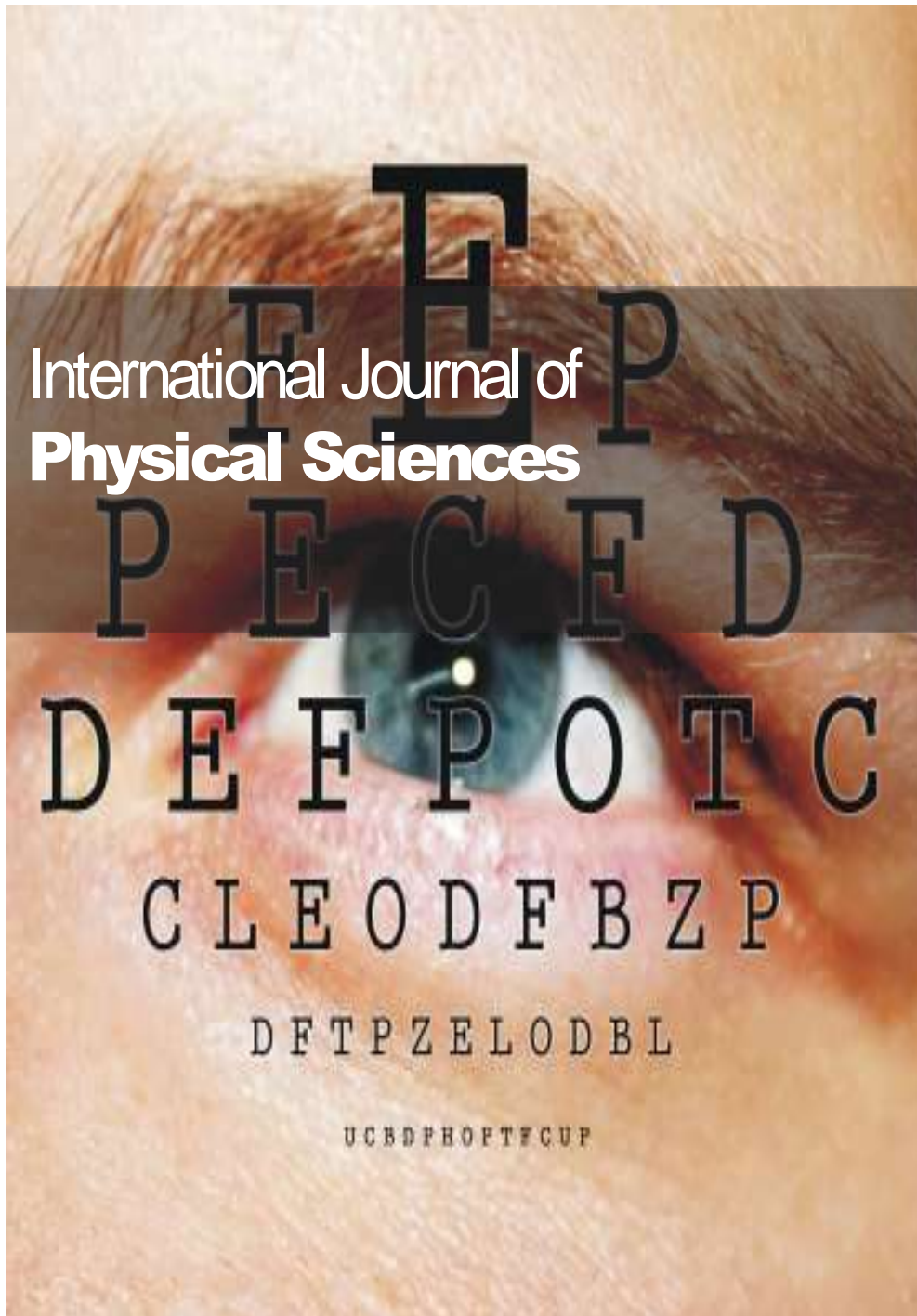


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**Theoretical models for prediction of methane production from anaerobic digestion:  
A critical review**

