

The use of artificial neural networks for compounds prediction in biogas from anaerobic digestion – A review

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In the survey, we summarized some of the most important researches on assessment and forecasting components of biogas and the substrate in the process of anaerobic digestion using artificial neural networks (ANNs). Here we consider especially hydrogen sulfide, ammonia, hydrogen, methane in biogas and heavy metals in substrate. The results show high prediction accuracy and usefulness of the ANNs. The predicted removal efficiency of a biofilter for treating hydrogen sulphide with ANN was validated with determination coefficient of 0.92. A simulating model for the performance of a granule-based H_2-producing was able to effectively describe the daily variations of the reactor performance, and to predict the steady-state reactor performance at various substrate concentrations using ANN network and genetic algorithm. The values of training determination coefficients for H_2 concentration in the biogas was 0.966, H_2 production rate 0.810, H_2 yield 0.882. The ANN learned the relationship between input and output well. The ANN model to predict the methane production on the basis of operational parameters was validated with correlation coefficient of 0.87. A back propagation artificial neural network (BP-ANN) algorithm for the simultaneous spectrophotometric determination of the cobalt and nickel complexes show the good regression between actual values and prediction values for cobalt and nickel concentration.

Key words: artificial neural networks, anaerobic digestion, prediction, biogas

INTRODUCTION

Anaerobic digestion (AD) also known as the biogas process has been widely utilised by the modern society for stabilising primary and secondary sludges in municipal wastewater treatment plants. The biogas process has also been applied as an alternative method for the treatment of animal manure, organic waste from households, urban areas and industries, often associated with energy recovery and the recycling of the nutrients from digested biomass to the agricultural sector. The proces is indigenous to natural anaerobic ecosystems and represents the microbiological conversion of organic matter to methane in the absence of oxygen. The digested organic matter resulting from the anaerobic digestion process is usually called digestate (Al Seadi et al. 2008).

Biogas is produced in different environments, e.g., in landfills, sewage sludge and biowaste digesters during anaerobic degradation of organic material. Methane, which is the main component of biogas, is a valuable renewable energy source, but also a harmful greenhouse gas if emitted into the atmosphere. Methane, upgraded from biogas, can be used for heat and electricity production or as biofuel for vehicles (Wellinger and Linberg 2000).

Biogas contains from 55% to 70% methane, 30% to 45% carbon dioxide and <1% nitrogen (Jönsson et al. 2003). Typically biogas also contains hydrogen sulphide and other sulphur compounds, ammonium, compounds such as siloxanes, aromatic and halogenated compounds, heterocyclic compounds, ketones, terpenes, alcohols and halogenated aliphatics (Allen et al. 1997; Spiegel et al. 1997; Eklund et al. 1998; Shin et al. 2002; Jaffrin et al. 2003). The presence of these compounds and their concentration during the reaction has a strong influence on the reaction path itself, and even more on the further use of biogas. Most of the produced biogas is used today to produce electricity and heat in internal combustion engines, microturbins or fuel cells. All these procedures require a relatively clean methane, whereas the majority of devices is very sensitive to the matter in the biogas. Therefore, detection and removal of these materials on time is important from both an economic and ecological point of view since the combustion of pure methane is relatively "clean". ANN according to the dynamics of the process and a number of unpredictable factors offer themselves as an effective tool for that. There are many different uses of ANN in AD but first of all we can summarize four important segments, which are closely linked: process control and diagnosis, fault detection on time to support decision-making system, process and its products prediction to support decision-making system, process modeling and simulation for optimization and indentification of process level. All these segments have a significant impact on the rapid development of new, high-speed measurement techniques and measurement tools that only provide up to date and accurate information that are necessary for further processing by the ANN in all process stages of AD.

When we talk about areas of use of ANN predictions in the AD process it is clear that an industrial use (waste) is in advantage compared to agriculture. This is reflected by a small amount of researches in agriculture and it is clearly from the perspective of modern society and the Western way of life because we produce huge quantities of various wastes, which represent a major ecological problem. It is very useful to turn waste into biogas and also environment friendly. ANN can play an important role in this process

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because of different starting substrates that contain unknown ingredients with significant influence on the course of the process and composition of biogas. They may also contain toxic substances, antibiotics, pesticides, etc., which are very dangerous for the conduct of the process (inhibition) and of course for the environment. In all such cases the prediction with the ANN is a powerful tool that has enormous economic and ecological benefits.

