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Comparative analysis of biogas production using artificial neural networks (ANNs) and classical methodologies

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ABSTRACT :*Biogas is a product of anaerobic digestion in sewage treatment plants and an important input used in the generation of electricity and cogeneration. In Brazil, there are countless plants using this technology in the treatment of sanitary sewage and potential biogas production. With this, it becomes important for its qualitative and quantitative study, aiming to subsidize several projects and policies, predicting its productive capacity. In this perspective, the present work uses different predictive models found in the literature to estimate biogas production and their responses arecompared with supervised artificial neural network (ANN) responses, considered a more intelligent technique, without limitations of classical techniques. For the purpose of comparison, the PROBIOGAS Program was used as a source of real measurements. After the tests with several different topologies, the final results, when compared with actual measurements, proved that the use of the neural network, when compared to other classical methodologies, was very promising. The best fit of the RNA synaptic weights, after the training and test phases, in order to minimize the E (error) function, presented R2 equal to 84.55 and 91.34, respectively. The standard deviation between the real measurement and the neural networks (Real x ANN) was the lowest obtained (1.76), while in the other methodologies the values were well above (example, UNFCCC x Real = 5.80, UNFCCC x ANN = 5.50). The results showed that all the classical methodologies presented considerable dispersion between themselves and with the real measurements, whereas the dispersion between the real data and neural network responses was much smaller. The architecture employed was able to generalize, concluding that the application of a set of unknown inputs to the training produced a set of desired outputs of biogas production and very close to reality.*
KEYWORDS *biogas, artificial intelligence, neural network, sewage treatment, anaerobic.*

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I. INTRODUCTION

Artificial Intelligence is a branch of Computer Science that deals with symbolic and non-algorithmic methods applied in problem-solving. An Artificial Intelligence system has three main components: Representation, reasoning, and learning and is able to perform the following situations: (i) Store knowledge; (ii) apply stored knowledge to problem-solving and (iii) acquire new knowledge through experience (HAYKIN, 2001). Artificial Intelligence has several techniques and methods that are used to create these intelligent systems and are applied in the solution of several problems that require decision making, among them, neural networks and Nebula Logic.

Neural networks are similar to biological neural networks, based on neurons with a smaller number of units and a much simpler way when compared to the complex biological structure.Inspiration is mainly based on the fact that parallel, fault-tolerant, and adaptive processing occurs in the brain (POMMERANZENBAUM, 2014).Figure 1 shows the artificial neuron model proposed by Mc Culloch and Pitts:

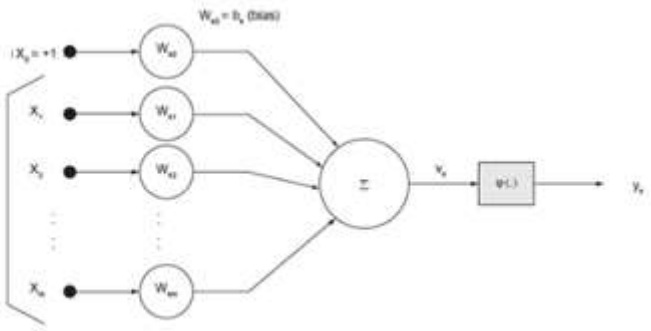

Fig.1. Artificial neuron model

(HAYKIN, 2001)

Before the use of any neural network in solving a problem, training must occur because the neural network needs to "learn" the problem to seek its solution. Thus, the neural network becomes useful (WUERGES, 2010).Biogas is an important product of anaerobic digestion and has added value, being used for electric power generation and cogeneration in many sewage treatment units.

The application of anaerobic digestion in domestic sewage treatment has grown annually at a rate of 25%. Although the process is recognized and implemented over several years, there is still much to study about its operation (LAUWERS, 2013). In Brazil, there are countless plants employing this technology in the treatment of sanitary sewage. Among the main advantages of using anaerobic processes as treatment can be highlighted the high capacity to treat biodegradable substrates at high and low concentrations, low production of sludge, production of important metabolites (such as biogas), low energy consumption and the possibility of recovery of the biogas produced (LARDON, 2004).

