linear transfer function in the output layer. The output is fed back to the input of the network through delays. The Levenberg-

Marquardt algorithm is used for training the network. The comparison of the two networks will verify which approach, the operational or the environmental one, is the most appropriate for prediction purposes of the impact of CAP on efficiency improvement of agriculture of EU countries.

**Table 1:** Basic statistics of Inputs

	<b>Agricultural Land</b>	<b>Chemicals</b>	<b>Energy</b>	<b>Fertilizers</b>	<b>Fixed capital consumption</b>	<b>Labour</b>
<b>Medium</b>	6,660.1	358.8	770.2	516.0	1,791.3	1,199.8
<b>Standard Deviation</b>	11,236.78	596.26	1049.89	1180.28	1800.68	1859.82
<b>Max</b>	35,177.8	3,021.5	4,502.7	4,604.5	12,377.4	7,307.4
<b>Min</b>	9.7	0.5	5.4	1.0	3.8	3.2

*Source: Eurostat*

**Table 2:** Basic statistics of Outputs

	<b>Animal Output</b>	<b>Crop Output</b>	<b>GHG Emissions</b>
<b>Medium</b>	5,032.9	6,624.2	17.8
<b>Standard Deviation</b>	8,658.58	5,695.11	28.65
<b>Max</b>	25,987.7	44,407.2	100.5
<b>Min</b>	67.3	43.2	0.1

*Source: Eurostat*

It is obvious that there is quite significant variation for every input and output being used. Such differences in such cases are expectable due to the considerably different sizes of primary sectors of EU countries.

## 4 Solutions and recommendations

For the implementation of ANNs two data sets were used, following the same approach with the DEA Window models. All models were trained, tested and validated by using the MATLAB® 2015<sub>b</sub> software. The first ANN aims to prognosticate crop and animal output, by using as inputs only the non-energy dependent ones, which are agricultural land, labour and capital. The second ANN aims to prognosticate not only the operational outputs, based on the operational inputs, but the GHGs too, by adding as inputs all the relevant energy depended ones, like fertilizers, agrochemicals and fuels.

The best performance of the first model was achieved by applying 12 hidden neurons and 3 delays. For this structure the Mean Square Error (MSE) is 0.052629 at the 5<sup>th</sup> epoch, with 11 epochs being tried. This score is significantly low and can be

considered as acceptable. The network was created and trained in an open loop form, in order to have the ability to get correct past outputs during the training period and produce the correct current outputs. The  $R^2$  for validation was 0.9744 which is acceptable too, with  $R^2$  for all three stages of the model to be 0.93524.

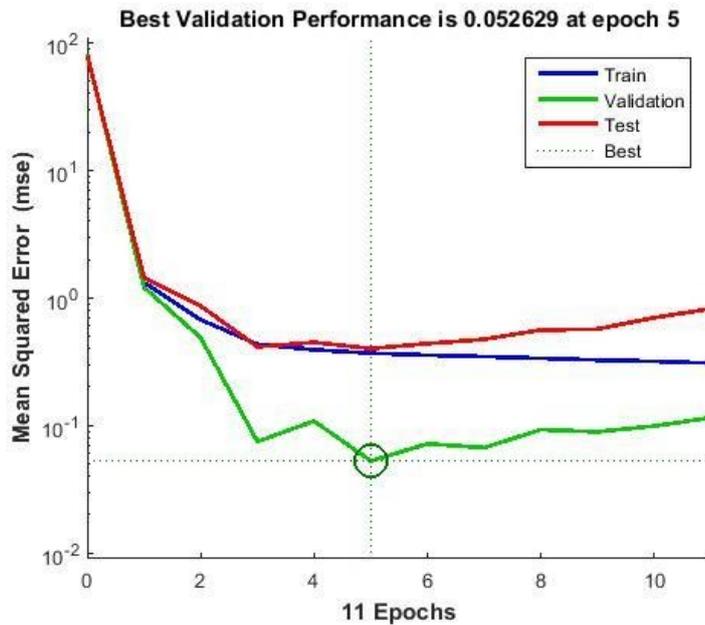


Figure 1. MSE scores operational ANN

The second ANN succeeds the best performance is a different structure. It consists of 11 hidden neurons and 4 delays. The following figure presents the MSE for training, test and validation of the model, achieving the best MSE for validation 0.11325 at epoch 5 after implementing 11 epochs. The  $R^2$  for validation is 0.97365 and the  $R^2$  for all three stages of the model to be 0.98344. Comparing the two models it is obvious that although the qualitative characteristics of both of them are quite satisfactory, the ANN using the energy dependent inputs and undesirable output performs better, because it requires a simpler structure and the  $R^2$  overall score is higher too. These findings provide considerable hints that using energy dependent data for efficiency estimations in agriculture is more safe, compared with the use of pure operational one, signifying at the same time that using market oriented data sets lead to more reliable forecasting results. It remains to be seen in the near future though, when there will be available data from non-energy pure operational inputs not affected by policy interventions, if this qualitative difference between ANNs will still remain or not.

