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Prediction of environmental indices of Iran wheat production using artificial neural networks

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Abstract

This study was carried out in the province of Esfahan in Iran in order to model field emissions of wheat production, using artificial neural networks (ANNs). Data were collected from 260 wheat farms in Fereydonshahr city with face to face questionnaire method. Life cycle assessment (LCA) methodology was developed to assess all the environmental impacts associated with wheat cultivation in the studied region. Global warming potential (GWP), eutrophication potential (EP), human toxicity potential (HTP), terrestrial ecotoxicity potential (TEP), oxidant formation potential (OFP) and acidification potential (AP) were chosen as target outputs. System boundary and functional unite were selected farm gate and one ton of wheat grain. All input energies and farm size were selected as inputs and six impact categories were chosen as outputs of the model. To find the best topology, several ANN models with different number of hidden layers and neurons in each layer were developed. Subsequently, we applied different activation functions in each hidden layer to assess the best performance with highest coefficient of determination (R^2), lowest root mean square error (RMSE) and mean absolute error (MAE). Accordingly, ANN model with 12-6-6-6 structure showed the best performance. RMSE for GWP, HTP, EP, OFP, AP and TEP were 45.82, 6.22, 7.47, 0.96, 0.28 and 0.09, respectively. Also, MAEs for this model were 14.9, 0.77, 1.5, 0.02, 0.14 and 0.02 for GWP, HTP, EP, OFP, AP and TEP.

Keywords: Life cycle assessment; Impact category; System boundary; Neural network.

1. Introduction

Agricultural production uses large quantities of locally available non-commercial energy, such as seed, manure and animate energy, as well as commercial energies, directly and indirectly, in the form of diesel fuel, electricity, fertilizer, plant protection, chemical, irrigation water, machinery etc. Efficient use of these energies helps to achieve increased production and productivity and contributes to the profitability and competitiveness of agriculture sustainability in rural living [1]. An agricultural activity is considered to be ecologically sustainable if its pollutant emissions and its use of natural resources can be supported in the long term by the natural environment. Intensive agricultural production is related to a number of environmental problems. High use of external inputs leads to adverse environmental impacts like demand for fossil energy resources, phosphorus or potassium, increase in global warming potential, loss of biodiversity, degradation of soil quality (e.g. by erosion, compaction or loss of organic matter) and pollution of water, soil and air [2]. For instance agricultural production has been identified as a major

contributor to atmospheric greenhouse gases (GHG) on a global scale with about 14% of global net CO_2 emissions coming from agriculture [3].
The first step in the assessment of ecological sustainability is assessment of its environmental impact [4]. LCA is a methodology for assessing all the environmental impacts associated with a product, process or activity, by identifying, quantifying and evaluating all the resources consumed, and all emissions and wastes released into the environment [5]. During the last century, it was mainly used in industrial fields but nowadays, most researchers have used it widely to assess the impacts of products, processes and activities on the environment [6-10]. Although, LCA has of late been more widely applied in agricultural than industrial fields, only few reports are available on its use for analyzing agricultural products (i.e. wheat, sugar beet and maize) and cropping systems' impacts on the environment [11-15].
Artificial neural networks (ANNs) have been widely used in different fields of agriculture like economic, energy and environmental modeling as well as to extend the field of statistical methods, in the Last few decades. The advantage of ANNs over statistical methods is reported in Zhang, Eddy Patuwo [16]. A big advantage of ANNs over statistical methods is that they require no assumptions about the form of a fitting function. Instead, the network is trained with experimental data to find the relationship; so they are becoming very popular estimating tools and are known to be efficient and less time-consuming in modeling of complex systems compared to other mathematical models such as regression [17, 18]. The advantages of ANNs for classification, prediction and solving difficult problems in the different fields of agriculture are reported in literature. Ermis, Midilli [19] analyzed world green energy consumption through ANNs. They analyzed world primary energy including fossil fuels such as coal, oil and natural gas, using feed forward back propagation ANN. Rahman and Bala [20] employed ANNs to estimate jute production in Bangladesh. In this study an ANN model with six input variables including Julian day, solar radiation, maximum temperature, minimum temperature, rainfall, and type of biomass was applied to predict the desired variable (plant dry matter). Pahlavan, Omid [18] developed a network for prediction of greenhouse basil production. Safa and Samarasinghe [21] used ANNs for determination and modeling of energy consumption in wheat production. They compared ANNs with Multiple Linear Regression and found that artificial neural networks can predict energy consumption better than regression models.
Based on the literature, there has been no study on environmental emissions modeling for wheat productions with respect to input energies using ANN. The purpose of this study was to model field emissions of wheat production in the different impact categories - global warming potential (GWP), human toxicity potential (HTP), eutrophication potential (EP), ecotoxicity potential (ETP), acidification potential (AP) and oxidant formation potential (OFP) - using artificial neural networks in order to predict the environmental indices of this production in Esfahan province of Iran..