Smarter methodologies are indicated in the prediction of systems composed of processes with varied dynamic behaviors, mainly caused by the unpredictability of the parameters. In addition, these systems are constantly strongly influenced by disturbances caused by the difference in sewage flow and effluent organic load, for example. From the process point of view, there are currently few sensors in the market that are acceptable to be used for predicting, even indirectly, intracellular processes which could facilitate the operation of these units.

The present article aims to implement, train and validate a neural network model to be used in the biogas production forecast, comparing its responses with the answers of classical calculation methodologies. The understanding of several aspects of anaerobic reactors such as thermodynamics, kinetics, and limitations in mass transfer is still a challenge for the understanding of the biogas production process. Given the often-erratic production rates, the present work shows promise in the possibility of employing a smarter and more accurate alternative approach, without the limitations of classical methods, such as the neural network, in the prediction of the biogas volume, demonstrating so NN can be considered an excellent method.

II. METHODOLOGY

As a general rule, the development of neural networks basically follows five steps: (1) obtaining data; (2) data set separation for training and verification; (3) neural network configuration; (4) training phase and (5) verification. The training and testing program used in this work was implemented in the Matlab software (Mathworks, 2014a).

There are two methodologies of implementing neural networks in this application: command lines or through a graphical interface. To implement the neural networks of this work, scripts were developed using a toolbox called nftool (Neural Fitting Tool) through command lines.

The methodology comprise 3 steps:

1 - Obtaining relevant operational data on the formation of biogas using the PROBIOGAS report (Ministry of Cities, 2014):

The following data were considered: treatment unit inflow, temperature, chemical oxygen demand (effluent and effluent - in mg/L), the unfiltered residue (affluent and effluent) and biogas flow (in m^3/h). Part of these analytical results has been included in the calculations of the classical methodologies entitled the United Nations Framework Convention on Climate Change (UNFCCC), the National Reference Center on Biomass (NRCB) and the Chemical Oxygen Demand Removed 1 and 2 - See Appendix A) to obtain the volume of biogas theoretically formed in each of them. For the classical methodologies, the results of Chemical Oxygen Demand (affluent and effluent), flow and temperature were considered. For the neural networks, besides these results, the results of total non-filterable residue (affluent and effluent) were also used.

2 - Creation of the model:

The data were inserted in the networks and later were trained and tested using the Neural FittingApp tool, Matlab® software, where the respective neural network outputs were generated. For the neural networks, each column presented approximately 3,500 to 5,000 results.

3 – Model validation:

In this step, the biogas production values estimated and measured by the PROBIOGAS Program were compared and the differences between the two results were analyzed through a statistical treatment.
Initially, training and validation of the neural network occurred to predict these biogas volumes. Subsequent to this phase, with the model properly trained and tested, these output values were compared with classical biogas calculation methodologies found in the literature. In both cases, the same input results were used.

The data selected for the input matrix were entered in the software with the format file * txt extension, containing the data previously processed in Excel and then imported into the neural network. The network is loaded and normalized. For a better convergence and processing speed of the network, in order to avoid poor performance, all data should be normalized, thus normalizing the input variables individually between the range of -1 to 1 (HAYKIN, 2001). In order to normalize the variables, the "mapminmax" function was used, which, at the end of the simulations, can be used again to denormalize them.

The performance function used was the Smallest Mean Square Error (MSE) function. Generally, this choice is used because it is the search for the smallest error between the observed values (real) and those predicted by the neural networks in the samples of tests (out of sample).

After defining the input variables and the target variable (neural network response), a network is obtained that will minimize the MSE. The results will tell if the network was able to learn the pattern that seeks to describe the studied system. It is an exhaustive trial and error procedure.