Because of the small amount of researches, the development of this area is at the beginning and therefore offers a wide range of new applications. ANN are becoming very important in many areas of human activity and agriculture is no exception. Even more, with its many biodynamic processes, which are not even fully known, it is an ideal field for new applications of ANN. Agriculture offers a huge stock of organic matter from various crops to different manure and organic waste. There is no problem with the unknown input substrates in agriculture biogas plants, so therefore the use of ANN prediction can be focused mainly on the detailed knowledge of the process in order to increase the yield of biogas and the search for optimal mixes of different starting substrates.

ARTIFICIAL NEURAL NETWORKS BACKGROUND AND MODELLING

An artificial neural network is a computational structure where many simple computational elements, called artificial neurons, perform a nonlinear function of their inputs. Such computational units are massively interconnected and are able to model a system by means of a training algorithm. This algorithm attempts to minimize an error measure that is computed in different ways depending on the specific technique used to adjust the connections (i.e., the learning algorithm). There are two major approaches to train an artificial neural network (i.e., to adapt its parameters): supervised and unsupervised learning. In the supervised learning approach, specific examples of a target concept are given, and the goal is to learn how to recognize members of the class or to build a regression model using the description attributes. In this case, the synaptic weights among neurons are adjusted in order to minimize the error between the known desired outputs and the actual output given by the neural network during the learning process. In the unsupervised learning approach, the set of examples is provided without any prior classification, and the goal is to discover underlying regularities and patterns, most often by identifying clusters or subsets of similar examples. Training in this case consists on looking for a compressed representation of the collected examples (original data) and the error is the difference between this representation of our original data and the original data (Bishop 1995). The attractiveness of ANNs comes from their remarkable information processing characteristics pertinent mainly to nonlinearity, high parallelism, fault and noise tolerance, and learning and generalization capabilities. Compared with conventional data processing methods, ANNs provide a model-free, adaptive, parallel-processing, and robust solution with fault and failure tolerance, learning, ability to handle imprecise and fuzzy information, and capability to generalize. An ANN is able to map process input and output without underlying assumption about the distribution of data. They are powerful in data processing and analysis and can handle engineering problems, which are highly complex and nonlinear. They provide a powerful method for practically accurate solutions of precisely or imprecisely formulated problems and for phenomena that are only understood through experimental data and field observations. ANNs have become the most popular soft computing methods for solving problems in engineering (Basheer and Hajmeerb 2002). They have been successfully used for a number of chemical engineering applications such as sensor data analysis, fault detection and process identification. Many cases show high utility value of various forms of ANN for different chemical processes (Hussain 1999).

CLASSIFICATION OF ANNS

ANNs may be classified in many different ways according to one or more of their relevant features. Generally, classification of ANNs may be based on the function that the ANN is designed to serve (e.g., pattern association, clustering), the degree (partial/full) of connectivity of the neurons in the network, the direction of flow of information within the network (recurrent and nonrecurrent), with recurrent networks being dynamic systems in which the state at any given time is dependent on previous states, the type of learning algorithm, which represents a set of systematic equations that utilize the outputs obtained from the network along with an arbitrary performance measure to update the internal structure of the ANN, the learning rule (the driving engine of the learning algorithm), and the degree of learning supervision needed for ANN training.

A vast number of networks, new or modifications of existing ones, are being constantly developed. A brief discussion of the most frequently used ANNs, presented in the order of their discovery, is given below.

Hopfield networks

This network is a symmetric fully connected two-layer recurrent network that acts as a nonlinear associative memory and is especially efficient in solving optimization problems. The network is suited to only bipolar or binary inputs and it implements an energy function. Learning is done by setting each weight connecting two neurons to the product of the inputs of these two neurons (van Rooij et al. 1996). When presented with an incomplete or noisy pattern, the network responds by retrieving an internally stored pattern that most closely resembles the presented pattern.

