Optimization of the selection process of the co-substrates for chicken manure fermentation using neural modeling

Andrzej Lewicki[1,a], Artur Bugała[2], Hanna Piekarska-Boniecka[3], Aleksandra Lewicka[4], Piotr Boniecki[1], Marta Cieślik[1]

[1] *Poznan University of Life Sciences, Institute of Biosystem Engineering, ul. Wojska Polskiego 28, 60-637 Poznan, Poland*
[2] *Poznan University of Technology, Institute of Electrical Engineering and Electronics, ul. Piotrowo 3a, 60-965 Poznan, Poland*
[3] *Poznan University of Life Sciences, Department of Entomology and Environmental Protection, ul. Wojska Polskiego 28, 60-637 Poznan, Poland*
[4]*Poznan University of Technology, Institute of Environmental Engineering, ul. Piotrowo 3a, 60-965 Poznan, Poland*

Abstract. Intense development of research equipment leads directly to increasing cognitive abilities. However, along with the raising amount of data generated, the development of the techniques allowing the analysis is also essential. Currently, one of the most dynamically developing branch of computer science and mathematics are the Artificial Neural Networks (ANN). Their main advantage is very high ability to solve the regression and approximation issues. This paper presents the possibility of application of artificial intelligence methods to optimize the selection of co-substrates intended for methane fermentation of chicken manure. 4-layer MLP network has proven to be the optimal structure modeling the obtained empirical data.

1. Introduction

Artificial Neural Networks (ANN) are an important application of cognitive methods used in the area of empirical research carried out in the area of widely understood artificial intelligence [1-4]. In particular, promising results are related to an application one of the important characteristics of ANN, i.e. the ability to solve the problems concerning regression and approximation issues. It gives the possibility of using of efficient ANN simulators, among others, in order to shape up the predictive issues. ANN can be successfully used practically in any situation, where the main objective is to estimate the value of a variable based on acquired (e.g. experimentally) characteristics (i.e. descriptors) [5-7].
However, in available literature related to the discussed topic there is little information concerning the use of ANN to model the process of biomethane emission [8, 9]. It seems highly appropriate to try to build the regression neural model, generated based on empirical data collected during research conducted under laboratory conditions. Developed and tested neural model can serve as a tool supporting the decision-making processes that occur during operation of biogas plants [10]. Its correct application improves and rationalizes the system for selecting the proper mixture of input substrates so that the methane fermentation process takes place under possibly optimal conditions.

The objective of the paper was to develop the neural estimator intended to predict the amount of emitted biomethane from the fermentation process of chicken manure with additions of other substrates. As a training set was used the database of the biogas efficiency of the substrates and their mixtures obtained in the Laboratory of Ecotechnology at the Poznan University of Life Sciences under the scientific supervision of Prof. Jacek Dach.

The Laboratory of Ecotechnology is the largest Polish biogas laboratory, with more than 250 fermenters operating according to DIN 38414/S8 [11].

[a] alewicki@up.poznan.pl

2. Methodology

In order to accomplish the aforementioned task, the following workflow has been proposed and then implemented (Fig. 1).

Figure 1. Action scheme

The most important step in ANN generating is to produce an adequate training set containing in its structure encoded empirical data. For this purpose, the Authors have defined the numeric input variables and predicted output variable resulted from the structure of the formulated scientific problem. Five input variables have been adopted as a share of respondents substrates:

- GRASS - grass [g Fresh Mass (FM)/reactor],
- STRAW - straw [g FM/reactor],
- CHICKEN - chicken manure [g FM/reactor],
- MAIZE - maize silage [g FM/reactor],
- INOCULU - inoculum [g FM/reactor].

  Jako 1 zmienną wyjściową przyjęto:
- BIOMETH - biomethane production efficiency [m3/Mg FM].

Using the obtained experimental results, set of empirical data consisting of 156 measurement cases has been generated. The above mentioned set has been used to create ANN and, therefore, has been divided into 3 subsets:

- training file including 78 cases,
- validation file including 39 cases,
- test file including 39 cases.

Some part of training file (cases: 33 to 39) intended for ANN generator is shown in Table 1.

Table 1. Fragment of the training file for the ANN simulator (BIOMETH – output variable)

No.	GRASS	STRAW	CHICKEN	MAIZE	INOCULU	**BIOMETH**
33	0.00	13.55	0.00	0.00	1192	**180.89**
34	0.00	13.55	0.00	0.00	1210	**175.45**
35	000	0.00	38.85	0.00	1164	**70.51**
36	0.00	0.00	38.95	0.00	1162	**68.19**
37	0.00	0.00	38.80	0.00	1161	**69.35**
38	0.00	0.00	0.00	43.	1156	**109.19**
39	0.00	0.00	0.00	43.	1156	**113.14**

The simulator of artificial neural networks implemented in a commercial Statistica package has been used for the design of neural models. The following types of neural networks have been subjected to testing:

- linear networks.
- MLP networks (MultiLayer Perceptron).
- RBF networks (Radial Basic Function).
- GRNN networks (Generalized Regression Neural Network – regressive networks).

