*Biological Forum – An International Journal* **7**(1): 375-381(2015)

**ISSN No. (Print): 0975-1130**
**ISSN No. (Online): 2249-3239**

# Modeling and Sensitivity Analysis of Environmental Impacts for Eggplant Production using Artificial Neural Networks

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*(Received 07 January, 2015, Accepted 13 February, 2015)*
*(Published by Research Trend, Website: www.researchtrend.net)*

**ABSTRACT: A model made of the composition of concepts and artificial inelegance is one of best methods for modeling. In this study, the artificial neural network was used for modeling of environmental impacts in eggplant production of Guilan province in Iran. The initial data were calculated from farmers in the studied area by questionnaire method in the studied region. The eleven environmental impacts were considered for life cycle assessment of eggplant production. Accordingly, the CML 2 baseline 2000 method was applied in SimaPro 8.0.3 software package. The results indicated the global warming potential was calculated about 253 kg $CO_2$ eq. as most important environmental index for production of 1 ton eggplant. As can be seen, machinery had the highest share of emission in all indices; followed by nitrogen and pesticides. In another hands, the ANN model developed based on Levenberg-Marquardt learning Algorithm. The seven items of life cycle inventory and environmental impacts was considered for inputs and outputs of model, respectively. The 7-8-8-11 structure was the best topology for prediction of environmental impacts. In the last part of this study, the sensitivity analysis was done for determination of robustness of calculated model. The results indicated the sensitivity values were varied between 0.638 and 0.996 and nitrogen had the most rates among all input for sensitivity analysis in most indicators; while the lowest rate of sensitivity was belonged to phosphate and potassium, approximately.**

***Keywords:*** Artificial neural networks; Eggplant; Environmental impacts; Prediction

## INTRODUCTION

Eggplant (*Solanum melongena*) is a species of nightshade commonly known in British English as aubergine and also known as brinjal, brinjal eggplant, melongene, garden egg, or guinea squash. As a member of the genus Solanum, it is related to both the tomato and the potato. It was originally domesticated in India from the wild nightshade, the thorn or bitter apple. China, Mainland China and India have the highest rate of eggplant production. After these countries, Iran had fourth largest producer of eggplant in the world (Nabavi-Pelesaraei et al., 2013a). Life cycle assessment (LCA) is defined as the “compilation and evaluation of the inputs, outputs and potential environmental impacts of a product system throughout its life cycle” (Guinée, 2004). Thus, LCA is a tool for the analysis of the environmental bur-den of products at all stages in their life cycle from the extraction of resources, through the production of materials, product parts and the product itself, and the use of the product to the management after it is discarded either by reuse, recycling or final disposal (in effect, therefore, ‘from the cradle to the grave’). The main applications of LCA are in: (a) analyzing the origins of problems related to a particular product; (b) comparing improvement variants of a given product; (c) designing new products; and (d) choosing between a numbers of comparable products (Guinée, 2004).

Artificial neural networks (ANNs) have high learning ability and capability of identifying and modeling the complex nonlinear relationships between the input and the output of a system (Nazghelichi *et al.*, 2011). It does not require a prior knowledge of relevance among parameters and estimates the respond based on the trained data in the investigated range (Karimi *et al.*, 2012). ANN can learn the complex transport processes of a system from given inputs and observed outputs, serving as an instrument for universal function approximation (Chen and Kim, 2006). The basic advantage of ANN is that it does not need any mathematical model since an ANN learns from examples and recognizes patterns in a series of input and output data without any prior assumptions about their nature and interrelations (Nourbakhsh *et al.*, 2014). In the recent years, many studied considered to environmental impacts assessment and their modeling by intelligence methods. LCA of bean production in the Prespa National Park was investigated by Abeliotis *et al.* (2013).

In another study carried out by Roy *et al.* (2007), Life cycle of rice was evaluated to determine environmental load and production cost of rice in Bangladesh.LCA of Italian citrus-based products was studied by Beccali et al. (2010). Khoshnevisan et al. (2013a) investigated the modeling of environmental impacts of potato production by ANN. The environmental impacts modeled using fuzzy method in traditional and consolidated rice production by Khoshnevisan *et al.* (2014).

