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Abstract

Purpose – The purpose of this present study is to find a scientific method for the evaluation of environmental impacts according to the requirement 4.3.1.

Design/methodology/approach – To realize the objectives, the authors worked with a representative sample from certified ISO 14001 organizations. The data aim to identify and evaluate (according to the organization's methodology) significant environmental impacts. In this study, the authors created two models for the evaluation of environmental impacts based on an artificial neural network applied in the pilot organization and compared the results obtained from these models with those obtained by applying an analytic hierarchy process (AHP) method. AHP is part of an multi-criteria decision making method and provides good multi-criteria support for decision making for problems that can be structured hierarchically.

Findings – This paper presents a new approach that uses a backpropagation neural network to evaluate environmental impacts regardless of the organization type.

Originality/value – This paper presents a unique approach for the reliable and objective evaluation of environmental impacts.

Keywords Evaluation, Decision making, Neural network, Artificial intelligence, Environmental management, ISO 14001, Environmental impacts, Analytic hierarchy process

Paper type Research paper

1. Introduction

ISO 14001 is the most important international standard for environmental management systems (EMS). This standard could be applied to all organizations regardless of their size and sector of activity. A certificate shows that an organization fulfilled the requirements of ISO 14001. The common focus of the EMS and the ISO 14001 standard lies in the 4.3.1 requirement, which relates to the identification and evaluation of environmental aspects and impacts. In fact, the key component of the ISO 14001 standard's requirements is founded on the knowledge about the significant environmental aspects and impacts (Jovanović, 2009). Therefore, the usefulness of the EMS depends mainly on this requirement.

However, the ISO 14001 does not propose a way to identify and evaluate environmental aspects and impacts. The standard allows an organization to create individually their methodology for environmental aspects and impacts evaluation. In fact, the standard ISO 14004 (ISO 14004:2004, 2004), requirement 4.3.1.5 indicates that "the importance is a relative concept and cannot be defined in absolute terms". The previous notion permits the organization complete freedom evaluation. Nevertheless, this approach can improve creativity inside the organization and simultaneously create the opportunity for potential data manipulation in the EMS.

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Based on the fact that the 4.3.1 requirement is of great importance (ISO 14001: environmental aspects) (ISO 14001:2004, 2004), we conclude that there is a lack of analyses that provide reliable and objective approaches to evaluate environmental aspects and impacts.

To establish a unique approach to evaluate environmental impacts that is applicable in all organizations (independent of their activity) and provides the necessary objectivity and reliability, we collected data on a representative number of environmental impacts from ISO 14001 certified organizations.

Because of data heterogeneity[1] and the significant number of marks of environmental impact collected, we argue that the utilization of an artificial neural network (Subašić, 1997; Milenković, 1997) could be a successful data handling strategy.

Artificial neural networks are useful for a great number of inputs over a short period of time and when the connectivity of the data are not known (Arsovski, 2008). Artificial neural networks are evolutionary optimization-based algorithms developed by Ozdemir and Temur (2009) and Quin (2009). A neural network is defined by the neurons and their connections. All neurons are organized into layers; the sequence of layers defines the order in which the activations are computed (Kumar and Roy, 2010).

Backpropagation is the best known and widely used learning algorithm in training multilayers, such as the feed forward neural networks (Choudhary and Rishi, 2011). The architecture of the feed forward backpropagation neural network is presented in Tiwari *et al.* (2011). Backpropagation provides a computationally efficient method for changing the weights in the feed forward neural network. Jin *et al.* (2010) proposes that the prediction accuracy increases when the backpropagation neural networks are applied and as the number of hidden neurons increases. For these reasons, the current research uses a feed forward backpropagation neural network with a higher number of hidden neurons to obtain faster convergence.

From six ISO 14001 certified organizations, we collected over two thousand environmental impacts marks evaluated according to the specific organization's methodologies. After considering the possible results of a feed forward backpropagation neural network built using the collected data, we established the following hypothesis:

H1. Two models based on neural networks provide objective and reliable evaluation of environmental impacts when used in the following way:

(1) Evaluation of environmental impacts through the application of a neural network based on the reduced matrix model.