The development of neural models was a 2-stage procedure. At the beginning, an effective option supporting the process of ANN designing has been used, i.e. *Automated Web Designer* implemented in Statistica computer system. This tool allowed to automate and simplify the procedures of preliminary seeking of a set with predictive neural networks modeling the investigated process.

In the second stage of neural models development another useful device has been used i.e. *User Networks Designer*. It offers the possibility of advanced interference in the parameters and training methods of generated neural networks. This tool has been activated frequently in order to modify both the initial settings of parameters, learning algorithms and the ANN structure itself.

3. Results

3.1 Artificial neural networks

From 100 of generated neural models, a file of 10 isolated neural topologies has been extracted as it shows Table 2 (ANN no. 10 is the best network).

Table 2. File of 10 generated ANN

	Type	RMS error	Imputs	Layer1	Layer2	Quality
1	RBF	11.953	5	9	-	0.29790
2	MLP	11.406	5	1	-	0.26561
3	RBF	9.8235	5	10	-	0.24572
4	RBF	9.1699	5	11	-	0.22898
5	MLP	8.5263	5	2	-	0.21456
6	RBF	5.3826	5	13	-	0.13413
7	MLP	4.4734	5	3	-	0.11134
8	MLP	3.7940	5	6	-	0.09538
9	RBF	3.5926	5	14	-	0.08896
10	**MLP**	**2.655757**	**5**	**8**	**4**	**0.0633**

where:

- RMS (Root Mean Square) error - it is a total error made by the network on a data set (learning, test or validation). It is determined throughout summing the squared individual errors, then dividing the obtained sum by the number of included values and determining the square root of the quotient obtained. RMS error is the most convenient single value to be interpreted that describes the total ANN error.
- Qality – the value of root mean square error regression.

4-layer MLP network with structure shown in Figure 1 turned out to be the optimal structure modeling obtained empirical data. The input layer is composed of five neurons with a linear PSP (Postsynaptic Function) and activation function. The first hidden layer is composed of two sigmoidal neurons, i.e. with linear PSP function and logistic activation function. The second hidden layer is built from three neurons with structure identical to the neurons from the first layer. The network output was one sigmoidal neuron. The developed neural model was trained using BP (Back Propagation) method in 3 cycles for 50 epochs and optimized with algorithm CG (Conjugate Gradients) for 196 epochs. The following parameters have been adopted during the training process with the algorithm of BP error:

- decreasing training coefficient: $\eta = 0.1$ do $\eta = 0.01$,
- momentum factor: $\alpha = 0.22$.

The structure of generated ANN, type MLP: 5-8-4-1, is shown in Fig.2.

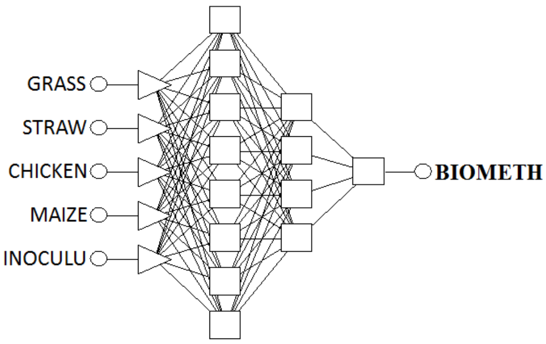

Figure 2. Structure of the optimal ANN, type MLP: 5-8-4-1, with 2 hidden layers.

Unidirectional MLP neural networks are commonly used in ANN topology practice. Multilayer Perceptron represents the so-called category of parametric neural models. Where characteristic is that the number of neurons constituting its structure is considerably less than the number of cases of the training set. The basic characteristics of MLP network include the following features:

- MLP is a unidirectional network,
- MLP is trained by „with-a-teacher" method,
- has a multi-layer structure, with the following layers: input, hidden, output
- architecture of the connections within the network allows communication only between the neurons located in contiguous layers,
- neurons being a part of ANN, MLP type, aggregate the input data by defining the inputs weighted sums (using the linear formula of aggregation),
- activation function of the input neurons is linear, hidden neurons - non-linear, while the nature of output neurons is generally nonlinear,
- due to the saturation level present (in the sigmoid activation functions), all the data processed by the network require an appropriate rescaling (preprocessing and post processing).

The quality of the generated MLP network, as a predictive tool, is identified by the so-called statistics of regression issues, which are shown in Table 3.