Based on the literature, there has been no study on environmental emissions modeling for eggplant production with respect to input emitter flow using ANN. The purpose of this study was to model field emissions of eggplant production in different impact categories. ANNs used for prediction the environmental indices of this production in Guilan province of Iran.

## MATERIALS AND METHODS

*A. Data collection and processing*

This study follows our previous study which was conducted on modeling and optimization of energy use and greenhouse gas emissions of eggplant production using artificial intelligence and multi-objective genetic algorithm (Nabavi-Pelesaraei *et al.,* 2013b). Accordingly, data used in this study were obtained from 60 eggplant farms from 5 villages in Guilan province of Iran in 2012–2013 crop years.

*B. Life cycle assessment (LCA)*

The working method for LCA is structured along a frame work that has become the subject of world-wide consensus and that forms the basis of a number of ISO standards. This frame work divides the entire LCA procedure into four distinct phases: goal and scope definition, inventory analysis, impact assessment, and interpretation. A full LCA includes each of these four components (Khoshnevisan *et al.*, 2013b).

Defining a meaningful boundary is very important because the environmental problems of agricultural systems can maintain during postharvest processes when products are taken out fields. If we define the farm gate as the system boundary, we disregard the differences in emissions due to transport and processing of products. We also ignored how differences in the end use of the product and its by-products can affect net environmental impacts.

Due to unavailability of complete set of data we only focused on farm emissions and we assumed that all the emissions were related to the input materials which used in potato cultivation in the farms. For instance, no significance was attached to transportation in this study. All direct and indirect field emissions were calculated as the proposed method by Nemecek and Kagi (2007). The impact categories used in this study are listed in Table 1. The CML 2 baseline 2000 developed by the Centre of Environmental Science of Leiden University was used as an impact-evaluation method (Khoshnevisan *et al.,* 2013a). The emphasis should be laid on the fact that this baseline does not encompass some impact categories like land use, water use, etc. For the environmental impacts analysis of the systems under study, the functional unit adopted was 1 ton of harvested eggplant.

**Table 1: Environmental impact categories and measurement units for each category.**

| Impact categories | Nomenclature | Units |
|---|---|---|
| Abiotic depletion | AD | kg Sb eq. |
| Abiotic depletion (fossil fuels) | ADF | MJ |
| Global warming potential | GWP | kg $CO_2$ eq. |
| Ozone layer depletion potential | ODP | kg CFC-11 eq. |
| Human toxicity potential | HTP | kg 1,4-DB eq. |
| Fresh water aquatic ecotoxicity | FAE | kg 1,4-DB eq. |
| Marine aquatic ecotoxicity | MAE | kg 1,4-DB eq. |
| Terrestrial ecotoxicity potential | TEP | kg 1,4-DB eq. |
| Photochemical oxidation | PO | kg $C_2H_4$ eq. |
| Acidification potential | AP | kg $SO_2$ eq. |
| Eutrophication potential | EP | kg $PO_4^{-2}$ eq. |

*C. Life cycle inventory (LCI)*

The life cycle inventory analysis phase (LCI phase) is the second phase of LCA. It is an inventory of input/output data with regard to the system being studied. It involves collection of the data necessary to meet the goals of the defined study (ISO, 2006).

In this section input materials, energy flows and assumptions considered in the LCI are elaborated. The detailed quantitative data for eggplant production systems upon which the analysis was based are summarized in Table 2.