(2) Review of the results obtained by the application of the classical neural network.

This hypothesis specifies that the two neural networks models provide objective and reliable results concerning environmental impacts in all four categories that are analyzed in this work (air, people, water and ground). This is an expansion of the hypothesis from the work of Krivokapić *et al.* (2009) which evaluated environmental impacts using neural networks.

Later in this text, the neural network models are explained in detail. It is important to underline that the classical neural network is a direct formation of a neural network based only on the collected data, confirming complete objectivity. The neural network of the reduced matrix model represents the model that we created for the evaluation of environmental impacts. More precisely, we created the model from the analysis of the advantages and disadvantages of the evaluation methodology of certified organizations.

From this work it is possible to formulate a hypothesis covering future environmental impacts for all categories, effectively increasing the sample size for all environmental categories. Hence, using only a classical neural network would provide a reliable assessment of the environmental impacts:

H2. The objective and reliable evaluation of the environmental impacts for the "people" category is possible by using only the classical neural network.

The classical neural network is objective because the formulation covers only data collected from certified organizations. The "people" category has the largest training sample.

2. The evaluation of environmental impacts

To show the possible manipulation of records for significant environmental aspects and impacts (because ISO 14001 certified organizations created their own methods for the evaluation of environmental impacts), we performed a comparative analysis of the evaluation methodologies and the results of the evaluations employed at three ISO 14001 certified organizations (Jovanović *et al.*, 2007; Krivokapić *et al.*, 2009). By comparing the evaluation methodologies and results in a JAVA computer program, the number of recorded significant environmental impacts could change by up to 20 percent depending on the applied evaluation method.

In creating neural networks, we collected data about environmental impacts from six organizations certified with the ISO 14001 standard (labeled as A, B, C, D, E and F for confidentiality reasons). From these six organizations, we collected data on over 2,000 recorded environmental impacts divided into four large environmental categories: air, people, water and ground. These data were the training sample for the neural network models. The objectivity and reliability of these models were tested using the AHP method in the pilot organization noted as X. AHP is a frequently used multi criteria decision making method (MCDM) used for problems that can be transformed into a hierarchical structure (Altuzarra *et al.*, 2007; Saaty, 1989; Ramanathan and Ganesh, 1994). AHP is a useful decision aid because the method allows the formulation of a final decision without totally overriding the initial tentative choice. Therefore, the AHP method can overcome some disadvantages in evaluation when qualitative values are given as definite numbers. This method is a scientific qualitative and quantitative evaluation tool (Yang, 2009). The reliability of the AHP method is important because it detects the highest and lowest priorities. Past observations suggest that the AHP method has provided an adequate support decision tool for many problems (Ishizaka *et al.*, 2010).

To establish the objective and reliable final record of significant environmental impacts for the four important environmental categories (air, people, water and ground), the evaluation of the environmental impacts identified in organization X was modeled in three ways:

(1) an AHP model;

(2) a classical neural network model; and

(3) a neural network for a reduced matrix model.

In organization X, we implemented the AHP model first. The marks of significance regarding identified impacts for each chosen criterion obtained from the AHP model were used to test the other models. The output values of all models are based on identical input values. To establish a convenient way to objectively and reliably evaluate environmental impact, all three methods must be compared, and this comparative analysis is described in the final portion of this paper.

3. Using the AHP model to evaluate environmental impacts in a pilot organization

AHP is one of the most commonly used MCDM tools. AHP assists the decision making process by allowing the organization of the criteria and alternative solutions in a hierarchical decision model. The conversion of elements into a hierarchically structured problem, and the determination of the solution by application of the AHP method are described by Young *et al.* (2010). In this paper, the AHP model maintains the alternatives (environmental impacts) on the lowest hierarchical level, while the evaluation criteria for the impacts are on the middle level and the goal is placed on the highest level.