Kohonen networks

These networks, also called self-organizing feature maps, are two-layer networks that transform n-dimensional input patterns into lower-ordered data where similar patterns project onto points in close proximity to one another. Kohonen networks are trained in an unsupervised manner to form clusters within the data (i.e., data grouping). In addition to pattern recognition and classification, Kohonen maps are used for data compression, in which high-dimensional data are mapped into a fewer dimensions space while preserving their content (Zupan and Gasteiger 1999).

Backpropagation network (BP)

These networks are the most widely used type of networks and are considered the workhorse of ANNs (Rumelhart et al. 1986). A BP network is an multilayer perceptron consisting of an input layer with nodes representing input variables to the problem, an output layer with nodes representing the dependent variables (i.e., what is being modeled), and one or more hidden layers containing nodes to help capture the nonlinearity in the data. Using supervised learning, these networks can learn the mapping from one data space to another using examples. The term backpropagation refers to the way the error computed at the output side is propagated backward from the output layer, to the hidden layer, and finally to the input layer. In BP-ANNs, the data are fed forward into the network without feedback (i.e., all links are unidirectional and there are no same layer neuron-to-neuron connections). The neurons in BP-ANNs can be fully or partially interconnected. These networks are so versatile and can be used for data modeling, classification, forecasting, control, data and image compression, and pattern recognition (Hassoun 1995).

Recurrent networks

In a recurrent network, the outputs of some neurons are fed back to the same neurons or to neurons in preceding layers. This enables a flow of information in both forward and backward directions, thus providing the ANN with a dynamic memory (Pham 1994). The BP recurrent ANNs are a simple variant of recurrent networks in which the 'memory' is introduced into static feedforward ANNs by a special data representation (e.g., time delay) followed by training using classic BP (Basheer and Hajmeer 2000).

Counterpropagation networks

These networks are trained by hybrid learning to create a self-organizing look-up table useful for function approximation and classification (Zupan and Gasteiger 1999). As input features are presented to the network, unsupervised learning is carried out to create a Kohonen map of the input data. Meanwhile, supervised learning is used to associate an appropriate output vector with each point on the map. Once the network has been trained, each newly presented feature vector will trigger a response which is the average for those feature vectors closest to it in the input data space, thus simulating a look-up table.

Radial basis function (RBF) networks

These networks are a special case of a multilayer feedforward error-backpropagation network with three layers (Schalkoff 1997). They can be trained by a variety of learning algorithms including a two-step hybrid learning. The hidden layer is used to cluster the inputs of the network (the nodes in this layer are called cluster centers). Unlike the sigmoid transfer function in BP-ANNs, these networks employ a radial basis function such as a Gaussian kernel (Haykin 1994). The RBF is centered at the point specified by the weight vector associated with the unit. Both the positions and widths of these Gaussian functions must be learnt from the training patterns. Each output unit implements a linear combination of these RBFs. The choice between the RBF networks and the BP-ANNs is problem dependent (Pal and Srimani 1996). RBF networks train faster than BP but are not as versatile and are comparatively slower for use (Attoh-Okine et al. 1999).

Biogas and its compounds

AD process is going on in a few stages. Each stage is characterised by the main activity of a certain group of bacteria. During the AD process, the bacteria decompose the organic matter in order to produce the energy necessary to their metabolism. Besides methan and carbon dioxide typically biogas also contains hydrogen sulphide and other sulphur compounds, ammonia, compounds such as siloxanes and aromatic and halogenated compounds. Although amounts of trace compounds are low compared to methane, they can have environmental impacts such as stratospheric ozone depletion, the greenhouse effect and/or reduce the quality of local air. Many volatile organic compounds (VOCs) harmful to the environment or to humans can occur in biogases as they have high vapour pressure and low solubility. Many toxic VOCs are emitted from or formed in household waste which includes cleaning compounds, pesticides, pharmaceuticals, plastics, synthetic textiles and coatings (Reinhart 1993). Aromatic and chlorinated hydrocarbons are widely used in industry as solvents and fluorinated hydrocarbons have been used as refrigerating aggregates, foaming agents, solvents and propellants (Scheutz et al. 2004). If biogas is used for energy production, compounds containing organosulphur or organochloride contribute to corrosion in vehicle or combustion engines (Allen et al. 1997). Biogas containing organic silicon compounds is harmful to engines because the silicon compounds are oxidised to silicon oxides during combustion, causing scuffing to engine parts (Wellinger and Linberg 2000). Biogas from sewage treatment and biogas plants is commonly used for heat and electricity production but also increasingly for vehicle fuel production. Landfill gas is used for heat and electricity production in many countries, but its use for vehicle fuel production is considered in many cases to be too complicated and thus expensive because it contains trace compounds, such as sulphur, chloride and silicon compounds (Shin et al. 2002).