Table 1 summarizes the parameters of the neural networks used:

Table 1 - Parameters of the neural networks used

Parameter	**Description**
Software/toobox	Matlab® (2014)/Neural Fitting Tool
Neural network type	Feedforward Backpropagation
Type of learning	Supervised
Insertion utilization	Script with command lines
Number of input variables	3 tp 6
Number of output variables	1
Numbers of intermediate layers	5 to 10
Normalization function	‘mapminmax’
Performance Function	Medium Quadratic Error
training algorithm	Levenberg-Marquardt backpropagation, Bayesian regulation backpropagation e Resilient backpropagation
activation function	Sigmoidal (tansig)
Data division	70% for training, 15% for the validation phase and 15% for the training phase
Stop parameter	Lowest incremental error

There is no standardized methodology for input choices, network parameterization, or architecture. It is a learning-by-learning procedure. Several parameters can modify the architecture of a neural network, among them, the number of neurons in the input layer, the number of intermediate layers, the type of training algorithm,

among others. In order to optimize the errors and adjust the weights of each neural network, all the architectures were run at least three times.
Table 2 shows the distribution of the parameters in function of each executed round:

Table 2 - Distribution of the parameters

#ID	Round	Test	Output	Temperature	COD a[1], COD e[2]	TNFAR a[3], TNFAR e
1	1, 2 and 3	Test 1	X	---	X	---
2	1, 2 and 3	Test 2	X	X	X	X
3	2 and 3	Test 3	X	---	X	---
4	1, 2 and 3	Test 4	X	X	X	X
5	1, 2 and 3	Test 5	X	X	X	X
6	1, 2 and 3	Test 6	X	---	X	---
7	1, 2 and 3	Test 7	X	X	X	X
8.1	1, 2 and 3	Test 8.14	X	X	X	X
8.2	1, 2 and 3	Test 8.2	X	X	X	X
8.3	1, 2 and 3	Test 8.3	X	X	X	X
9	1, 2 and 3	Test 9	X	X	X	X
10	1, 2 and 3	Test 10	X	X	X	X
11.1	1, 2 and 3	Test 11.15	X	---	X	---
11.2	1, 2 and 3	Test 11.2	X	---	X	---
11.3	1, 2 and 3	Test 11.3	X	---	X	---
12	1, 2 and 3	Test 12	X	---	X	---
13	1, 2 and 3	Test 13	---	---	X	---
14	1, 2 and 3	Test 14	---	---	X	---
15	1, 2 and 3	Test 15	---	---	X[6]	---
16	1, 2 and 3	Test 16	---	---	X[7]	---

Several multi-layered and supervised multi-layer Perceptron topologies were studied, with a total of twenty arrays as shown in Table 2, using different input numbers for each of the three types of algorithms (LM - Levenberg-Marquardt backpropagation; BAY – Bayesian regulation backpropagation e RB – Resilient backpropagation) and number of hidden layers that ranged from 5 to 10.

In Appendix B, the configurations of the topologies used in the 16 networks are presented. The configuration used was the number of inputs/training algorithm/number of hidden layers - architecture #round#. This is the network creation phase.

The simpler the architecture, the greater the likelihood of adequate generalization. However, for example, with the number of neurons in the intermediate layer being less than 5, the network may not achieve the desired performance. Therefore, in the methodology suggested here, we chose between 5 and 10 neurons, testing the performance through R2. Therefore, it is not necessary for the network to know all the input possibilities to obtain the output, so that the application of a set of unknown inputs to the training produces a set of desired outputs.

[1]COD a – Affluent Chemical Oxygen Demand; COD e - Effluent Chemical Oxygen Demand.
[2]Effluent
[3]TNFAR a – Total non-filterable affluent residue; TNFAR e – Total non-filterable effluent residue.
[4]The three training algorithms were used: LM - Levenberg-Marquardt backpropagation; BAY – Bayesian regulation backpropagation e RB – Resilient backpropagation
[5]The three training algorithms were used: LM - Levenberg-Marquardt backpropagation; BAY – Bayesian regulation backpropagation e RB – Resilient backpropagation
[6]Only affluent COD.
[7]Only affluent COD.

