Estimate of the ball-king biodigester´s volume using artifical neural networks

Estimación del volumen de un Biodigestor tipo balón usando redes neuronales artificiales

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Abstract

Biomass, as an alternative source of energy, can be converted into biogas through the anaerobic digestion of organic material. The device used for this purpose is called biodigester, and several protocols have been studied aimed at estimating the volume and quantity of the gas obtained. These protocols use a combination of the origin, of the biomass and equations involving environment temperature, biological load and retention time. The treatment of organic residues and the systematization of the activity on livestock farms requires the intervention of expert users or the implementation of intelligent systems, which allow for quantitative and qualitative variables. In this paper, we use Artificial Neural Networks (ANN) to estimate the production volume of a bio-digester ball. The networks are designed for this use on both livestock and farming residues. The efficiency of the estimation is evaluated using R Correlation Coefficient. Results show that the technique is reliable and can be used in practice.

Keywords: alternative energy; biomass; bio-digester; artificial intelligence; artificial neural networks.

Introduction

The alternative, renewable or soft energy sources, in opposition to the ones coming from hydrocarbon, highlight the solar energy, wind energy, the biomass, the hydraulic energy, the tidal energy, among others (Correa, 2007). The biomass, amount of products obtained through photosynthesis, is prone to be transformed into fuel, and can come from stockbreeding and agrarian wastes (Rodríguez et al., 2013).

The stockbreeding activity produces wastes in an organic way, and every stockbreeding specie is a source of this commonly known source known as manure, and even man feces have been considered as energy

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source (González, 2010). On its part, the stockbreeding activity produces wastes, mainly of fruit shells, seeds, leaves and rotting fruit. Both residues called agricultural biomass (González, 2010).

The agricultural biomass becomes a traditional fuel, the biogas, which corresponds to a methane and other gases mix produced during the anaerobic degradation of the organic matter, in a digestive compartment or well channeling it in a controlled landfill (FAO, 2011). In the first case, denominated as biodigester, the temperature is kept around 50°C, a pH between 6, 2-8,0, favoring the microorganism activates and biochemical degradation between 10-25 days, so in the three stages (acidogenesis, acetogenesis and methanogenesis) is carried the biogas production (FAO, 2011).

Several authors quoted by (Olaya & González 2009, pp 8-10), consider inside the process in the first stage of the mentioned, a denominated hydrolysis; the Figure 1 summarized the different characteristics of each one of the different stages, grouped with their respective chemical composites that intervene in them (Martí, 2008, Olaya & González, 20 09, p.10).