2. Material and methods

2.1 Data collection and processing

The province of Esfahan is located within 30-42° and 34-30° north latitude and 49-36° and 55-32° east longitude. The data were collected from 260 wheat farms in Fereydonshahr city in Esfahan province using face to face questionnaire method.
The sample size was calculated, using the Neyman method [22], to be equals 260, then selection of 260 wheat producers from the population were randomly carried out. In order to assess environmental impacts, LCA method was selected. System boundaries need to be defined for correct accounting of emissions associated with inputs, within field/farm activities, and after the product leaves the farm [23]. Functional unit and system boundary were determined one ton of wheat grain and the farm gate, respectively. Kuesters and Lammel [24] who investigated the energy efficiency of winter wheat fertilization proposed a similar comparison per hectare and ton of grains. In their study efficiency of the wheat production system was taken into account by a functional unit per ton of wheat grain, while its intensity was represented by the functional unit per hectare.
Defining a meaningful boundary is very important because the environmental problems of agricultural systems can arise postharvest when products leave the field. 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 ignore 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 energies which used in wheat cultivation in the

farms. All the direct and indirect field emissions were calculated as [25]. The impact-evaluation method used was the CML baseline [26].

The impact categories of GWP, EP, HTP, TEP, OFP and AP are summarized in Table 1. GWP was used to express the contribution that gaseous emission from the arable farm production systems make to the environmental problem of climate change. The indicator result is expressed in kg of the reference substance, CO_2. HT covers the impacts on human health of toxic substances present in the environment. TE refers to impacts of toxic substances on terrestrial ecosystems. HTP and TEP are expressed in kg 1,4-dichlorobenzene equivalent. Eutrophication covers all potential impacts of excessively high environmental levels of macronutrients, the most important of which are nitrogen (N) and phosphorus (P). EP is expressed in kg PO_4^{-3} equivalent. Photo-oxidant formation is the formation of reactive chemical compounds such as ozone by the action of sunlight on certain primary air pollutants. These reactive compounds may be injurious to human health and ecosystems and may also damage crops. This indicator result is expressed in kg of the reference substance, ethylene. AP has a wide variety of impacts on soil, groundwater, surface waters, biological organisms, ecosystems and materials. AP is expressed in kg SO_2 equivalents [26].

Table 1. Environmental impacts associated with the production of wheat in the studied region

Index	Equation	Equation No.
Global warming potential*	$GWP = \sum_i GWP_{a,i} \times m_i$	(1)
Human toxicity potential*	$HTP = \sum_i \sum_{ecom} HTP_{ecom,i} \times m_{ecom,i}$	(2)
Terrestrial ecotoxicity potential*	$TEP = \sum_i \sum_{ecom} TETP_{ecom,i} \times m_{ecom,i}$	(3)
Eutrophication potential	$EP = \sum_i EP_i \times m_i$	(4)
Oxidant formation potential	$OFP = \sum_i POCP_i \times m_i$	(5)
Acidification potential	$AP = \sum_i AP_i \times m_i$	(6)