**Table 2: Life cycle inventory data for eggplant production.**

| Items | Units | Average | Min | Max |
|---|---|---|---|---|
| 1. Machinery | kg | 23.05 | 4.11 | 61.77 |
| 2. Diesel fuel | L | 24.21 | 5.92 | 59.17 |
| 3. Chemical fertilizer | kg | | | |
| (a) Nitrogen | | 13.94 | 4.26 | 32.21 |
| (b) Phosphate ($P_2O_5$) | | 5.96 | 1.82 | 13.78 |
| (c) Potassium ($K_2O$) | | 3.44 | 1.05 | 7.95 |
| 4. Pesticide | kg | 0.68 | 0.10 | 1.76 |
| 5. Seed | kg | 0.04 | 0.02 | 0.05 |

*D. Development of ANN model*

During the past 15 years there has been a substantial increase in the interest on artificial neural networks. The basis of ANN modeling methods is biological neuron activities. Neurons in the brain learn to respond to a situation from a collection of examples represented by inputs and outputs. Scientists have tried to mimic the operation of the human brain to solve various problems by using mathematical methods. They have found, and used, various networks to solve practical problems. Neural networks include a wide range of mathematical methods and artificial neural networks (ANNs), the commonly used term to differentiate them from biological neural networks, have become one of the most important modeling method that have been used more than other modeling methods for complex input-output dependencies (Taki *et al.*, 2012). In this study, the LCI items were considered as inputs of ANN model; while the outputs of ANN model were environmental impacts. Moreover, the Levenberg-Marquardt learning Algorithm was used for training ANNs. The Levenberg-Marquardt algorithm is the most widely used optimization algorithm. It outperforms simple gradient descent and other conjugate gradient methods in a wide variety of problems (Ranganathan, 2004). Also, the one and two hidden layers were the connecter between inputs and outputs for ANN modeling.

All links between input layers and hidden layers composed the input weight matrix and all links between hidden layers and output layers composed the output weight matrix. Weight (*w*) which controls the propagation value (*x*) and the output value (*O*) from each node is modified using the value from the preceding layer according to Eq. (1) (Zhao *et al.,* 2009):

$$O = f\left(T + \sum w_i x_i\right) \qquad (1)$$

where '*T*' is a specific threshold (bias) value for each node. '*f* ' is a non-linear sigmoid function, which increased monotonically. Error was calculated at the end of training and testing processes based on the differences between targeted and calculated outputs. The error function can be expressed as (Deh Kiani et al., 2010):

$$E = \frac{1}{p}\sum_{p}\sum_{k}\left(t_{pk} - z_{pk}\right)^2 \qquad (2)$$

where '*p*' is the index of the p training pairs of vectors, '*k*' is the index of element in the output vector, '$z_{pk}$' is the k$^{th}$ element of the output vector when pattern p is presented as input to the network, and '$t_{pk}$' is the k$^{th}$ element of the p$^{th}$ desired pattern vector.

The mean square error (MSE) is one of the most common measures used to forecast accuracy in ANN. It is an average of the squares of the difference between the actual observations and those predicted. The squaring of the errors tends to heavily weight statistical outliers, affecting the accuracy of the results. Moreover, the MSE can be showed networks capability in modeling.

The MSE can be written as:

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{i}^{n}\left(t_i - z_i\right)^2 \qquad (3)$$

where '$t_i$' and '$z_i$' are the actual and the predicted output for the ith training vector, and '*N*' is the total number of training vectors (Safa and Samarasinghe, 2011).

The coefficient of determination ($R^2$) and mean absolute percentage error (MAPE), which show the mean ratio between the error and the experimental values, are defined as:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2}\right) \qquad (4)$$

$$MAPE(\%) = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{(t_i - z_i)}{t_i}\right| \qquad (5)$$

where 'n' is the number of the points in the data set, and 't' and 'z' are actual output and predicted output sets, respectively (Tang and Yin, 2012).

*E. Sensitivity Analysis*

Sensitivity Analysis via ANN (SAANN) can rank and select the major and input variables through its analysis. SA with partial differential is based on a calculation of input, weights and output variables from the ANN simulation. The calculation of sensitivity, S is as follows (Sung, 1998):

$$S = \frac{\partial O}{\partial I} = O' \left(\sum_{J=1}^{J} w_{ij}^{1}\ H'\ w_{ij}^{2}\right) \tag{6}$$

$$S = \frac{\partial f(O)}{\partial X} \sum_{J=1}^{J} \left(w_{ij}^{1}\ \frac{\partial f(H)}{\partial X} w_{ij}^{2}\right) \tag{7}$$

Where *O* is output and *H* is a hidden node that has to be differentiated, $w_{ij}^{1}$ and $w_{ij}^{2}$ are the weights with respthe the hidden layerirst and second connection of hidden layer. The first connection is for input and hidden layer and the second connection is for hidden node and the output layer (Sung, 1998).