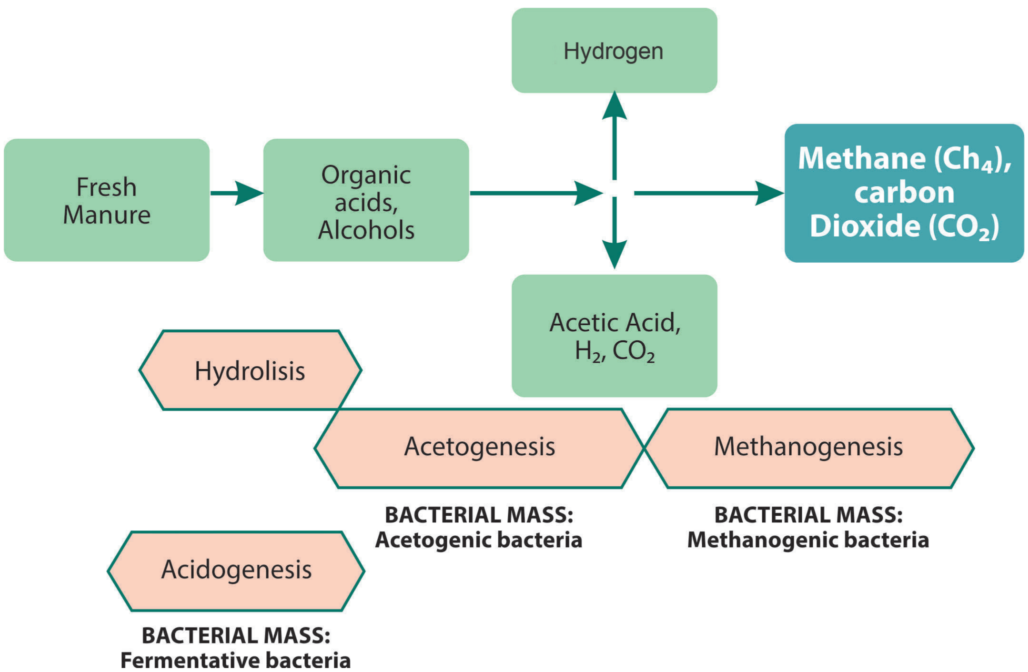

Figure 1. Synthesis of the present anaerobic digestion stages
Source: (Martí, 2008; Olaya and González, 2009).

The installation of biodigesters are also systems for the treatment of organic wastes, which are avoided to be dumped in water sources, which at the same time generate fuel, generally used for space heating and food cooking, and in the last years as fuel in utilitarian plants of electric generation (González, 2011).

The biodigesters are of three kinds (Olaya & González, 2009): tubular or ball-kind, of fixed dome, and of mobile dome; the installation of these last two are more expensive, due to these are built with masonry or concrete, while the ball-kind (Figure 2), is built out of plastic tubular foils commercially available, and successful installation cases of these have been reported from the community (Moncayo, 2008).

Figure 2. Tubular or ball-kind biodigester
Source: (González, 2010).

Takes relevance then, the search of elements and techniques that allow to systematize the biogas production process to potentiate the use of this fuel, mainly, in country communities. However, the design protocol of the biodigesters mix the use of planks that contain energetic capacities according to the biomass original source, and equations to estimate the biodigester volume and the produced biogas, involving qualitative and quantitative variables in this process(Martí, 2008).

Regarding this, Martí (2008, p.31), based in a theoretical substantiation, proposes a design methodology to estimate the ball-kind biogas and biodigester volume, valid for any thermal floor, as it can be seen on Figure 3.

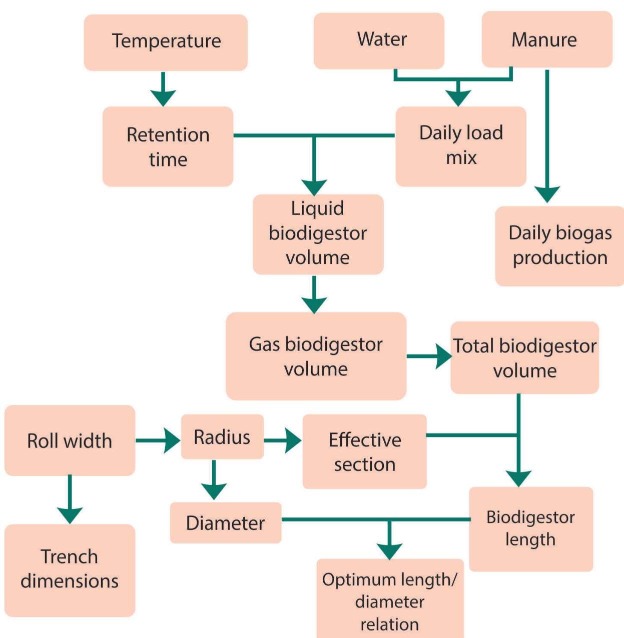

Figure 3. Methodological proposal for the ball-kind biodigesters
Source: Martí, 2008, p.31

On its part, the artificial intelligence, term coined in the year 1960 by Minsky, who in its widest sense indicates the capacity of an artifact to conduct the same functions that characterize the human thinking, and in these terms, his methods are an answer for the desire to approximate the human behavior and thinking to several systems for the solution of determined problems (Cagnina, 2010). One of these, is the method of Artificial Neural Network (ANN), functional abstraction of the biologic neuronal structure of the central nervous system (Figure 4), recreating from the biological perspective, the human brain structure (Bishop, 2006).

The ANN are nowadays considered as powerful pattern recognizers and classifiers (Bishop, 2006), used in the solution (prediction) of engineering problems, as an alternative in complex characterized systems by interaction factors, or in non-linear statistic approximation systems, or in the computational based solutions of complex and extensive algorithms (Haykin, 2005), that involve quantitative and qualitative variables, and that in these last, to relate them with a mathematical model turns out difficult.