Nechansky (2011) emphasized the explicit and well-defined processes used in decision-making. Therefore, the hierarchical problem structure of the evaluation of environmental impacts in organization X using the AHP method is performed by an environmental manager. The environmental manager not only coordinates the evaluation of the environmental impacts by applying the AHP method but also structures the decision-making method.

Three criteria in the AHP model hierarchy are labeled as the most significant in the ISO 14004 standards. These criteria are as follows:

- the volume of impacts;
- the power of impacts; and
- the probability of the impacts appearing.

The AHP model created for the environmental impacts for all environmental categories (air, people, water and ground) is shown in Figure 1.

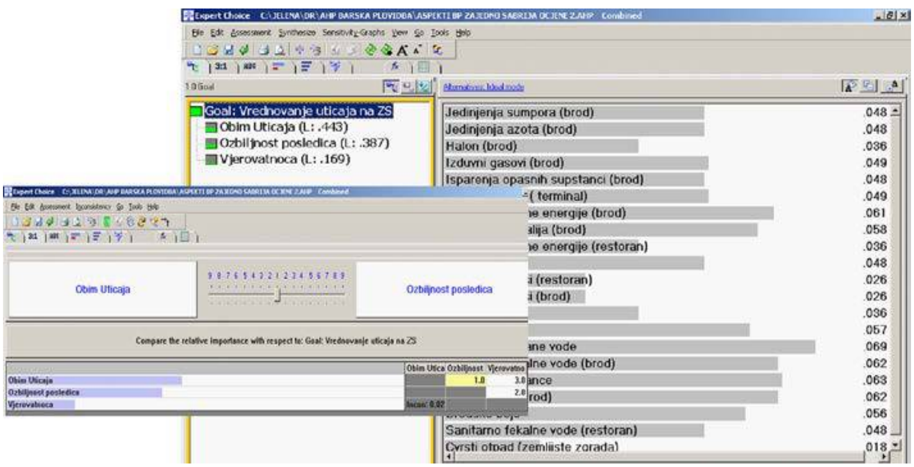


Figure 1.
The AHP model for the evaluation of the environmental impacts of an organization

Evaluations performed by applying the AHP method represent an improvement compared to the individual mathematical methodologies of the ISO 14001 certified organizations. The reason for this is because the AHP method is wide spread of mathematical model for the decision making based on facts whose verification is realized worldwide. Evaluation of the criteria compared to the goal was performed by mutual comparison, whereas the evaluation of impacts compared to the criteria was performed by the direct input of values from 1 to 4.

After evaluating the hierarchical levels, the model provides the list of significant identified environmental impacts (Figure 2).

The significance level for the environmental impacts was based on a detailed analysis with the EMS manager from organization X. The calculated limit was 0.048, resulting in 13 significant impacts from a total of 21 initially identified. The discussion of the results obtained is possible only after the application of other evaluation models, when we will perform comparative analysis.

4. Using the backpropagation neural network to evaluate the environmental impacts (the classical neural network model)

To evaluate the environmental impacts using neural networks, it is necessary to order the environmental impacts to obtain the network specific instructions for each category separately. In the training sample, the number of recorded environmental impacts of organizations A, B, C, D, E and F in each category is shown in Figure 3.

To build the neural network, the data must inputted into the software package MATLAB and harmonized. As the marks for all organizations are obtained on the base of different methodologies, it is necessary to harmonize the input data according to the organization with the biggest range of marks. After harmonization, the neural network is trained separately for each environmental category and the results are checked, i.e. the simulation of the model is performed on the data for organization