* 100 years was considered

In Eq. 1 '$GWP_{a,i}$' is the GWP for substance 'i' integrated over 'a' years (we considered 100 years), while 'm' (kg) is the quantity of substance 'i' emitted. In Eq. 2 and 3 '$HTP_{ecom,i}$' and '$TETP_{ecom,i}$' are the HTP (the characterization factor) and TEP for substance 'i' emitted to emission compartment '$ecom$' (=air, fresh water, seawater, agricultural soil or industrial soil), while '$m_{ecom,i}$' is the emission of substance 'i' to medium '$ecom$'. 'EP_i' in Eq. 4 is the EP for substance 'i' emitted to air, water or oil, while 'm_i' is the emission of substance 'i' to air, water or soil. . '$POCP_i$' in Eq. 5 is the Photochemical Ozone Creation Potential for substance 'i', while 'm_i' is the quantity of substance 'i' emitted. In Eq. 6 'AP_i' is the Acidification Potential for substance 'i' emitted to the air; while 'm_i' is the emission of substance 'i' to the air [26].

2.2 Selecting inputs for the ANN model and model development

To model field emissions, finding the appropriate independent variables was the first step of model creation. Accordingly, all relevant variables and their correlations were studied. Variables were selected on the basis of having no significant correlation between them, but a high correlation with field emissions. The used sample size in this study was 260 farms. NeuroSolutions 5.07 package randomly selected a sample of 156 farms (60%) for training, a sample of 39 farms (15%) for cross validation and remaining 65 farms (25%) were used for test. Input energies (labor, chemical fertilizers, FYM, diesel fuel, Water for irrigation, electricity, pesticides and machinery) and farm size were selected as inputs and the six impact categories (GWP, HTP, EP, ETP, AP and OFP) were selected as outputs of the model.

A feed-forward back-propagating (BP) multilayered perceptron (MLP) was used to develop prediction models for environmental indices. A feed-forward network is a common ANN architecture that requires relatively little memory and is generally fast [27]. Data move through the layers in one direction, from the input through the hidden to the output layers, without loops as opposed to feedback networks. An ANN structure usually consists of a layer of input neurons, a layer of output neurons and one or more hidden layers. The model can be written mathematically as [18, 28, 29]:

$$\mathrm{y_t} = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j} \right) + \varepsilon_t \qquad [\mathrm{i} = 1,..., \mathrm{m\ and\ j} = 1,..., \mathrm{n}] \tag{7}$$

where ‘m’ is the number of input nodes, ‘n’ is the number of hidden nodes, ‘α_j’ denotes the vector of weights from the hidden to output nodes and ‘β_{ij}’ denotes the weights from the input to hidden nodes. ‘α_0’ and ‘β_{0j}’ represent weights of arcs leading from the bias terms which have values always equal to 1 and ‘f’ is a sigmoid transfer function.

Multiple layers of neurons with non-linear transfer functions allow the network to learn nonlinear and linear relationships between input and output parameters. The linear output layer lets the network to take any values even outside the range -1 to +1; while if the last layer of a multilayer network has sigmoid neurons, then the outputs of the network will be only in a limited range [18].
For making a comparison between different topologies we needed some indicators in order to get a good vision of various structures. Mean square error (MSE) is very applicable to compare different models; it shows the networks ability to predict the correct output. The MSE can be written as [21]:

$$\mathrm{MSE} = \frac{1}{\mathrm{n}} \sum_{i}^{n} (t_i - z_i)^2 \tag{8}$$

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.
Mean absolute error (MAE) between the predicted and actual values and coefficient of determination (R^2) were calculated using the following equations [18]:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| (t_i - z_i) \right| \tag{9}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2} \right) \tag{10}$$

where ‘t_i’ and ‘z_i’ are respective predicted and actual output for the ith farmer.