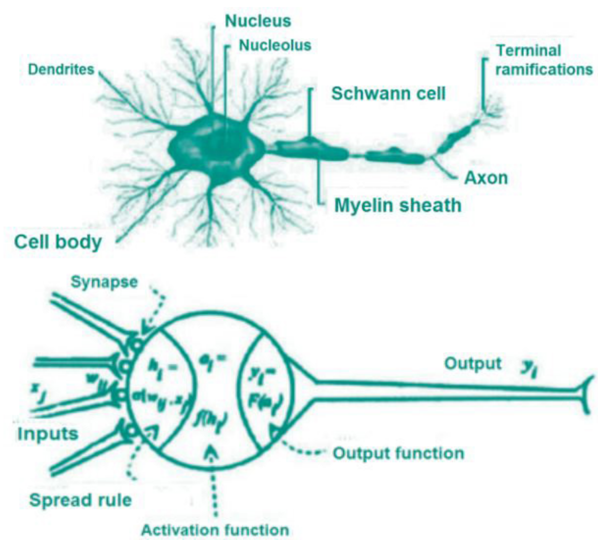

Figure 4. Similarity between a biologic neuron and a computational one, respectively
Source: (Isasi, 2007; Bertona, 2005).

In its historical context, the ANN started as a monolayer network, denominated as Simple Perceptron that could only perform Solutions from some logical functions, such as OR, AND and NOT, without numerical estimations. Later, its development allowed numerical estimations, being known as ADALINE network. Nowadays, many engineering problems are addressed from networks with different layers, and get the name of Multilayer Perceptron, with a supervised learning procedure, that is to say, they are trained from the approximation error against the real results (Bishop, 2006).

In this work, a Multilayer ANN is elaborated with supervised training and backpropagation adjustment, trained for the estimation of ball-kind biodigester estimation and biomass source.

Methodological Procedure

Training set construction for the artificial neural network

For the ANN training a base data is prepared formed by patterns or information vectors that allow the model to predict the predictable relations that exist between the input neurons (variables) that lead to the result of the predictable neuron (output variable). For this, according with the biodigester design protocol proposed by Martí, (Figure 3), a relevant input variable selection is made in the volume determination of a ball-kind biodigester problem.

These are the following: organic residue source [OS], environmental temperature in °C [T], organic matter retention time inside the biodigester in days [t], manure load according with l/day load [C], organic residue in % [%SO], biogas production according the organic solid content in m^3/kg de %SO [PBG], and plastic tubular perimeter commercially available for the biodigester construction [P]. As an output variable, this information is linked for each ball-kind volume biodigester pattern in m^3[V].

The OS variable corresponds to a qualitative variable, which is treated as a graded quantitative variable, procedure than consists in converting a symbolic or discrete variable to a pseudo-discrete variable, in which, drawing from an established order by the graded position of the discrete variable answer, sub-intervals are established for each binary neuron, 0 to 1, as described by March, 2001.

Forward to the input and output variable determination, which is elaborated with the general database which determines the training set, formed by 90 information vector (input and output vectors), using the ball-kind biodigester design protocol presented by (Martí, 2008).

Elaboration, training, conducting, validation and artificial neural network for the ball-kind biodigester volume estimation

The training set mentioned in the 2.1. section is used, in which the input variables are related with the output variables, a Multilayer ANN proposal is conducted fed forwardly and with feed-forward training/backpropagation learning methodology (Figure 5), whose characteristics are defined by Rumelhart et al., 1986; Hinton 1987, 1988, respectively.

The neuronal connections between the input layer to each hidden later, is done using the sigmoid function described by Hinton, 1987, 1988; the neuronal connections in the last hidden layer and the neuron to be estimated located in the output layer, which is done using a linear function, in a way that, it allows to compare the estimation with the real result, as described in the supervised training (Rumelhart et al., 1986, and Hinton 1987, 1988).

For this, Tabarquino, 2014, elaborated 82 ANN conformations, and evaluated them from the lineal R co-relation; for its computational functioning, the ANN was codified using the M programming language, characteristic from the MATLAB® mathematical software tool for the Windows® platform, the code used the library contained in the Neural Networks Toolbox from the same software, thus, allowing to implement the ANN model types that have been described.