The data set was parameterized for the neural network as 70% for the training, 15% for the validation phase and 15% for the training phase. For tests 8 and 11 (Table 1), it can be observed that three different algorithms were used for the training phase, two more, besides the Levenberg-Marquardt backpropagation, used in the other tests. The trainlm function, considered Matlab's standard algorithm, is used as a faster method of training high-performance feedforward networks. Looking for a more comprehensive study in the tests, in test 8, all parameters were used. In test 11, only flow, COD affluent and effluent. This choice is justified because both have different analytical parameters and this will allow the analysis of the impacts on the results of the neural network.

From each round, errors and deviations were calculated for the tested architectures: mean error (ME), mean absolute deviation (MAD), mean square error (MSE), mean percentage error (MPE), mean absolute error (MAE).

Then, the configurations were chosen with the architectures that presented the best performance.After the steps of testing and validation of the model, the test was finally performed with a group of real values employing the architecture presented in the previous steps the best performance or minor error.

Table 3 presents the errors of all tested architectures:

Table 3 - Calculated errors

Architecture	Scenarios	ME[8]	MAD[9]	MSE[10]	MPE[11]	MAE[12]
1	3/LM/5[13]– a1r2	0,63	1,89	6,15	-2,30	13,57
2	6/LM/5 – a2r2	0,52	1,88	5,98	1,05	13,05
3	3/LM/10 – a3r2	0,56	1,89	6,08	1,27	13,06
4	6/LM/5 – a4r2	0,62	1,90	6,10	1,76	13,06
5	6/LM/5 – a5r2	0,53	1,90	6,08	1,12	13,15
6	3/LM/5 – a6r2	0,63	1,92	6,25	1,71	13,26
7	6/LM/5 – a7r2	0,54	1,88	5,91	1,18	13,01
8.1	6/BAY/10 – a8.1r2	0,52	1,87	5,85	1,09	12,98
8.2	6/LM/10 – a8.2r2	0,51	1,90	6,05	0,96	13,18
8.3	6/RB/10 – a8.3r2	0,51	1,90	6,16	0,93	13,21
9	6/LM/5 – a9r2	0,60	2,29	8,56	0,66	14,89
10	6/LM/10 – a10r2	0,49	2,26	8,31	-0,04	14,83
11.1	3/BAY/5 – a11.1r2	0,40	2,27	8,38	-0,74	14,97
11.2	3/LM/5 – a11.2r2	0,52	2,24	8,16	0,25	14,65
11.3	3/RB/5 – a11.3r2	0,50	2,26	8,26	0,07	14,81
12	3/LM/10 – a12r2	0,54	2,26	8,34	0,35	14,80
13	2/LM/5 – a13r2	0,61	2,36	9,16	0,51	15,42
14	2/LM/10 – a14r2	0,51	2,36	9,06	-0,18	15,50

[8]Mean error (ME)
[9]Mean absolute deviation (MAD)
[10]Mean square error (MSE)
[11]Mean percentage error (MPE)
[12]Mean absolute error (MAE)
[13]The arrangements of the scenarios are arranged as inputs/training algorithm/number of neurons in the hidden layer.

15	1/LM/5 – a15r2	0,58	2,37	9,25	0,23	15,45
16	1/LM/10 – a16r2	0,54	2,35	9,01	0,04	15,42

It is important to note that each error presented by Table 3 refers to the average of all errors between the neural network response (predicted value) and the value found in each classical methodology. After the calculation of the errors, the smallest deviations for each scenario were identified, thus demonstrating that the scenario that best represented the actual values (observed). The tests demonstrated that the 6/BAY/10 - a8.1r2 scenario, that is, composed by the structure architecture 6-10-1, was able to obtain the smallest set of errors. As shown, the structural composition that presented the best results (real x neural networks answers) used 6 input parameters and used the training algorithm called Bayesian regulation backpropagation.