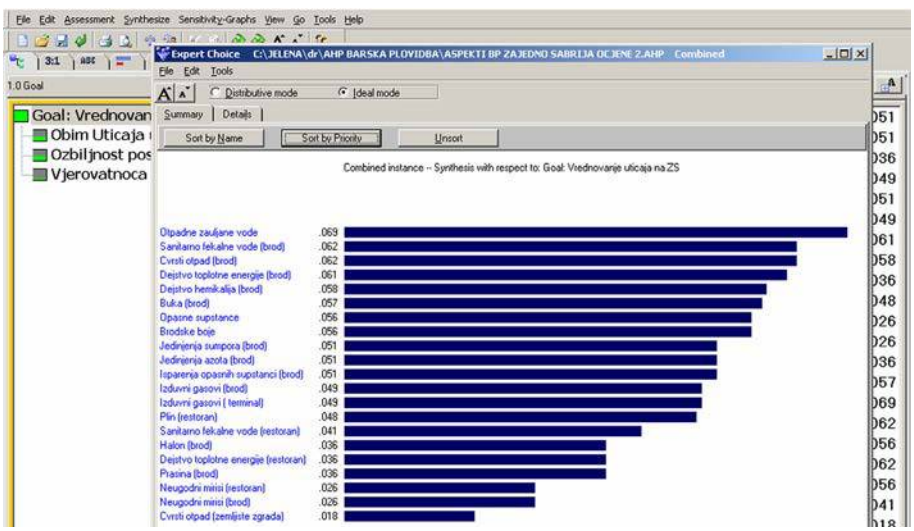
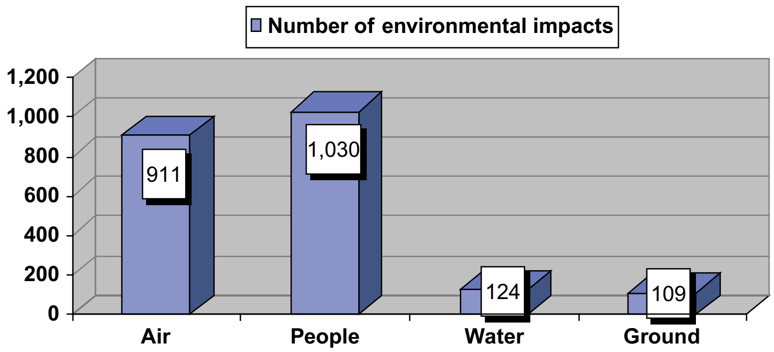


Figure 2.
List of the significant environmental impacts



Note: These numbers were found for the six organizations based on the training sample

Figure 3.
The number of recorded impacts for each environmental category

X according to the input values from the AHP model. This model is called a classical neural network. The classical neural network model for the "air" category is shown in Figure 4.

After testing the network on the simulated sample for air from organization X, we obtained the outputs shown in Figure 5.

By simulating the classical neural network on the data from organization X, we obtained results for six identified impacts in the air category. A value close to $+1$ or the lower-limit -1 categorizes the impact as "significant", or "insignificant", respectively. In analyzing the results, all identified impacts in the air category were significant. The results do not match for only one impact when compared to the AHP model.

This procedure was also applied for the other environmental categories and we obtained a good match to the results. For the categories of both "people" and "ground", the result is identical, whereas for "water", we note a deviation in two of the six impacts.

Because the results from the AHP model and the classical neural network in organization X did not match, we used a third method which can help in evaluating environmental impacts.