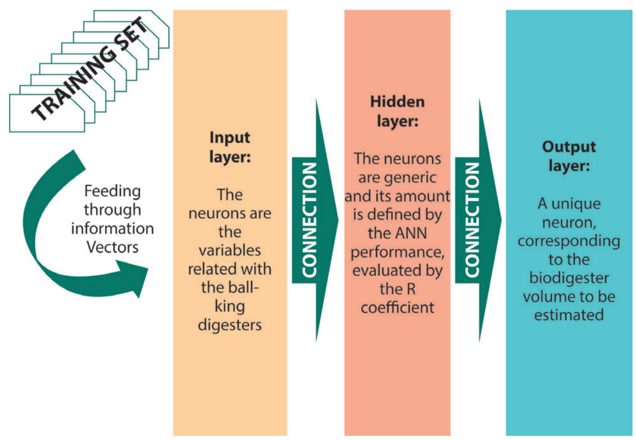

Figure 5. Neuronal model proposed for the ball-kind biodigester volume estimation
Source: The authors.

The results of this process, are not present in this article, showed that the architectures with two or three hidden layers, and using Lebenberg-Marquardt learning, Cuasi-Newton conjugate gradient method, classic conjugate gradient, Powell-Beale conjugate gradient, Pollak-Ribiére gradient conjugate, Secant unit step function, and descendant gradient of variable training rate methods, obtained better, adequate and trustable performances (R > 0.98), than using the Bayesian Regulation and Resilient Backpropagation methods. So, the ANN architecture is configured with an input layer with 7 input variables, a first hidden layer with 20 neurons, a second hidden layer with 10 neurons, an input layer with an answer variable and a Levenber-Marquartd backpropagation algorithm (Figure 6).

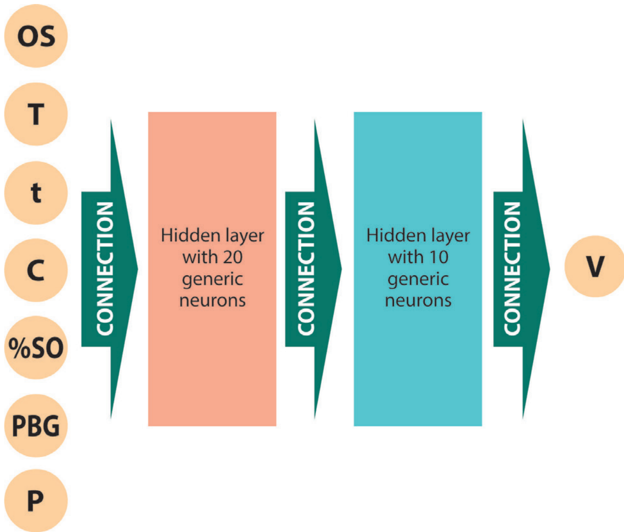

Figure 6. Architecture and topology from the selected ANN for the biodigester estimation.
Source: The authors.

Results and discussion

Drawing from the ANN elaboration, corresponding to a supervised Multilayer Perceptron neuronal network, with feed-forward training/backpropagation learning, the volume for the ball-kind biodigester was made. The neuronal model consisted in a ANN formed by an input layer with 7 input variables (which one of them is of quantitative type with treatment of graded numeric variable), a first hidden layer with 20 neurons, a second hidden layer with 10 neurons, an output layer with an answer variable corresponding to the ball-kind biodigester volume estimation, and a Levenber-Marquartd learning algorithm.

The Figure 7, displays the performance results of the selected ANN, for each one of the training stages of such (training, test, computational validation and with all the training set). For all the stages, a comparison was made between what was obtained by the ANN (output) and the obtained value using the design protocol (target), which for the linear R co-relation factor was used.

The performance was based in the R co-relation factor (R > 0.99), according with Ascombe, 1973, and Aschen, 1982, they show a strong positive linear relation between the biodigester volume obtained, coming from the design protocol proposed by Martí, 2008, and the one obtained through the ANN prediction, thus, allowing to conclude that the computational tool is adequate and trustable for such estimations.