III. RESULTS AND DISCUSSION

After the determination of the best architecture and with the learning phase completed, the chosen topology was submitted to the training phase where 5 rounds were used. Analyzing the output values, it was observed that round 4, according to Table 4, presented the best adjustments in its synaptic weights, after each round, being able to conclude that in this round the smallest deviations occurred between the output value produced (network response neural) and desired (real value - PROBIOGAS). Round 4 presented the best fit of the synaptic RNA weights, after the training and test phases, in order to minimize the E (error) function, with R2 equal to 84.55 and 91.34, respectively.

Table 4 - Actual and predicted values - Rounds 1, 2, 3, 4 and 5 - Scenario 6/BAY/10 - a8.1r2

Real values (in m^3/h)	Round 1	Round 2	Round 3	Round 4	Round 5
15	15	16	15	15	15
13	15	16	14	15	16
17	15	16	15	15	15
15	15	16	15	15	15
19	15	16	15	16	15
13	15	16	15	15	15
13	15	16	15	15	15
18	15	16	15	16	15
19	15	16	15	16	15
13	15	16	15	15	15
19	15	16	15	16	15
16	15	16	15	15	15

The classical methodologies considered critical parameters in the biogas formation, as well as in the calculations by the neural networks. The same input values were used to test and validate the neural network model. The data of affluent and effluent Chemical oxygen demand, the inflow of the tributary, temperature, non-filterable residual affluent and effluent and the percentage of removal of organic load were used. With the neural network tested and ready and the calculations already carried out by the classical methodologies, the following output values were obtained (Table 5):

Table 5. Results of biogas in m^3/h

UNFCCC	NRCB	COD R1	Real	RNA
4	11	39	15	16
7	21	75	13	16
3	8	28	17	16
6	17	63	15	16
5	15	54	19	16
6	17	61	13	15
5	14	52	13	15
8	24	86	18	16
4	11	41	19	16

5	15	54	13	15
5	14	52	19	16
4	12	44	16	16

Analyzing the degree of dispersion, presented in Figure 2, it can be concluded when comparing the outputs of the neural network with the results obtained in the treatment plant (real) that the differences were much larger when related to the values obtained in relation to the other results of the calculations using classical methodologies, although these also present dispersion.