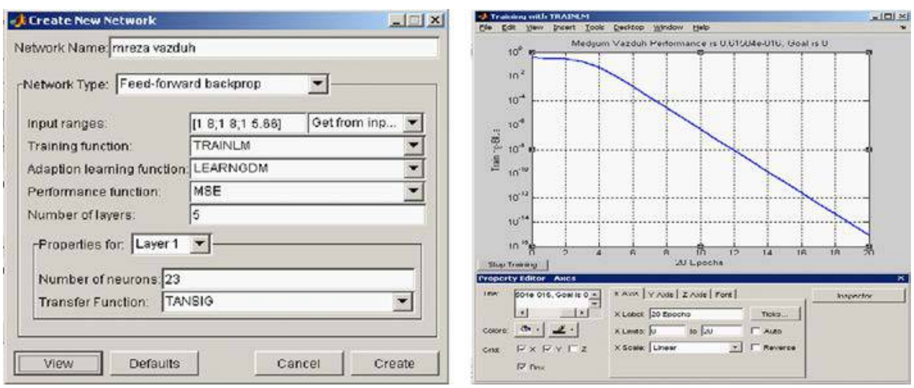


Figure 4.
A model of the classical neural network for the "air" category

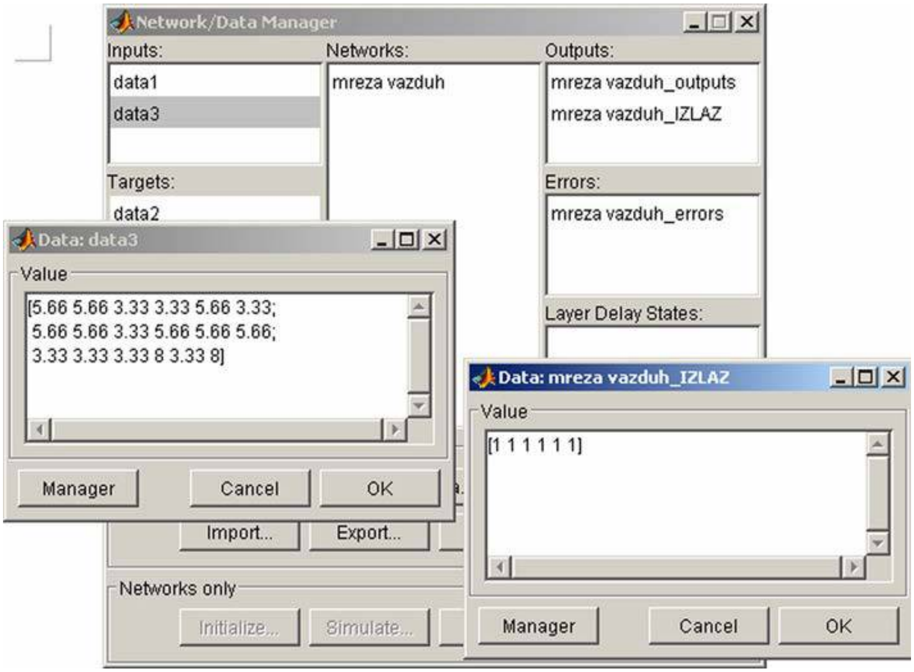


Figure 5.
The simulation of the neural network for the air category

5. The application of a neural network of a reduced matrix model

We collected data from the certified organizations (A, B, C, D, E and F) to analyze their own methodologies for evaluation of environmental impacts. We created a model attempting to remove the associated limitations. This model almost eliminates the deficiencies that are observed in the available evaluation methodologies. Hence, the model could be used as a supplementary model to evaluate and review the significance of environmental impacts. The model was named the reduced matrix model for the evaluation of environmental impacts because it is inspired by the theory of "Risk management" (Standards Australia and Standards New Zealand AS/NZS 4360:2004, 2004).

The reduced matrix model is composed of two matrices (Figure 6). Each matrix consists of two criteria. The mandatory criterion of every matrix is called the "Power of impacts". The other criteria in the matrix are identical to those in the classical neural network model:

- the volume of impacts; and
- the probability of the impacts appearing.

Volume of impacts	Power of impacts			
	1	2	3	4
Very Big				
Big				
Medium				
Small				

Probability of the impacts appearing	Power of impacts			
	1	2	3	4
Very Big				
Big				
Medium				
Small				

Figure 6.
The two reduced matrix model matrices

The results are obtained via those two matrices, or more precisely, based on those three criteria. The impact is considered significant if its value in both matrices resides in the greyed fields.

This model appears simple but is actually complex for many environmental impacts because a large number of matrices are required for the final evaluation. To accelerate and automate the evaluation process, we used a backpropagation neural network based on the data obtained from organizations A, B, C, D, E and F. These data were previously evaluated with the reduced matrix model.

Before creating and training a backpropagation neural network based on the reduced matrix model, the evaluated environmental impact values from the six observed organizations were transformed into reduced matrix model values.