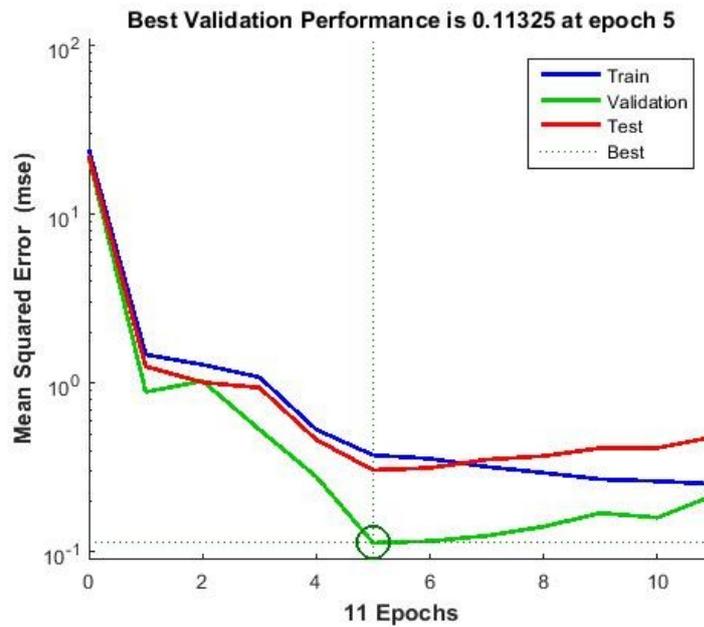


Figure 2. MSE scores environmental

## 5 Conclusion

Efficiency in agriculture, especially after the recent and radical reforms of CAP towards more liberalized subsidy management practices, is a top priority issue for farmers, policy makers and taxpayers. It is proven that when farming managerial practices are driven by market forces, there is an improved efficiency outcome, verifying that CAP reforms are heading towards the right direction, having as precondition a globalized trading environment for agricultural products. Implementation of ANNs propose a new methodological approach for *ex ante* policy evaluation, utilizing knowhow from other activities, like engineering and economics, which are more market oriented, compared with the majority of agricultural products being produced in the EU. The widely accepted advantages of this methodology are expected to provide safer prognoses regarding operational activities and environmental safety, increasing by this way the level of

success of CAP, improving at the same the utility of financial transfers from taxpayers to farmers.

## References

1. Bach, C.F. Frandsen, S.E., Jensen, H.G. (2000). Agricultural and Economy-Wide Effects of European Enlargement: Modelling the Common Agricultural Policy. *Journal of Agricultural Economics*, 51(2), 162-180.
2. Chinchuluun, R., Lee, W.S., Bhorania, J., Pardalos, P.M. (2009). *Clustering and Classification Algorithms in Food and Agricultural Applications: A Survey*. P.J. Papajorgji, P.M. Pardalos (eds.), Advances in Modeling Agricultural Systems, Springer Science + Business Media, LLC
3. European Commission (2013). *Overview of CAP reform 2014-2020*. Retrieved May 19, 2016, from [http://ec.europa.eu/agriculture/policy-perspectives/index\\_en.htm](http://ec.europa.eu/agriculture/policy-perspectives/index_en.htm)
4. Ghasemi Mobtaker, H., Akram, A., Keyhani, A., Mohammadi, A. (2012). Optimization of energy required for alfalfa production using data envelopment analysis approach. *Energy for Sustainable Development*, 16, 242-248.
5. Heidari, M.D., & Omid, M. (2011). Energy use patterns and econometric models of major greenhouse vegetable productions in Iran. *Energy*, 36, 220-225.
6. Hertel, T. (1997). *Global Trade Analysis: Modeling and Applications*. Published by Cambridge University Press.
7. Khoshnevisan, B., Rafiee, S., Omid, M., Mousazadeh, H. (2013). Applying data envelopment analysis approach to improve energy efficiency and reduce GHG (greenhouse gas) emission of wheat production. *Energy*, 58, 588-593.
8. Khoshnevisan, B., Rafiee, S., Omid, M., Mousazadeh, H. (2013). Reduction of CO<sub>2</sub> emission by improving energy use efficiency of greenhouse cucumber production using DEA approach. *Energy*, 55, 676-682.
9. Lakes, T., Muller, D., Kruger, C. (2009). Cropland change in southern Romania: a comparison of logistic regressions and artificial neural networks. *Landscape Ecology*, 24, 1195-1206.
10. McDougall, R.A., A. Elbehri, T.P. Truong (1998). *Global Trade Assistance and Protection: The GTAP 4 Data Base*, Center for Global Trade Analysis, Purdue University.
11. Meijl, H.V., Rheenen, T.V., Tabeau, A., Eickhout, B. (2006). The

impact of different policy environments on agricultural land use in Europe. *Agriculture Ecosystems and Environment*, 114, 21-38.

12. Pahlavan, R., Omid, M., Rafiee, S., Mousavi-Avval, S.H. (2012). Optimization of energy consumption for rose production in Iran. *Energy for Sustainable Development*, 16, 236-241.
13. Seiford, L.M. and Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, 142, 16-20.