Basic information on LCI of eggplant production was entered into Excel 2010 spreadsheets, Matlab R2014a and SimaPro 8.0.3 software package.

## RESULTS AND DISCUSSION

*A. Environmental impact assessment of eggplant production*

Studying the articles and essays which we formerly had a review of them in the review of literature had provided us with the handy hints on a constructive selection of the impact categories for the present study. The prevalence of the selected impact categories were observed in the most of studies which we had investigated, additionally, the employment of CML 2 baseline 2000 to calculate impact categories had been the most frequent approach. However some impact categories such as stratospheric ozone depletion potential (ODP), fresh water aquatic ecotoxicity potential (FAETP) and photochemical ozone creation potential (POCP) could be included in the conduct of the current study, Brentrup *et al.* (2004a) argued that the selected impact categories; the above mentioned selected impact categories play the most pivotal role to carry out a LCA study. Therefore the others like POCP and ODP are regarded as dispensable categories for arable crop production (Abeliotis *et al.,* 2013). Farm emissions encompassed emissions to air, water and soil from the field. After calculating all emissions, all of them were converted into the reference substances according to each impact category (characterization factors). For instance in the impact category of GWP all the emissions were converted to $CO_2$ equivalent according to CML guidelines (Guinée *et al.,* 2002). The results of the potential environmental impacts of the eggplant cultivation are illustrated in Table 3. The results revealed the total GWP was calculated as 252.99 kg $CO_2$ eq. $t^{-1}$. The another impacts including AD, ODP, HTP, PO, AP and OP were computed as 0.003 kg Sb eq., 1.54E-05 kg CFC-11 eq., 0.13 kg $C_2H_4$ eq., 1.23 kg $SO_2$ eq., 3.84 kg $PO_4^{-2}$ eq., respectively.

**Table 3: Environmental impact categories and measurement units for each category.**

| Impact categories | Units | Values |
|---|---|---|
| Abiotic depletion | kg Sb eq. | 0.003 |
| Abiotic depletion (fossil fuels) | MJ | 2946.53 |
| Global warming potential | kg $CO_2$ eq. | 252.99 |
| Ozone layer depletion potential | kg CFC-11 eq. | 1.54E-05 |
| Human toxicity potential | kg 1,4-DB eq. | 302.25 |
| Fresh water aquatic ecotoxicity | kg 1,4-DB eq. | 95.83 |
| Marine aquatic ecotoxicity | kg 1,4-DB eq. | 224455.46 |
| Terrestrial ecotoxicity potential | kg 1,4-DB eq. | 0.31 |
| Photochemical oxidation | kg $C_2H_4$ eq. | 0.13 |
| Acidification potential | kg $SO_2$ eq. | 1.23 |
| Eutrophication potential | kg $PO_4^{-2}$ eq. | 3.84 |

Nemecek *et al.* (2011) in their studies showed that the $N_2O$ and $CO_2$ emissions of chemical fertilizers made high contribution to GWP. Management of using chemical fertilizers can be an appropriate way for reducing the environmental impacts on potato production. The evaluation of the type of fertilizer illustrates the necessity of knowing the composition of the fertilizers and provides explicit possibilities to optimize fertilization practices. In some situations, the type of mineral fertilizer is the main determinant of emissions at the whole farm level and changing the type of fertilizer could significantly reduce the environmental impact (Charles *et al.,* 2006). The use of chemical fertilizers should happen cautiously due to their permanent effect on environment. Other LCA studies have demonstrated that, for example, the use of urea or organic fertilizers (e.g. slurry) as N sources results in much higher APs (Küsters and Jenssen, 1998).