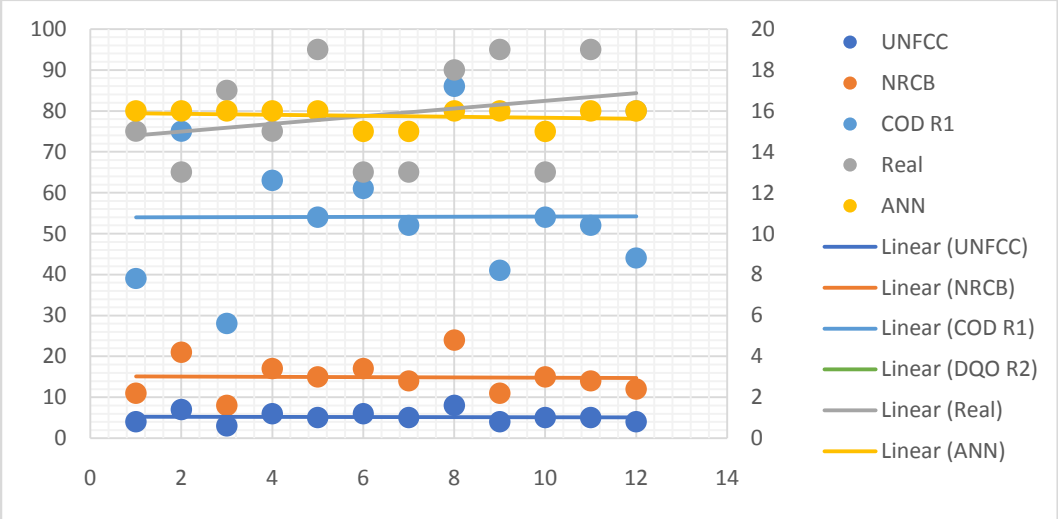

Fig.2. Dispersion of the presented values

As shown in Table 5, all classical methodologies presented results very different from those obtained from the output in the neural network. However, it is important to emphasize that the methodologies used here are methane determination and that according to the literature, part of the results discrepancies verified in these works can be attributed to the solubilization of part of the methane formed in the effluent itself, but regardless of this factor, the responses presented are very different. Thus, this work used as a correction factor of methane for biogas the value of 0.60, that is, an increase of 60% in each of the results obtained (Ministry of Cities, 2014).

Table 6 presents a statistical treatment of the generated results.

Table 6 - Statistical treatment of biogas results in m³/h

Parameters	**UNFCCC**	**NRCB**	**COD R1**	**Real**	**RNA**
Mean	5	15	54	16	16
Maximum	8	24	86	19	16
Minimum	3	8	28	13	15
Sum. Diff.[14]	-127	-10	460	1	-
DP[15]	1,40	4,44	15,88	2,52	0,45
CV[16]	0,27	0,29	0,29	0,15	0,02
CP[17]	-0,07	-0,05	-0,06	0,67	1

[14]Sum of the differences between the methodology and the outputs of neural networks.
[15]Standard deviation only of the values calculated by each classical methodology.
[16] Coefficient of variation.
[17] Pearson correlation coefficient: The correlation analysis indicates the relationship between 2 linear variables and the values will always be between +1 and -1. The signal indicates the direction, whether the correlation is positive or negative, and the size of the variable indicates the strength of the correlation.

Table 7 presents the standard deviation results of the classic methodologies, of the real measurements and RNA responses.

Table 7 - Calculation of the standard deviation

UNFCCC x Real	UNFCCC x RNA	Real x RNA
5,80	5,50	1,76
NRCB x Real	NRCB x RNA	Real x RNA
3,56	3,11	1,76
COD R1 x Real	COD R1 x RNA	Real x RNA
22,47	22,44	1,76

Note that the lowest standard deviation is the one calculated considering the results obtained in the actual measurements and the neural network responses. All classical methodologies varied, on average, 30% of the presented values in relation to the average of each methodology. It is also observed that this variation is smaller, considering the groups of values of the real results and the outputs of the neural networks, is only 2% in the responses of the neural networks.

When calculating Pearson's correlation coefficient, between the results of each classical methodology and the neural network, it can be observed that all the methodologies presented negligible correlation, demonstrating that the values have a low correlation. However, the actual values presented a strong correlation with the values of neural network responses, indicating that the values strongly approximated each other. The neural network showed results closer to reality; therefore, its use in the estimation of biogas may be possible.

IV. CONCLUSION

The present work demonstrated that the use of neural networks provides results closer to those obtained in real measurements when compared to the classic methodologies of calculation of biogas production. The proposed model of volume prediction using neural networks was very promising in the modeling of biogas generation when compared to the classic methodologies. Therefore, the results validated the trained RNA and the correct architecture chosen that were able to yield results close to real, used in the comparison.

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APPENDIX A - CLASSICAL BIOGAS CALCULATION METHODOLOGIES

UNFCCC Methodology

The United Nations Framework Convention on Climate Change (UNFCCC) methodology was developed by the United Nations Convention on Climate Change and is based on the assessment of the baseline carbon dioxide emission used in recovery and use of methane produced through treatment of sanitary sewage, according to the Clean Development Mechanism. The baseline is calculated in tons of carbon dioxide per year (tons CO2/year). In its calculation should be considered the so-called global warming power of methane (GWP), equal to 21 tons of CO2. The following equation (equation 1) was adapted through the work of GERVASONI (2011):

$$P_{CH4} = Q * S_0 * \eta_{rem} * CP_{CH4} * FCM * FCI \text{(eq. 1)}$$

Where:

PCH4 = Production of methane from a treatment plant, in tons/year;
Q = afluent volume (input to the treatment plant), in m³/year;
S0 = Chemical Oxygen Demand Concentration (COD), in tons/m³;
η_{rem} = Efficiency of organic load removal;
CPCH4 = methane production capacity, equal to 0.25 tons CH4/tons of COD;

FCM = correction factor of methane according to the type of treatment;
FCI = Correction factor due to uncertainties, this value being equal to 0.89.
The values of FCM will be according to the technology used in the treatment plant, as shown in Table 1:

Table 1 - Correction factor according to the type of treatment (GERVASONI, 2011)

Treatment type	FCM
Discharge of wastewater into the sea, rivers or lakes	0,10
Aerobic treatment	0,00
Aerobic treatment (precarious)	0,30
Anaerobic digester for sludge, without recovery of methane	0,80
Anaerobic reactor without recovery of methane	0,80
Shallow anaerobic lagoon (up to 2 m deep)	0,20
Deep anaerobic lagoon (more than 2 m deep)	0,20
Septic system	0,50

The values of methane production capacity (CPCH4) and correction factor (uncertainties) were obtained through the inventory of greenhouse gases prepared by the Intergovernmental Panel on Climate Change (IPCC), as well as the FCM factor of 0,10 (this choice is made because it is a factor that is closer to the technology of the treatment system considered by the present work).

Thus, the calculation of methane production (in tons/year) can be calculated by the following equation (equation 2):

$$P_{CH4} = 0{,}02225 * \eta_{rem} * COD_t \text{(eq. 2)}$$

In this formula, the factor of 0.02225 is obtained through the product between 0.25 t of CH4/tons of COD, by FCM = 0.10 and FCI = 0.89. The term CODt originated from the product between the values Q and S0.

NRCB Methodology

This methodology was developed by Professor Carlos Augusto de Lemos Chernicharo of the Federal University of Minas Gerais (UFMG in portuguese) and uses the so-called stoichiometric ratio among the reagents participating in the anaerobic process. The production of methane (in m³/year) is given by the following equation (Equation 3):

$$P_{CH4} = COD_{CH4}/K(T) \text{(eq. 3)}$$

Where:
CODCH4 = Charge of COD converted to methane (in tons COD/year);
K(T) = Correction factor for temperature (in tons COD/m³ CH4).
The conversion of the COD load into methane is given by the following equation (Equation4):

$$COD_{CH4} = Q * (S_0 - S) * F_{SVT} \text{ (eq. 4)}$$

Where:
Q = flow of tributary to be treated (in m³/year);
S0 - S = COD concentration removed during treatment (in tons COD/m³);
Where Fsvt = Factor due to total Volatile Solids. The Fsvt factor can be broken down into two parts:
Fsvt = 1 - Yobs (coefficient of production of total volatile solids in the system) and K solids is equal to the conversion factor of SVT in COD.
The following values were adopted: 0.18 tons SVT/ tons COD for Yobs and 1.42 tons COD/tons SVT for Ksolid, according to the work of GERVASONI (2011).
By a rearrangement and considering the universal gas law (PV = nRT), the following equation (equation 5) is reached for the K (T) term:

$$K(T) = P * KCH4/_{R * T} \text{(eq. 5)}$$

Where:
P = Atmospheric pressure (in atm);
KCH4 = COD corresponding to 1 mole of methane (equal to 64 g COD/mol CH4);
R = Universal gas constant (equal to 8,206 * 10^{-5} atm.m³ (mol.K-1)).
T = Temperature (in kelvin).

The KCH4 value originates from the stoichiometric removal balance in terms of COD, where 1 mole of methane reacts with 2 moles of oxygen to produce carbon dioxide and water. Thus, 64 grams of oxygen are consumed to produce 1 mole of methane.