By comparing the detailed description of the individual values for each organization with the training sample, we determined correlations in the evaluation processes. For the environmental impacts in organizations A, B, C, D, E and F, a mathematical correlation was established inside the matrix by using a JAVA based program (Lemay and Cadenhead, 2001; Charatan and Kans, 2002). We obtained outputs for all input values. By obtaining a training sample in this way, we were able to train the backpropagation neural network based on the reduced matrix model.

Furthermore, to simplify the evaluation procedure for environmental impacts, we created one feed forward backpropagation neural network based on the reduced matrix model. The training sample was collected from all environmental categories in the A, B, C, D, E and F organizations. This network was justified because the evaluation of all input values is analogous to the reduced matrix model. We obtained output values based on an identical model in the reduced matrix model. A neural network for the representative sample converges, as shown in Figure 7.

The simulation of the created and trained neural network is possible for all identified environmental impacts simultaneously. However, to simplify the comparative analysis of the results obtained for all three models, we performed a separate

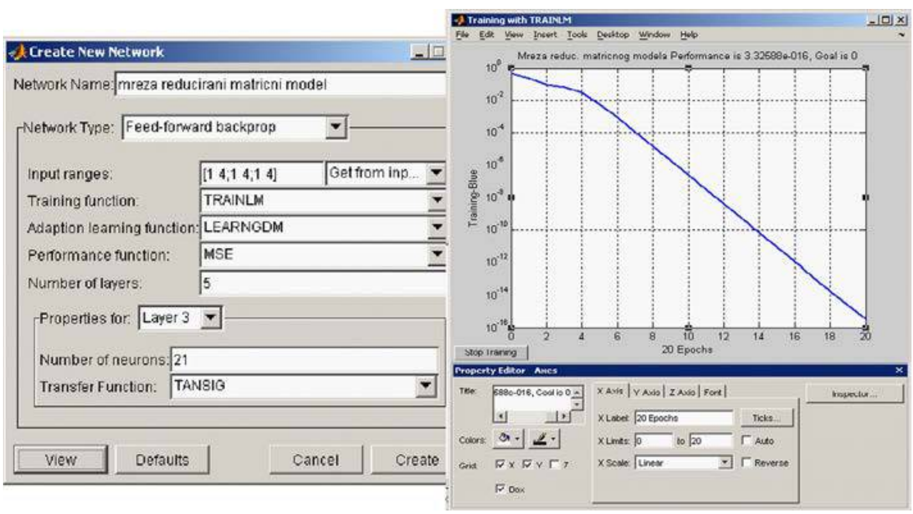


Figure 7.
The performance of a backpropagation neural network based on a reduced matrix model with a convergence diagram

reduced matrix model for each environmental category. The simulation results for the category "air" in the organization X are shown in Figure 8.

The results from the air category simulation match the results from the AHP model. This procedure was also applied to other environmental categories, and we obtained a good match of the results with those of the AHP model. For the people and ground categories, we obtained identical results as in the AHP model, whereas the water category displayed a deviation in two of six impacts.

6. A comparative analysis of the models to evaluate the environmental impacts

After comparing the results for organization X obtained from the AHP model, the classical neural network and the neural network of the reduced matrix model, we noted the differences underlining the advantages and disadvantages of the models.

In the comparative analysis section, we will use the following labels:

- Model 1 (AHP model of the organization X).
- Model 2 (classical neural network).
- Model 3 (neural network of a reduced matrix model).

Figure 9 shows the comparison of Models 2 and 3 to Model 1 for the results obtained for the organization X test sample.