The distribution of emissions of each input is demonstrated in Fig 1. The results indicated that machinery had the highest share of emission in all of environmental impacts; followed by nitrogen fertilizer and pesticide, respectively. The import of non-standard machinery and them was the main reason of machinery share in total emissions. In another hand, the false opinion of studied area farmers was the reason for irregular consumption of chemical fertilizers (especially nitrogen) and pesticides. In fact, the farmers believed the more use of chemical inputs can be increased the yield, significantly. So, the education of true pattern can be improved this bad condition of environmental impacts. Moreover, the lack of proper pricing policy (for example low price of chemical fertilizer and same price of chemical products and organic products) was another main problem in the agricultural system of the Guilan province Iran. Obviously, the farmers like to more yield and applied more chemical inputs when these price is low. Accordingly, it's suggested the supervision of input pattern should be done by local experts because the local farmers had the trust to them.

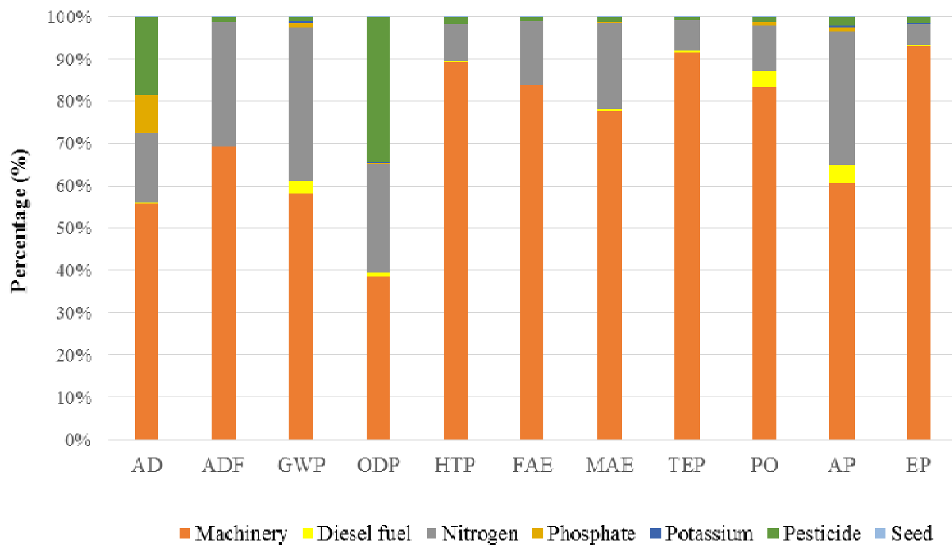


**Fig. 1.** Contribution of inputs to environmental impact categories.

*B. Evaluation and analysis of model*

The ANN model developed for the prediction of environmental impacts based on LCI inputs. From 60 farmers, 45 units were considered for training (75% of total). Obviously, 15 units remained for testing of calculated topology. The results indicated that the topology with 7-8-8-11 structure had the best model for modeling of environmental impacts. As is clear, the two hidden layers results were better than one layer.

As above-mentioned, the $R^2$, RMSE and MAPE were calculated for description of model. Accordingly, the results of them are given in Table 4. Based on results, the $R^2$ were varied between 0.913 and 0.977. Moreover, 0.007 to 0.060 was the range of RMSE in the ANN model and the range of MAPE was found between 0.015 and 0.101. So, it can be said the ANN model was appropriate for prediction of environmental impacts, significantly.