3. Results

3.1 Environmental impact assessment of wheat production

Previous studies in Esfahan province on other crops showed a high consumption of input energies especially chemical fertilizers [18, 30]. High consumption of fertilizers causes serious environmental problems in the long term, due to different emissions to water, soil and air. Accordingly, at the first step of field emissions modeling, we needed to calculate the related emissions for each surveyed farm. All emissions were calculated as Nemecek and Kagi [25]. Since we considered farm gate as the system boundary, the emissions of factory processes were disregarded in this study. So, we only focused on the farms as the system boundary.
Emissions to water from agricultural soils are determined as substances that leave the root zone of the plants. Thereby, the topsoil is regarded as a part of the techno-sphere. E.g. nutrients are added to the soil

and most of it is assimilated and harvested by the crops. Emissions are only related to the phosphate, i.e. the difference between inputs to and removals from the field.
After calculating all emissions we converted them to the reference substances according to the each impact category (using characterization factors). For instance, in the impact category of Global warming potential all the emissions were converted to CO_2 equivalent according to CML guidelines [26]. By using Eqs. 1-6 values of the potential environmental impact of the wheat cultivation were calculated.
Table 2 summarizes the average of each impact category for wheat cultivation in the studied area. In a study on optimization of wheat production systems in Swiss, it was revealed that in order to reduce the adverse environmental impacts of chemical fertilizers usage the yields should increase. Subsequently, the emissions, resulting from the use of chemical fertilizers, will be modified [31]. Brentrup [32] concluded that a good environmental performance in wheat production was achieved by maintaining high-yields in order to use land most efficiently, to apply fertilizers according to crop demand and to limit emissions of NO_3, NH_3 and N_2O.

Table 2. Values of the potential environmental impact of the wheat cultivation

Impact category	Unit	Quantity
Global warming potential[a]	kg CO_2 eq.	906.1
Eutrophication potential	kg PO_4^{-2} eq.	15.18
Human toxicity potential[a]	kg 1,4-DCB eq.[b]	1092
Terrestrial ecotoxicity potential[a]	kg 1,4-DCB eq.[b]	0.22
Acidification potential	kg Ethylene eq.	10.11
Oxidant formation potential	kg SO_2 eq.	0.0073

[a] Considering 100 years.
[b] DCB= Dichlorobenzene.
Note: emissions are calculated per ton of grain produced

3.2 ANN models: Evaluation and error analysis

Several MLP networks were designed, trained and generalized, using the NeuroSolutions 5.07 software package [33]. Different topologies were designed, using different algorithms and diverse number of hidden layers and neurons in each layer. Also we applied various activation functions in each layer to investigate which topology gave the best performance. To make a comparison between different topologies we used some indices as mentioned above. Table 3 summarizes the best results of the various topologies. Among these, the best model consisted of an input layer with twelve input variables, two hidden layers with six neurons in each layer, and an output layer with six output variables (12-6-6-6 structure), highlighted in Table 3.

Table 3. Network performance of environmental prediction for different number of hidden layer (H)

		RMSE						**R2**					
No.	**H**	GWP	HTP	EP	OFP	AP	TEP	GWP	HTP	EP	OFP	AP	TEP
1	1	511.9	66.4	13.9	1.7	3.8	0.5	0.979	0.976	0.969	0.989	0.99	0.991
2	1	209.4	27.2	**5.3**	**0.6**	2.1	0.3	0.994	0.992	**0.99**	0.995	0.995	0.983
3	2	406.3	53.1	10.1	1.3	6.9	0.9	0.9766	0.95	0.96	0.949	0.944	0.985
4	2	361.1	46.8	9.2	1.2	3.8	0.5	0.981	0.989	0.958	0.984	0.981	0.992
5*	2	**45.8**	**6.2**	7.4	0.9	**0.28**	**0.09**	**0.999**	**0.997**	0.97	**0.998**	**0.999**	**0.995**
6	3	649.6	84.1	18.1	2.3	8.3	1.1	0.972	0.973	0.919	0.967	0.966	0.966
7	3	239.5	31.1	6.9	0.9	2.5	0.3	0.992	0.989	0.976	0.995	0.993	0.999

Note the highlighted numbers shows the best performance of the network
* The best topology of ANNs

Back propagation algorithm was chosen to build these models. The used algorithm in the best topology was logsig. Figure 1 shows desired outputs and actual network outputs. It can be seen the desired outputs closely follow the actual ones.