Mohamed Mahmoud ALI, Nourou DIA, Boudy BILAL and Mamoudou NDONGO



*Full Length Research Paper*

# Theoretical models for prediction of methane production from anaerobic digestion: A critical review

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This work presents a critical analysis for three models group of methanogen potential prediction. The first group allows determination of the methane productivity of substrates, through three models (BMPthCOD, BMPthAtC and BMPthOFC). The BMPthCOD is suitable for a first approximation calculation. BMPthAtC and BMPthOFC are more accurate; however, require a complex characterization of substrates. The second models group predicts the cumulative methane production using seven models. The analysis shows that the Artificial Neuron Network (ANN) is more accurate; moreover, it allows carrying out an optimization of the cumulative methane production. The third group of models is particularly involved in the determination of daily flow of methane by a biodigester. The Hashimoto model, which uses the operating parameters, has been identified as the most suitable.

**Key words:** Biochemical methane potential (BMP), anaerobic digestion, kinetics, methane production, artificial neuron network (ANN), substrate.

## INTRODUCTION

Global energy consumption is largely based on fossil fuels. As a result of this systematic use of fossil fuels, there is a massive release of polluting gases. Similarly, a rapid sedentarization observed in several developing countries, contributes to the production of large quantities of polluting waste. Open dumps or landfills are responsible for significant CH<sub>4</sub> emissions. The reduction of greenhouse gas emissions has led to negotiations at the global level. These are aimed at introducing control measures to increase the share of non-polluting energy in the energy mix of countries. Thus, renewable energies can be an essential alternative to fossil fuels because of their low impact on the environment. However, less than

8% of global energy consumption (about 15 TW per year) is obtained from renewable sources (Roopnarain and Adeleke, 2017). In this sector, biomass provides more than 11.5% of global primary energy and about 79.7% of global energy consumption (Maghanaki et al., 2013). Biogas technology is attracting interest, both for sustainable energy production, natural fertilizers for agriculture (Roopnarain and Adeleke, 2017; Maghanaki et al., 2013), and for the recovery of a large proportion of municipal waste and all rural waste. Biogas technology is an alternative option to generate low-cost energy to address the environmental and health risks of untreated waste that can be used as a source of usable and

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renewable energy (Okolie et al., 2018). The methanogen potentials of the substrates used are often poorly known. A good assessment of potential is in favor of adequate sizing and optimized operation of biogas plants. Currently, the evaluation of the methanogen potential for an organic waste landfill becomes very important. The methane productivity and kinetics of methane production vary from one substrate to another. Several theoretical models have been used on this subject. Nielfa et al. (2015) carried out a study on the theoretical methane production generated by the co-digestion of the organic fraction of municipal solid waste and biological sludge. They compared the results of three predictive models of methane productivity (BMPthCOD, BMPthAtC and BMPthOFC) using organic compositions. As compared to experimental result (BMPexp), a thorough knowledge of the organic composition of a substrate is necessary to determine the methane productivity as well the best configuration of co-digestion with saving of time and cost (Nielfa et al., 2015). Ware and Power (2017) studied the modeling of kinetic methane production of complex poultry slaughterhouse waste using four sinusoidal growth functions (Logistic, Gompertz, Richards and Stannard). Gompertz and Logistic models for three parameter present limitations for complex substrates. When it comes to complex substrates, the Richards model introduces a fourth parameter (Shape coefficient of the curve) that allows a better correlation with the experimental curve (Ware and Power, 2017).

A new model to predict the potential of the methane through anaerobic digestion exists in the literature (Kurtgoz et al., 2018; Antwi et al., 2017; Nair et al., 2016). Artificial Neuron Network (ANN) allows predicting the potential of methane production with the possibility of choosing the number of input parameters. Also, it allows building an algorithm with several output parameters. The main objective of this study is to make an inventory of methane production models in order to propose a more complete model allowing a more accurate prediction of the biogas production.