Hydrogen sulfide (H_2S) is a very undesirable component of biogas because of its corrosivity. In boilers and in internal combustion engines it oxidises to sulphuric acid which can dissolve the metal and destroy the engine parts. It is also very toxic for all common fuel cells (NETL 2000). Removal of H_2S is therefore a prerequisite for safe biogas utilisation. H_2S is the end product of the reduction of sulfate and other sulphur containing compounds in anaerobic digestion. Concentrations in biogas up to 5.7 vol.% H_2S were reported (Braun 1982). At this moment no effective tool exists to prevent H_2S production during the anaerobic treatment of sulfaterich wastewater (Hulshoff Pol et al. 2001). Even in the practice applied measures of sulfide precipitation with iron salts (Stachowske 1991) or air injection (Chambers and Potter 2002) are not effective enough to reach the fuel cells tolerances of a few ppm H_2S (NETL 2000). From this point of view a pre-treatment technology, like a bio-scrubber combined with a chemical cleaning, is a good possibility to upgrade the biogas quality to fuel cells tolerances. Therefore, predictive model based control will be necessary so H_2S in biogas production is regulated and pre-treatment functioning is assured (Strik et al. 2005).

Ammonium occurs primarily in biogas from thermophilic digestion and/or if the feed contains considerable amounts of nitrogen (e.g. protein-containing waste). It is the end product of ammonification processes in anaerobic digestion. As a component in biogas it has not been researched until now. Still there is no literature available which constitutively demonstrates the presence of ammonia in biogas. Only Schomaker (2000) noted that 450 ppm ammonia was measured at a biogas plant. Nevertheless, from the Henry constant of ammonia (Stumm and Morgan 1996) and possible reactor conditions it was easily calculated that, when gas transfer limitation is excluded, ammonia should be present in the biogas phase. Some fuel cells tolerate ammonia as a fuel, but other fuel cells like the Proton Exchange Membrane Fuel Cell (PEMFC) or the Phosphoric Acid Fuel Cell (PAFC) are certainly not resistant to ammonia (NETL 2000). For these type of fuel cells research of the ammonia production and prediction in biogas is required. In the combustion process, nitric oxide (NO) is formed from ammonium, which further reacts forming other nitric oxides in the atmosphere. The ammonium concentration in landfill gas is often not more than a few ppm. Also the ammonium concentration in the gas produced in bioreactors is normally quite small. The following factors may cause the ammonium concentration to rise in sludge digestion: the pH value of the process is > 8.3 (e.g. using chicken manure as feed raises the pH value), periodic pumping into the gas space of the fermenter, or turbulent manure inlet (ammonium is stripped from the sludge into the gas) or too fast mixing. An increased pH is more common in high temperature, and high concentrations of ammonium appear mostly in thermophilic processes. Fast mixing or agitation of the sludge contributes to separating the ammonium from the liquid into the gas phase, where the ammonium concentration of the gas rises (Strik et al. 2005; Arnold 2009).