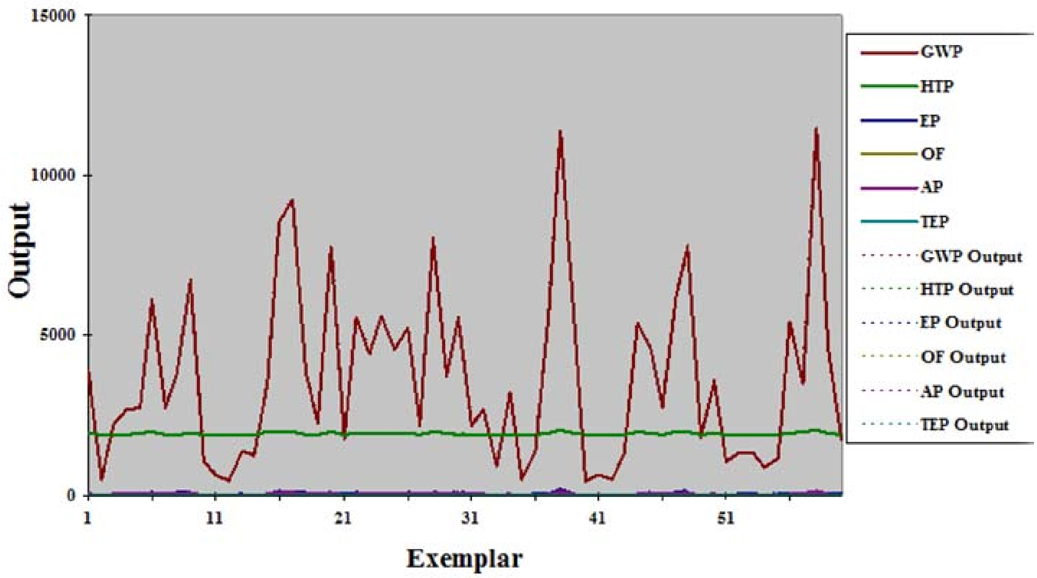

Figure 1. Desired output and actual network output

MAEs for the chosen model were 14.9, 0.77, 1.5, 0.02, 0.14 and 0.02 for GWP, HTP, EP, OFP, AP and TEP, respectively. This topology produced the highest coefficient of determination for different impact categories (except for EP) and the lowest values of MAE and RMSE. Figures 2-4 show R^2 for impact categories of GWP, HTP and EP based on the best topology of the ANN model. These results indicate that, this model can predict the environmental burdens quiet closely to the actual ones. So, this model was selected as the best one for estimating the environmental burdens on the basis of input energies and farm size in the studied region.