The main equation of the model is given in m³/year, and it is necessary to convert the term into t CH4/year, multiplying the term by the specific mass of methane (0.7143 kg/m³ or 7.143 x 10-4 tons/m³). Substituting the terms of specific mass, R, KCH4, Yobs, Ksolids and atmospheric pressure (equals 1), equation (Equation 6) becomes:

$$P_{CH4} = 6{,}818 * 10^{-4} * T * \eta_{rem} * COD_T \text{(eq. 6)}$$

Here also we used the relation Q * (S0 - S) = COD removed * CODT. Equation 6 represents the calculation of methane production for this methodology.

APPENDIX B - NEURAL NETWORK ARCHITECTURES USED IN THE TESTS

Architectures[18]	Round 1	Round 2	Round 3	Output	Matrices[19]	Matrix [20]
1	3/LM/5 – a1r1	3/LM/5 – a1r2	3/LM/5 – a1r3	1	112x4	1:4/5:5
2	6/LM/5 – a2r1	6/LM/5 – a2r2	6/LM/5 – a2r3	1	921x7	1:8/9:9
3	-	3/LM/10 – a3r2	3/LM/10 – a3r3	1	981x421	1:5/6:6
4	6/LM/5 – a4r1	6/LM/5 – a4r2	6/LM/5 – a4r3	1	981x7	1:8/9:9
5	6/LM/5 – a5r1	6/LM/5 – a5r2	6/LM/5 – a5r3	1	1481x7	1:8/9:9
6	3/LM/5 – a6r1	3/LM/5 – a6r2	3/LM/5 – a6r3	1	1481x7	1:8/9:9
7	6/LM/5 – a7r1	6/LM/5 – a7r2	6/LM/5 – a7r3	1	3481x7	1:8/9:9
8.1	6/BAY/10 – a8.1r1	6/BAY/10 – a8.1r2	6/BAY/10 – a8.1r3	1	3481x7	1:8/9:9
8.2	6/LM/10 – a8.2r1	6/LM/10 – a8.2r2	6/LM/10 – a8.2r3	1	3481x7	1:8/9:9
8.3	6/RB/10 – a8.3r1	6/RB/10 – a8.3r2	6/RB/10 – a8.3r3	1	3481x7	1:8/9:9
9	6/LM/5 – a9r1	6/LM/5 – a9r2	6/LM/5 – a9r3	1	4981x7	1:8/9:9
10	6/LM/10 – a10r1	6/LM/10 – a10r2	6/LM/10 – a10r3	1	4981x7	1:8/9:9
11.1	3/BAY/5 – a11.1r1	3/BAY/5 – a11.1r2	3/BAY/5 – a11.1r3	1	4981x4	1:5/6:6
11.2	3/LM/5 – a11.2r1	3/LM/5 – a11.2r2	3/LM/5 – a11.2r3	1	4981x4	1:5/6:6
11.3	3/RB/5 – a11.3r1	3/RB/5 – a11.3r2	3/RB/5 – a11.3r3	1	4981x4	1:5/6:6
12	3/LM/10 – a12r1	3/LM/10 – a12r2	3/LM/10 – a12r3	1	4981x4	1:5/6:6
13	2/LM/5 – a13r1	2/LM/5 – a13r2	2/LM/5 – a13r3	1	4981x3	1:4/5:5
14	2/LM/10 – a14r1	2/LM/10 – a14r2	2/LM/10 – a14r3	1	4981x3	1:4/5:5
15	1/LM/5 – a15r1	1/LM/5 – a15r2	1/LM/5 – a15r3	1	4981x2	1:3/4:4
16	1/LM/10 – a16r1	1/LM/10 – a16r2	1/LM/10 – a16r3	1	4981x2	1:3/4:4

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[18] 20 architectures =14 LM-type architectures and 6 architectures with the 3 training algorithms.
[19] In this column, the first number refers to the number of analytical results of the parameters and the second refers to the number of columns.
[20]Configuration of matrices in the input of Matlab.
[21] For rounds 2 and 3.