The anaerobic digestion of biomass is a multi stage process involving different types of microorganisms. In addition to macronutrients such as carbon, nitrogen, phosphorus and sulphur, trace elements play a crucial role in the growth and metabolism of anaerobic microorganisms (Takashima and Speece 1989; Goodwin et al. 1990) where they are essential for many physiological and biochemical processes. Many trace elements are metals (Zandvoort et al. 2003). The effect was already investigated by using diverse synthetic media such as acetate in combination with nickel and cobalt (Kida et al. 2001). Several nickel or cobalt ion-containing enzymes involved in methanogenesis have been identified. The nickel tetrapyrrole, coenzyme F_{430}, is known to bind to methyl-S-CoM reductase which catalyzes methane formation from methyl-S-CoM in both aceticlastic and hydrogenotrophic methanogens (Ferry et al. 1993, Ermler et al. 1997). A corrinoid, such as vitamin B_{12}, containing a cobalt ion is known to bind to coenzyme M [CoM] methylase, such as N^5-methyl tetrahydromethanopterin: coenzyme M methyltransferase, which catalyzes a methyl-transferring reaction forming methyl-S-CoM in both aceticlastic methanogens and hydrogenotrophic methanogens (Kenenly 1981; Becher et al. 1992). Adequate availability of essential trace elements for the bacterial community is still a problem when single substrates rather than complex mixtures of materials are used for biogas production. The bioavailability of trace elements for metabolic pathways of the anaerobic bacteria is in most cases not related to the total amount measured in the medium since only a fraction is present in solution (Oleszkiewicz and Sharma 1990). Many parameters such as shifts in pH-value or temperature may lead to precipitation and/or chelation of trace elements thus reducing bioavailability (Mosey et al. 1971; Zandvoort et al. 2003). Especially biogas plants operating with maize silage as single substrate show consistently a lack of trace elements and consequently a decrease of biogas production. This limitation leads to reduced methane yields and to considerable problems due to increasing process instability.

Because critical nickel and cobalt ions in the process of methanogenesis, the determination of two elements in the substrate can be an important point that describes the quality and quantity of microorganisms in the latest, most important stage of the formation of methane. There are many different techniques for their determination in different samples such as atomic absorption, atomic fluorescence, X-ray fluorescence, voltammetric and spectrophotometric methods. Quantitative spectrophotometry has been greatly improved by the use of multivariate statistical methods, particularly principal component regression, partial least square regression and ANNs (Rezaei et al. 2001).

Because of comprehensive topic we focused in the survey on prediction of some most important compounds of biogas. Although the amount of research in this direction is currently small, but their number has become increasing in recent years. We summarized several major cases for the yield predict of methane and some other compounds by means of ANN.

UTILIZATION AND APPLICATION

Elias et al. (2006) used artificial neural network to model the removal efficiency of a biofilter for treating H_2S. They used an experimental database consisting of 194 daily cases. The experimental lab-scale biofilter used for obtaining the data consisted of a PVC column divided into three modules with an inner diameter of 0.10 m and a total height of 1 m. The biofilter was filled with a previously selected material consisting of pig manure and sawdust. This organic packing material itself (specially the pig manure residues) provided the active biomass for H_2S biodegradation and, consequently, no inoculation was necessary. Furthermore, no nutrient supply was carried out during operation. The removal efficiency of the reactor was considered as a function of the changes in the air flow and concentration of H_2S entering the biofilter. In order to obtain true representative values, the removal efficiencies (outputs) were measured 24 h after each input was changed. A MLP (multilayer perceptron 2-2-1) model with two input variables (unit flow and concentration of the contaminant fed into the biofilter) rendered good prediction values with a determination coefficient of 0.92 for the removal efficiency within the range studied. This means that the MLP model can explain 92% of the overall variability detected in the biofilter corresponding to a wide range of operating conditions.

Strik et al. (2005) developed ANNs to predict H_2S and NH_3 (ammonia) in biogas. The experiments concluded that NH_3 in biogas can indeed be present up to 93 ppm. To gain data for model training and validation, two 20 l lab-scale anaerobic completely stirred tank reactors (CSTRs) were operated at 60 °C with a hydraulic retention time of 40 days. One reactor for H_2S production and one reactor for NH_3 production. H_2S and NH_3 concentrations in biogas were modelled successfully using the MATLAB Neural Network Toolbox. A script was developed which made it easy to search for the best neural network models' input/output-parameters, settings and architectures.

The models were predicting the trace compounds, even under dynamical conditions. The resulted determination coefficients were for H_2S 0.91 and for NH_3 0.83. Several model predictive control tool strategies were introduced which showed the potential to foresee, control, reduce or even avoid the presence of the trace compounds.