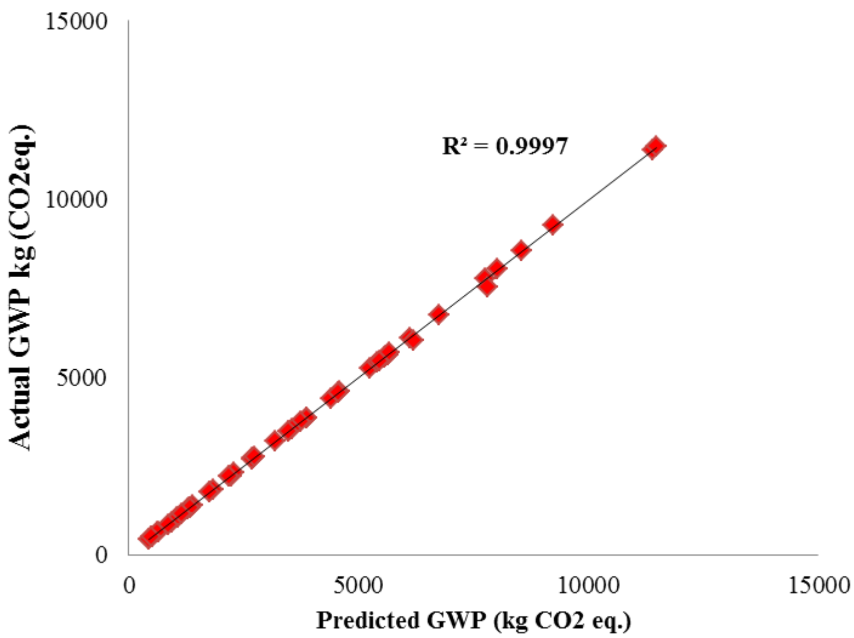

Figure 2. Correlation between actual and predicted GWP based on the best topology

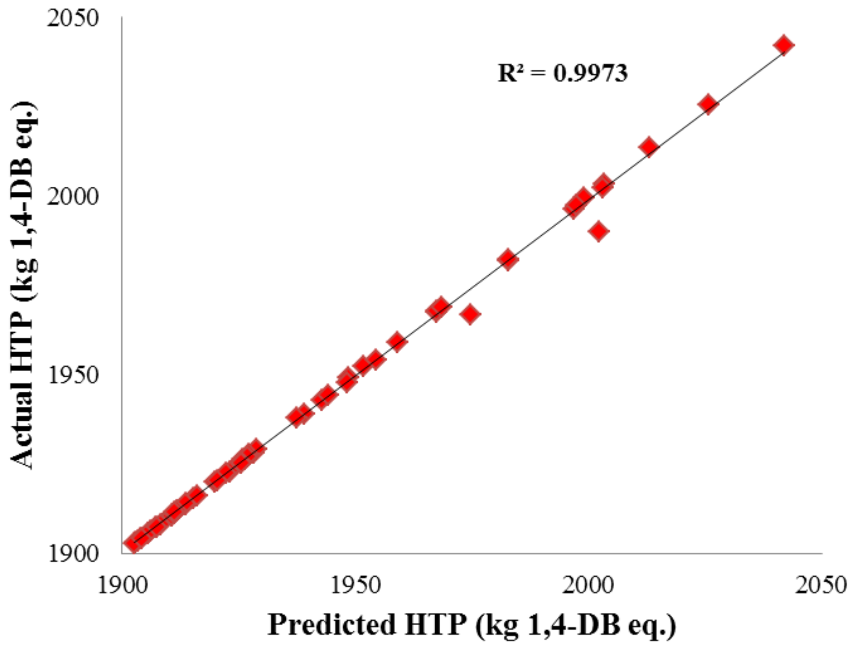

Figure 3. Correlation between actual and predicted HTP based on the best topology