**Table 4: Network performance of environmental prediction for the best topology.**

| Environmental indices | $R^2$ | RMSE | MAPE |
|---|---|---|---|
| AD | 0.997 | 0.023 | 0.096 |
| ADF | 0.947 | 0.030 | 0.022 |
| GWP | 0.948 | 0.045 | 0.063 |
| ODP | 0.957 | 0.007 | 0.015 |
| HTP | 0.953 | 0.059 | 0.080 |
| FAE | 0.913 | 0.052 | 0.095 |
| MAE | 0.933 | 0.060 | 0.064 |
| TEP | 0.936 | 0.056 | 0.084 |
| PO | 0.939 | 0.039 | 0.040 |
| AP | 0.919 | 0.035 | 0.060 |
| EP | 0.977 | 0.030 | 0.101 |

Khoshnevisan *et al.* (2013a) reported the ANN model with 11-10-6 structure was the best model for prediction of environmental indices of potato production in Esfahan province of Iran. Their results showed the ANN model can be predicted the environmental impacts with high accuracy. In another study, researchers founded the two hidden layers can be use for achieving more accuracy in ANN model for modeling of environmental impacts of strawberry production (Khoshnevisan *et al.,* 2013b).

*C. Sensitivity analysis of environmental impacts*

The robustness of ANN model was determined by sensitivity analysis of LCI in environmental impacts. Table 5 illustrated the results of sensitivity analysis in this study. According to results, the rate of sensitivity value was calculated between 0.638 and 0.996. So, it can be said the high robustness was existed in calculated ANN model. As can be seen in Table 5, the nitrogen was the high sensitive rate among all input, approximately; while the other chemical fertilizers (phosphate and potassium) had the lower value of sensitivity in this study.

**Table 5: Sensitivity analysis of life cycle inventory.**

| Sensitivity | AD | ADF | GWP | ODP | HTP | FAE | MAE | TEP | PO | AP | EP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Machinery | 0.973 | 0.904 | 0.729 | 0.664 | 0.913 | 0.692 | 0.793 | 0.962 | 0.900 | 0.638 | 0.736 |
| 2. Diesel fuel | 0.991 | 0.876 | 0.887 | 0.933 | 0.721 | 0.740 | 0.759 | 0.996 | 0.671 | 0.710 | 0.747 |
| 3. Nitrogen | 0.723 | 0.960 | 0.726 | 0.977 | 0.699 | 0.986 | 0.943 | 0.952 | 0.867 | 0.667 | 0.706 |
| 4. Phosphate ($P_2O_5$) | 0.924 | 0.710 | 0.662 | 0.694 | 0.722 | 0.758 | 0.796 | 0.729 | 0.878 | 0.961 | 0.653 |
| 5. Potassium ($K_2O$) | 0.687 | 0.888 | 0.717 | 0.730 | 0.906 | 0.722 | 0.660 | 0.940 | 0.864 | 0.691 | 0.801 |
| 6. Pesticide | 0.793 | 0.795 | 0.878 | 0.871 | 0.762 | 0.939 | 0.861 | 0.948 | 0.724 | 0.921 | 0.710 |
| 7. Seed | 0.756 | 0.996 | 0.708 | 0.786 | 0.700 | 0.699 | 0.814 | 0.808 | 0.959 | 0.779 | 0.692 |

Khoshnevisan *et al.* (2013a) reported that the area has the inflectional effect on GWP, followed by nitrogen, electricity and irrigation water in potato production. In another study, the high sensitivity rate on GWP was belonged to potassium in hazelnut production (Sabzevari and Nabavi-Pelesaraei, 2015).

## CONCLUSION

In this study the environmental impacts of eggplant production was determined and the ANN method was used for modeling and sensitivity of the LCA indices. It should be noted, this research was done in Guilan province of Iran as one of main eggplant producer in north of Iran. However, the results indicated the high consumption of non-renewable resources was the main reason for high rate of emissions in several environmental impacts. The rate of GWP was calculated about 253 kg $CO_2$ eq. for eggplant production. Also, machinery was the most effective inputs in all of impacts. The modeling results demonstrated ANN model with 7-8-8-11 structure was the best topology for prediction of environmental impacts. According to sensitivity analysis results, the sensitivity values were varied between 0.638 and 0.996 and nitrogen had the most rates among all input for sensitivity analysis in most indicators.

## ACKNOWLEDGMENT

The authors express their deep appreciation to Mr. Hossein Nabavi's for helping them revise the study.

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