Mu and Yua (2007) have made a simulating model for the performance of a granule-based H_2-producing upflow anaerobic sludge blanket (UASB) reactor using neural network and genetic algorithm. A model was designed, trained and validated to predict the steady-state performance of the reactor. Organic loading rate, hydraulic retention time (HRT), and influent bicarbonate alkalinity were the inputs of the model, whereas the output variables were one of the following: H_2 concentration, H_2 production rate, H_2 yield, effluent total organic carbon, and effluent aqueous products including acetate, propionate, butyrate, valerate, and caporate. Predictions were performed using the validated model to determine the effects of substrate concentration and HRT on the reactor performance. The simulation results demonstrate that the model was able to effectively describe the daily variations of the UASB reactor performance, and to predict the steady-state reactor performance at various substrate concentrations and HRTs. The values of training determination coefficients for H_2 concentration in the biogas (0.966), H_2 production rate (0.810), H_2 yield (0.882), effluent total organic carbon (0.920) and effluent aqueous products including acetate, propionate, butyrate, valerate, and caporate demonstrate that the ANN learned the relationship between input and output well. The validating coefficients of determination for H_2 concentration in biogas (0.719), H_2 production rate (0.806), H_2 yield (0.843), and effluent total organic carbon (0.854) suggest that the trained GA–NN (genetic algorithm-GA and neural network-NN) model showed no systematic over- or under-prediction with regard to output variables. GA is a class of parallel iterative and global search algorithm with certain learning ability, which repeats evaluation, selection, crossover, and mutation after initialization until the stopping condition is satisfied (Gen and Cheng 1997). Therefore, the model was appropriate to predict the output of the H_2-producing UASB reactor.

Abu Qdais et al. (2009) used the ANN and GA as tools for simulating and optimizing of biogas production process from the digester. The study considered the effect of digester operational parameters, such as temperature (T), total solids (TS), total volatile solids (TVS), and pH on the biogas yield. A multi-layer ANN model with two hidden layers was

Table 1: Structure, architecture and settings of the best found models predicting, respectively, H_2S and NH_3 (Strik et al. 2005)

	H_2S model	NH_3 model
Inputs	Sulfate loading rate (g SO_4-S $m^{-3}d^{-1}$)	Total nitrogen loading rate (g N $m^{-3}d^{-1}$)
	Organic loading rate (kg COD $m^{-3}d^{-1}$)	Organic loading rate (kg COD $m^{-3}d^{-1}$)
	H_2S in biogas (ppm)	NH_3 in biogas (ppm)
		Biogas productivity (m^3 biogas $m^{-3}d^{-1}$)
		Ammonia in reactor (mg N-NH_3L^{-1})
Output	Hydrogen sulfide in biogas (ppm)	Ammonia in biogas (ppm)
Layers	2	2
Hidden neurons	5	7
Transfer functions	Tansig/pureline	Tansig/pureline
Train function	Batch gradient descent with momentum algorithm	Batch gradient descent with momentum algorithm
Learning rate	0.001	0.001
Train epochs	5000	5000
Performance goal	0.02	0.02
Minimum performance gradient	$1X10^{-8}$	$1X10^{-8}$
Momentum constant	0.9	0.9
Maximum performance inc	1.04	1.04
Number of train data	100	131
Number of validated data	35	27

trained to simulate the digester operation and to predict the methane production. The performance of the ANN model is verified and demonstrated the effectiveness of the model to predict the methane production accurately with correlation coefficient of 0.87. The developed ANN model was used with genetic algorithm to optimize the methane size. The optimal amount of methane was converged to be 77%, which is greater than the maximum value obtained from the plant records of 70.1%. The operational conditions that resulted in the optimal methane production were determined as temperature at 36 °C, TS 6.6%, TVS 52.8% and pH 6.4. The study illustrated the importance of model learning with history in accurate description of the methane production process. Integration of the ANN model with GA model resulted in identification of the optimal operational digester parameters that lead to increase of methane yield by 6.9%. The study demonstrated that ANN and GA are useful tools for simulating and optimizing the biogas production from biogas digester under various operational conditions.