Table 3. Regression statistics of generated model for the files: training. validation and test

	biomethane for training file	**biomethane** for validation file	**biomethane** for test file
Data mean	70,81500	79,05513	89,66154
Data S.D.	45,39954	52,06174	40,76000
Error mean	0,442888	-0,07916	0,304094
Error S.D.	3,655942	4,18808	3,908609
Abs E. Mean	2,672447	2,971817	2,857903
S.D. Ratio	**0,080530**	**0,080440**	**0,095890**
Correlation	**0,996799**	**0,996759**	**0,995508**

where:

- Data mean - the mean value of the output variable, calculated on the basis of the preset values of this variable, collected (respectively) in the training, validation or testing set. The regression statistics are calculated independently for the training, validation and test set.
- Data S.D. - the standard deviation calculated for the specified (as above) values of the output variable.
- Error mean - mean error (module of the difference between the reference value and the value obtained at the output) for the output variable.
- Error S.D. - the standard deviation of the errors for the output variable.
- Abs E. Mean - mean absolute error (the difference between the reference value and the value obtained at the output) for the output variable.
- S.D. Ratio - quotient of the standard deviations both for errors and data. This is the main indicator of the quality of the regression model developed by the network.
- Correlation - standard R.Pearson correlation coefficient for the setpoint value and the value obtained at the output.

Table 3 shows that the correlation is at the level of 0.99 for the following files: training, validation and test one, while the quotient of standard deviations for errors and the data ranges from 0.08 in case of validation file up to 0.09 for the test file.

The assessment of sensitivity of developed MLP on individual input variables has been performed in order to determine the level of significance of representative parameters used to build the neural model. The procedure of sensitivity analysis is implemented in the Statistica package as a tool for assessing the impact of the various input variables on the quality performance of generated neural model. The sensitivity analysis provides an insight into the usefulness of particular input variables. Moreover, it indicates high-ranking variables that without any loss of quality of the network can be omitted. Furthermore it also points the key variables (low rank value), which must not be ignored.

Table 4. The values of quotients of errors and rank for the five input variables

	grass	**straw**	chicken	**maize**
Rank	**3**	**1**	4	**2**
Error	17.69924	67.48457	17.64613	32.38631
Ratio	4.614127	17.59298	4.600281	8.442992

gdzie:

- Rank - significance level of input variable, organizes the variables by importance: 1 is the dominant variable.
- Error - the network quality in the absence of a variable: the lower the rank number of the ANN input variable, the higher error of reduced network (without the input variable).
- Ratio - quotient of the error of the reduced network by the ANN error obtained using all variables. If the Ratio is less than one, than removal of the variable improves the quality of the network.

The sensitivity analysis of the MLP neural model 5-8-4-1 on the input variables of analyzed process showed that the most important parameters in the process of neural estimation of the amount of generated biomethane are (in order):

- Rank 1: STRAW
- Rank 2: MAIZE
- Rank 3: GRASS

In order to visualize the behavior of the generated neural model, depending on the values of the main descriptors (STRAW, MAIZE, GRASS) Figure 3 shows the three surfaces of ANN responds illustrating the biomethane efficiency in a function of key input variables of developed neural model.

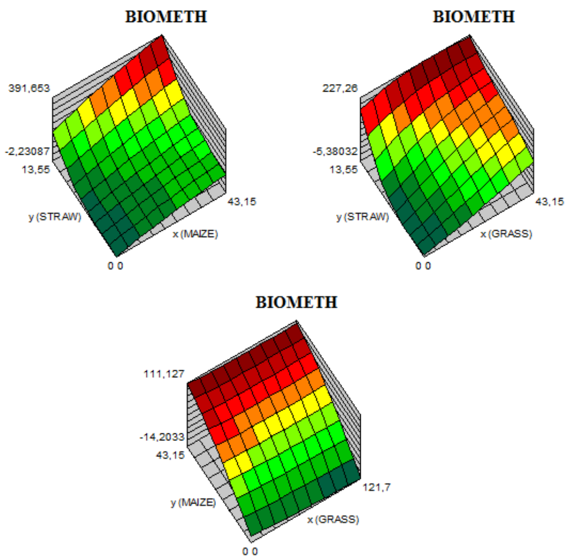

Figure 3. Answer surfaces for network MLP:5-8-4-1

4. Discussion

The analysis of the empirical results obtained during the tests or received in the course of industrial processes control sometimes is very complex. Usually it is related to a large amount of data obtained.

During continuous processes such as industrial production of biogas throughout methane fermentation we have to deal with a specific case. In the aforementioned situation it is possible to obtain a very extensive training set based on a number of variables analyzed over a long period of time [12, 13]. In order to properly interpret the multifactorial results it is necessary to refer to advanced statistical methods based on Artificial Intelligence. According to [14; 15**]** application of this type of analysis enables defining the trends, dependencies and proper control of the processes, not only in the laboratory scale but mainly in the industrial one.