For the people category that had the largest training sample, Models 2 and 3 produced identical results to those of Model 1. By analyzing the input values for all

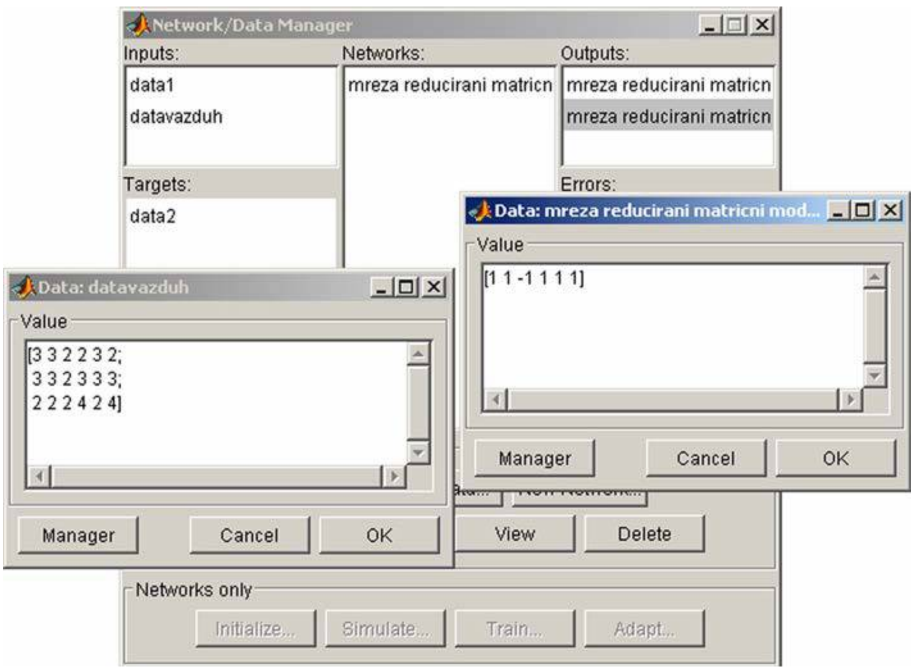
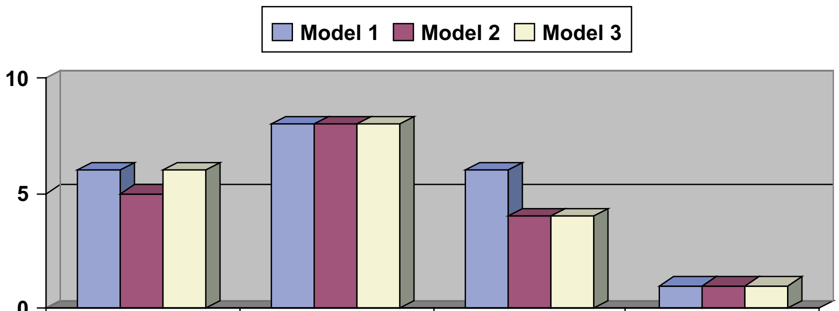


Figure 8.
The simulation of a neural network based on a reduced matrix model (for the "air" category)



	Air	People	Water	Ground
Model 1	6	8	6	1
Model 2	5	8	4	1
Model 3	6	8	4	1

Figure 9.
A comparison of the results of Models 2 and 3 with Model 1

impacts for each criterion separately, we conclude that the defined significance of the impacts in the people category is as expected.

The training sample for the air category was smaller than for the people category. The size of the training sample is the critical factor for the validity of the neural network model (Subašić, 1997; Milenković, 1997). Accordingly, the compatibility in five of six impacts in the air category is satisfactory. One impact is significant according to Model 2, but is insignificant according to Models 1 and 3. This indicates that the classical neural network model for air category is sensitive in the evaluation of significant impacts.

For the water category, we did not have a large enough training sample as compared to the training samples for the people and air categories. However, the identical results of the environmental impacts on the water category predicted by Models 2 and 3 require more detailed analysis. The two controversial impacts have identical marks for all three evaluation criteria, collapsing into a single impact. Regarding that these impacts are valued with the lowest possible mark (mark 1) for criterion "the probability of the impacts appearing", result obtained by neural network models (Models 2 and 3) is insignificant as expected. For all environmental categories, Models 2 and 3 ascribe a low probability of appearance to the impacts, making these impacts as potentially dangerous. Therefore, these impacts should be treated separately with the procedures outlined by the ISO 14001 standard. The criterion "the probability of the impacts appearing" in Model 1 is the lowest in importance as compared to the other two criteria, and the importance of this criterion is lower still in the AHP model. This approach categorizes these impacts as significant. A relatively small training sample for the water category does not permit the acceptance of the results obtained with Model 2. However, results for the water category underline the compatibility of the results for four of six impacts and enlarge the training sample to provide an objective evaluation of the impacts in the water category.