Ozkaya et al. (2007) did a study where they presented a neural network model for predicting the methane fraction in landfill gas originating from field-scale landfill bioreactors. Landfill bioreactors were operated with (C2) and without (C1) leachate recirculation. They monitored the leachate and landfill gas components for 34 months, after which they modeled the methane fraction in landfill gas from the bioreactors (C1 and C2) using artificial neural networks; leachate components were used as input parameters (Fig.1). To predict the methane fraction in landfill gas as a final product of anaerobic digestion, they used input parameters such as pH, alkalinity, chemical oxygen demand, sulfate, conductivity, chloride and waste temperature. They used a two-layer neural network with a tan-sigmoid transfer function for the hidden layer and a linear transfer function for the output layer. Fig. 1 shows the neural network structure of methane prediction of landfill gas.

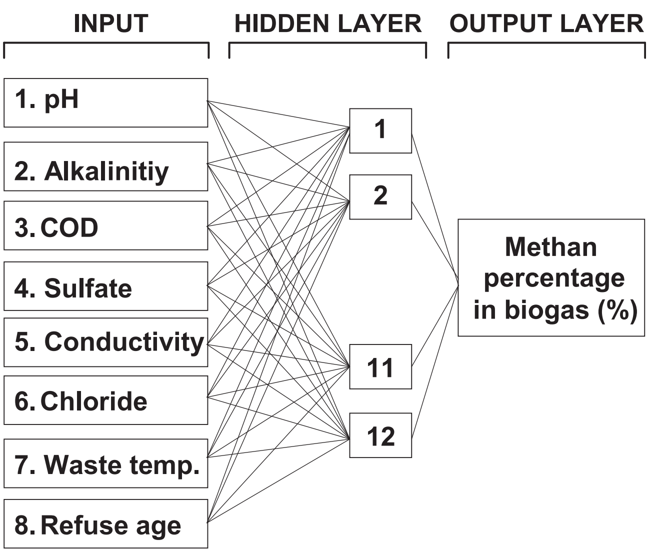

Fig. 1. Optimal neural network structure for methane prediction (Ozkaya et al. 2007)

This ANN has k input and one output parameter that are essential for accurate modeling of the methane percentage of landfill gas from the C1 and C2 test cells. The input parameters and number of neurons within the hidden and output layers should be determined according to the current data. They performed a regression analysis of network response between the network output and the corresponding target. Taking into account the non-linear dependence of the data, the output appears to track the targets reasonably well. Correlation coefficien values are 0.951 and 0.957, and the obtained mean square error values are 0.00263 and 0.00250 for predicted methane percentage of the C1 and C2 test cells, respectively. This study presents neural network methane modeling by considering environmental factors such as water addition (recirculation), waste temperature and leachate components. The neural network modeling can be further developed in terms of predicting hourly methane production based on leachate parameters, control strategies can be extended with the objective of increasing methane production, providing optimization of the conversion to energy of methane gas in landfills, determining the optimum construction time of a waste energy plant at landfill sites, and determining leachate recirculation strategies and strategies for reducing of greenhouse gases.

Rezaei et al. (2001) developed a metod for the simultaneous spectrophotometric determination of the cobalt (II) and nickel (II) based on formation of their complexes with pyrolidine and carbon disulfide. A spectrophotometer was used for recording absorbance spectra. They used a BP-ANN algorithm to handle such non-linear pectoral data. The results showed that the BP-ANN technique is quite satisfactory for treating the non-linearity embedded in the data. The network learns by calculating an error between desired and actual output and propagating this error information back to each node in the network. The results show the good regression between actual values and prediction values for concentration of both elements. Under the optimized conditions, cobalt (II) and nickel (II) can be determined in the range of 0.005 to 0.500 µg/ml. The limits of detection for cobalt (II) and nickel (II) were 0.005 and 0.006 µg/ml, respectively. This procedure allows the simultaneous determination of the mentioned ions in alloy and synthetic samples. Good reliability of the determination was proved.

CONCLUSIONS

It is obvious that ANN are also becoming a powerful tool in the field of biogas production. In spite of the fact that biogas systems are very different, considering tehnological differences and differences of input substrates in areas such as municipal, agriculture, industry, water treatment plants etc., ANNs show a high degree of usability. The results of the summarized researches show high prediction accuracy and usefulness of the ANN which thereby become strong competition to conventional methods of measurement and data processing. Even more, the fusion of both methods and the complementary functioning of soft and hard computing brings many benefits beyond the capabilities of each individual method.

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