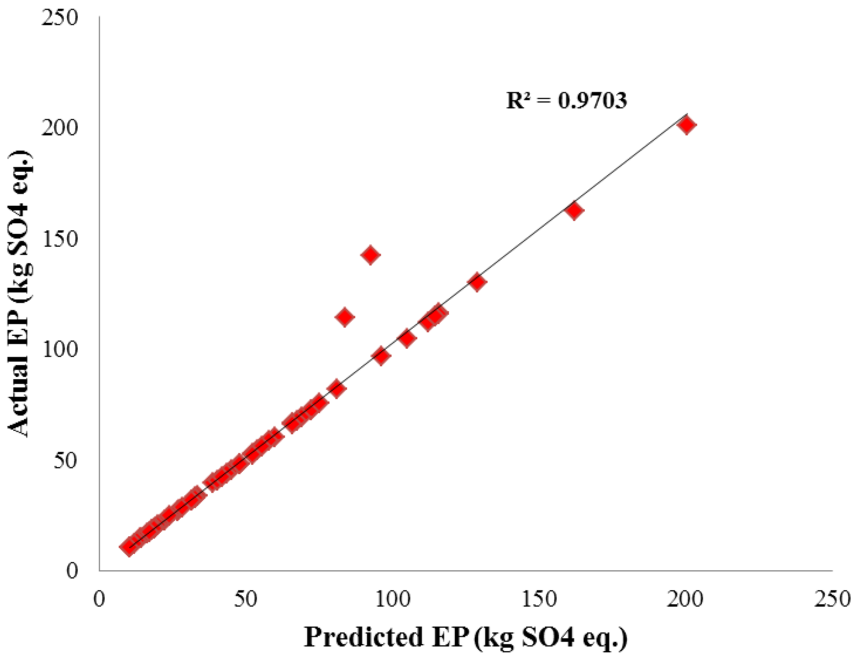

Figure 4. Correlation of actual and predicted EP based on the best topology

3.3 Sensitivity analysis

A sensitivity analysis was performed using the best network selected in order to assess the predictive ability and validity of the developed model (Table 4). The robustness of the model was determined by examining and making a comparison between the outputs produced during the validation stage and the calculated values. According to the results in Table 4, the share of each input item of developed MLP model on desired outputs can be seen clearly. Sensitivity analysis provides perception of the usefulness of individual variables. By the help of this kind of analysis it is possible to judge what parameters should be considered as the most significant and least significant ones during generation of the satisfactory MLP [18]. Farm size had the highest sensitivity on GWP and followed by FYM and nitrogen. Farm size had the highest sensitivity on all impact categories and Potassium had the lowest sensitivity on all ones.

Table 4. Sensitivity analysis results for input energies

Sensitivity	GWP	HTP	EP	AP
Farm size	26.0703	2.2884	0.5999	0.8278
Labor	0.0319	0.0013	0.0007	0.0007
Nitrogen	0.0608	0.001	0.0004	0.0008
Phosphate	0.0043	0.0001	0.0051	0.0001
Potassium	0.0005	0.0001	0.0001	0.0001
FYM	0.8798	0.0227	0.0043	0.0157
Diesel	0.0477	0.0025	0.0001	0.0001
Electricity	0.0058	0.0001	0.0001	0.0001
Seed	0.0015	0.0001	0.0002	0.0001
Pesticide	0.0108	0.0105	0.0001	0.0003
Machinery	0.0016	0.0001	0.0001	0.0001
Water for irrigation	0.0398	0.0002	0.0006	0.0005

According to these results we can recognize which input in each impact category is the most effective parameter on the output parameters. Subsequently we can eliminate the insignificant parameters from the model and develop new models based on the fewer inputs. We should highlight that some inputs like farm size has indirect effect on the outputs. Previous studies in the region showed that there were significant differences between large and small farms from the energy consumption point of view [30]. Accordingly, it can be justified why farm size had high impacts on outputs. In the impact category of GWP, farm size, FYM, nitrogen, diesel fuel, irrigation and pesticides played the most important role, respectively.

4. Conclusions

The objective of this study was to model field emission of wheat production in Esfahan province of Iran in six impact categories using artificial neural networks. The considered environmental indices were global warming potential (GWP), human toxicity potential (HTP), eutrophication potential (EP), ecotoxicity potential (ETP), acidification potential (AP) and oxidant formation potential (OFP).

Results of this study revealed that LCA was a good tool for evaluation of environmental burdens. Average of the GWP, EP, HTP, TEP, OFP and AP were 906.1 kg CO_2 eq., 15.18 kg PO_4^{-2} eq., 1092 kg 1,4-DCB eq., 0.22 kg 1,4-DCB eq., 0.0073 kg Ethylene eq. and 10.11 kg SO_2 eq., respectively.

This paper demonstrated the valuable application of Multilayer Feed Forward Networks in modeling the environmental burdens of wheat production in the studied region. The ANN model with 12-6-6-6 structure gave the best performance for prediction of the different impact categories. This topology produced the highest coefficient of determination and the lowest values of MAE and RMSE. The power of the model was assessed by examining and comparing the output produced during the validation stage with the calculated values. Farm size had the highest sensitivity on all impact categories, whereas potassium had the lowest sensitivity on all impact categories.

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