On Figure 8, the ANN estimated results are simultaneously represented, and the ones obtained by the Martí, 2008 design protocol, with the goal to verify the relation in the prediction adjustment, departing from the graphical comparison between the two results, as suggested by Martínez (2005, p.22). The corroboration for each register in the result approximation obtained by prediction, allows to conclude that the computation model based in the ANN can be used as methodology design for ball-kind biodigesters.

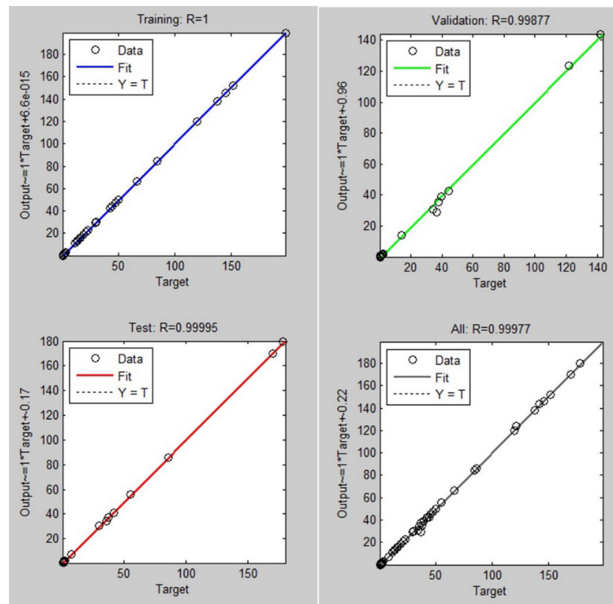

Figure 7. ANN performance result selected for the ball-kind biodigester volume estimation
Source: The authors

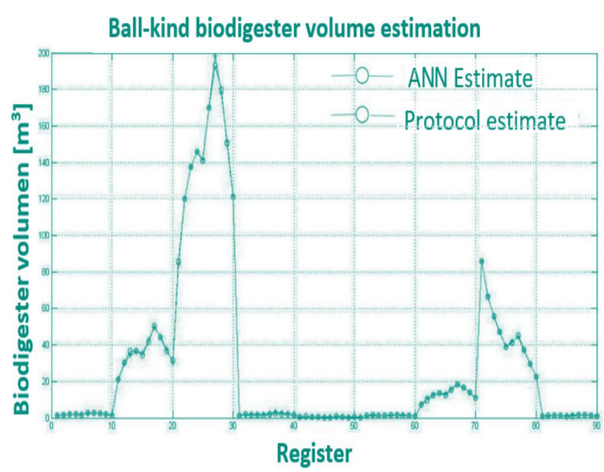

Figure 8. Graphic comparison of the results obtained by the Artificial Neural Network and the ones obtained by the design protocol
Source. The authors

The literature reports the use of ANN in the design for the use of alternative energies, such as solar (Gandolfo et al., 2011, González, 2013), wind (López et al., 2007) and hydraulic energies (Villada et al., 2008); however, there are no similar reports in the design of biodigesters, reason why the ANN utilization model in such field is an innovating application.

Conclusions and recommendations

An Artificial Neural Network was elaborated for the ball-kind biodigester volume estimation, which adequately generalized the obtained results in the conventional protocols for such design. The obtained results allow to chart the following conclusions and recommendations for future agenda

The considered performance indicator, the linear co-relation factor, shows that the artificial neural network is trustable for the biodigester volume estimation, according to the results that would be obtained through conventional designing methods

The consideration in the variable neural model represent the source of organic matter, and variability in the influencing factors such as the environmental temperature and the retention time, allow to have a universal prediction tool in the ball-kind biodigester volume.

Hence, the artificial neural network allows to consider a qualitative variable, which in this case confers advantage to other mathematical models with similar goals.

The artificial neural network can potentiate its use a computational tool for systematization processes in the agricultural activities that generate organic material residues aimed to the biogas production as an alternative fuel.

The possibility to control the input variables, allows to make adjustments of such, according to dynamics proper of the residue generation, through new trainings and learning of the own artificial neural network.

A future agenda is opened for this research, when extending the neural model for the design of other types of biodigesters, and the using of biomass as an alternative energy source for the biogas production.

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