5. Conclusions

The results analyzed using ANN have shown that the optimum structure modeling obtained empirical data is a 4-layer MLP network. The received visualizations and statements are consistent with the experience of a biogas plant staff and scientists studying the efficiency of biogas substrates. It proves that chosen method can be successfully implemented into the planned application - optimizing the selection of the co-substrates for fermentation of the chicken manure in order to obtain the highest possible of biomethane production.

Acknowledgement

This paper was created as a result of the realization of the project entitled “The innovative energy production in biogas plant through utilization of poultry manure with the alternation of a plant substrate for algae” financed by The National Centre for Research and Development (contract no.: GEKON1/O5/214528/34/2015).

References

1. Czekała W., Dach J., Ludwiczak A., Przybylak A., Boniecki P., Koszela K., Zaborowicz M., Przybył K., Wojcieszak D., Witaszek K.. *Proc. SPIE. 9631, Seventh International Conference on Digital Image Processing (ICDIP 2015),* **963117**. (doi: 10.1117/12.2197041 (2015)
2. Przybył K., Koszela K., Boniecki P., Mueller W., Raba B., Lewicki A. Proc. SPIE **9159**, *Sixth International Conference on Digital Image Processing (ICDIP 2014),* **91590W**; doi:10.1117/12.2064243 (2014)
3. Raba B., Nowakowski K., Lewicki A., Przybył K., Zaborowicz M., Koszela K., Boniecki P. SPIE 9159, *Sixth International Conference on Digital Image Processing (ICDIP 2014),* **91590H** (April 16, 2014); doi:10.1117/12.2064091 (2014)

4. Dach J., Koszela K., Boniecki P., Zaborowicz M., Lewicki A,., Czekała W., Skwarcz J., Qiao W., Piekarska-Boniecka H., Białobrzewski I. Renewable and Sustainable Energy Reviews **56**, 603–610 (2016)

5. Boniecki P., Piekarska-Boniecka H., Koszela K., Zaborowicz M., Przybył K., Wojcieszak D., Zbytek Z., Ludwiczak. A., Przybylak A. , Lewicki A. *Proc. SPIE. 9631, Seventh International Conference on Digital Image Processing* (ICDIP 2015), **963115**. (July 06, 2015) doi: 10.1117/12.2197029 (2015)

6. Koszela K; J. Otrząsek; M. Zaborowicz; P. Boniecki; W. Mueller; B. Raba; A. Lewicki; K. Przybył. Proc. SPIE 9159, *Sixth International Conference on Digital Image Processing (ICDIP 2014),* **915913**; doi:10.1117/12.2064274 (2014)

7. Kujawa S., Tomczak R.J., Kluza T., Weres J., Boniecki P.,. *4th International Conference on Digital Image Processing. Kuala Lumpur (Malaysia), proceedings of SPIE,* Vol. **8334**, Article Number: 83341R, DOI: 10.1117/12.949899 (2012)

8. Gueguim Kanaa E.B., Olokeb J.K., Lateefb A., Adesiyanb M.O. Renewable Energy, Volume **46**, Pages 276–281

9. Lewicki A., Boniecki P., Dach J., Janczak D., Czekała W., Zbytek Z., Cieślik M.. *4TH International Conference on Materials Engineering for Advanced Technologies (ICMEAT 2015)* Pages: 649-653 (2015)

10. Cerbin S., Nowakowski K., Dach J., Pilarski K., Boniecki P., Przybyl J., Lewicki A., *4th International Conference On Digital Image Processing (ICDIP 2012). Proceedings of SPIE.* Vol.: **8334** Article Number: 83342A Doi: 10.1117/12.954164 (2012)

11. Janczak D., Marciniak M., Lewicki A., Czekała W., Witaszek K., Rodríguez Carmona P. C., Cieślik M., Dach J., *Procedia Technology,* Vol. **8**, 209–214. DOI: 10.1016/j.protcy.2013.11.029 (2013)

12. Li J., Wei L., Duan Q., Hu G., Zhang G. Bioresource Technology, Volume **156**, Pages 307–313 (2014)

13. Li J., Kong C., Duan Q., Luo T., Mei Z., Lei Y. Bioresource Technology, Volume **193**, Pages 62–67 (2015)

14. Ozkaya B., Demir A., Sinan Bilgili M. Environmental Modelling & Software, Volume 22, Issue **6**, Pages 815–822 (2007)

15. Abu Qdaisa H., Bani Hanib K., Shatnawia N. Resources, Conservation and Recycling, Volume **54**, Issue 6, Pages 359–363 (2010)