For the ground category, we obtained results that are completely compatible for all models. However, because of the small training sample and test sample size, the results cannot support a general conclusion.

7. Conclusion

A methodology to evaluate the environmental impacts is not explicitly defined in the ISO 14001 or ISO 14004 standards, but analyzing the different methodologies of ISO 14001 certified organizations; we conclude that a lot of possibilities for data manipulation exist. Therefore, this paper presents the evaluation of environmental impacts by the application of the neural network model and the AHP method of multi-criteria decision making.

The results of a comparative analysis of neural network-based environmental impact evaluation models indicated that Model 2 for the people category, which had the largest training and test sample size, produced identical results to Models 1 and 3. Model 2 is built solely from the data of the certified organizations. Therefore, the obtained results are objective. Moreover, because similar results were obtained from two models (Models 1 and 3), the evaluation method was considered reliable. The results are consistent with those from Jovanović *et al.* (2007). The authors, working on a small training sample size, found that the classical neural network model was reliable for the people category in a large simulation of four organizations. In this case, the classical neural network precisely evaluated 24 of the 26 impacts for the people category. The increase in the training sample size also increases the reliability of the classical neural network. Therefore, we conclude that the results from this research confirm our *H2*, which suggests that the objective and reliable evaluation of environmental impacts for the people category can be realized only with the classical neural network model.

In the case of the air category, there is some deviation in the values obtained for one of the impacts when assessed by Model 2 as compared to Models 1 and 3. Because the two models (Models 1 and 3), one of which is based on the AHP method, gave identical results for the contradictory impact and, after inspection of input values, were confirmed as valid for the air category, we can accept the final results provided from Models 1 and 3. Moreover, even with limited training samples for the water category, deviations were found in only two of the six impacts when Models 2 and 3 were compared to Model 1. These two impacts evaluated as insignificant in Models 2 and 3 but as significant in Model 1. After analyzing the input values of those impacts that were contradictory in the models, we conclude that the probability of their appearance is low. However, they could not be considered as controlled significant impacts, and we recommend that they should be handled by using a preventative procedure. For the ground category, even though all the models displayed identical results, we do not recommend using only Model 2.

The people category maintained a sufficiently large training sample size to allow for the objective and reliable evaluation of environmental impacts by applying the classical neural network. This was not achieved for other environmental categories. Considering this fact and that the neural network of a reduced matrix model was the most reliable solution applicable for all environmental categories, we recommend the double evaluation of environmental impacts:

(1) Evaluating a neural network of a reduced matrix model.

(2) Comparing the results obtained in (1) with those from a classical neural network.

In determining the significance of environmental impacts, the advantage is given to the neural network of a reduced matrix model between these two methods large enough training samples for all environmental categories do not exist and because this model (Model 3) gave us the best results after detailed analysis.

By comparing Models 2 and 3 to Model 1 and understanding the limitations regarding the size of the training sample, we describe the models as being reliable and objective for the evaluation of environmental impacts. Hence, we support *H1* of this paper.

In this work, we support two hypotheses that create an approach for the objective and reliable evaluation of environmental impacts, removing the possibility of data manipulation. This is one of the most important requirements of ISO 14001 (4.3.1 environmental aspects).

Future work should focus on this field because the classical neural network provided the most reliable results for the people category, which had the largest training sample. Considering that the classical neural network provides complete objectivity because it is formalized on the data from certified organizations, use of this type of model would motivate authors to orient their research using larger sample sizes for all environmental categories.

Note

1. Data heterogeneity – marks of environmental impacts based on the three most important environmental criteria, namely, the volume of impacts, power of impacts and probability of the impacts appearing.

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