## THEORETICAL MODELS FOR PREDICTION OF METHANE PRODUCTION

### Methane productivity of substrates

The methane productivity of substrates is defined as the amount of methane produced by an organic substrate during its biodegradation under anaerobic conditions. The need for substrates that can be used as sources of biogas production is continually increasing. The evaluation of methane productivity is increasingly recognized as a necessary parameter for determining the productivity of a substrate. The determination technique called biochemical methane potential (BMP) provides a range of information on the methanogen potential (Ware and Power, 2017). The BMP test is a respirometric test to determine the amount of methane produced under normal conditions of temperature and pressure, knowing the amount of waste (Lesteur et al., 2010). The performance of anaerobic digestion as a biological treatment of various substrates is generally

evaluated by applying BMP tests. Many BMP test protocols have been developed (Nielfa et al., 2015; Lesteur et al., 2010; Raposo et al., 2011; Altas, 2009). Several methods have been used to determine the potential for methane; however, no standard protocol for methanogen potential determination has been presented. It is important to note that several factors can influence the anaerobic biodegradability of organic matter. In several cases, these factors are not described in the procedures (Raposo et al. 2011). Methodologies meant to save cost and time have been developed by several authors (Nielfa et al., 2015; Lesteur et al., 2010; Raposo et al., 2011). Three types of methods for obtaining fast BMP test results have been used: the BMPthAtC model which uses empirical relationships based on the chemical composition of the substrate; the BMPthCOD model based on the COD layer in the substrate and the BMPthOFC model which uses the percentages of the various polymers in the substrate (carbohydrates, lipids and proteins) (Nielfa et al., 2015; Lesteur et al., 2010; Raposo et al., 2011). Tables 1 and 2 presents respectively, a critical description of the three theoretical models for determining the BMP and the analytical equations corresponding to each model, and a description of their parameters.

### Kinetics of production

The kinetics of biogas production represents the variation of the production as a function of time. It consists of modified mathematical models to introduce biological parameters into the model. Numerous models have been used to evaluate cumulative methane production (Gioannis et al., 2009; Lo et al., 2010; Pavlostathis and Giraldo, 1991; Altas, 2009; Manjula and Mahanta, 2014; Li et al., 2012; Jagadish et al., 2012; Kaffle and Chen, 2016; Kurtgoz et al., 2018; Antwi et al., 2017; Nair et al., 2016). Altas (2009) emphasized on the effect of heavy metal inhibitors (Cr, Cd, Ni and Zn) on anaerobic granular methane-producing sludge. It uses the Logistic, Gompertz and Richards models (Table 4 and Equations 1, 2 and 3) to determine the cumulative methane production from the volume of methane produced by a mass of substrate introduced into the digester and the final time of digestion. These three models all agree with experience as mentioned in the references (Ware and Power, 2017; Pavlostathis and Giraldo, 1991; Altas, 2009; Manjula and Mahanta, 2014; Li et al., 2012). However, the results obtained by Gompertz and Richards models are similar and give a better correlation coefficient than that obtained from the Logistic model (Ware and Power, 2017; Altas, 2009). Lo et al. (2010) have realized a comparative study of four models (Gompertz, linear, Gaussian and exponential) as a function of substrate density from the bioreactor. This study has shown that the exponential model better calculates the cumulative methane production for a density of 10  $\text{g l}^{-1}$ , while the Gaussian model is more suitable for a density of 20  $\text{g l}^{-1}$ . The linear and exponential models give a better correlation coefficient, for a density of 100  $\text{g l}^{-1}$ , as compared to descending part of the Gaussian model. On the other hand, the Gompertz model provided the best correlation of methane accumulation for all bioreactors (Lo et al., 2010). Using several digesters, Jagadish et al. (2012) discovered that the Gompertz equation allows determining three kinetic parameters: potential of methane production, maximum rate of methane production and the duration of the phase delay time. These parameters are estimated for each digester using the POLYMATH software, with a study of the influence of pH and the dry matter concentration. This study has allowed determining the optimal values of these parameters. Li et al. (2012) estimated the performance parameters of pretreatment methods from anaerobic digestion of energy grass. For this purpose, they used three models, Logistic, Gompertz and transfert (Li et al., 2012). The model results provide good determination coefficients ( $R^2 > 0.980$ ). The transfert model gives a better concordance with the

**Table 1.** Description of the models BMPth.

Models	Model description	Observation	Advantages	Disadvantages
BMPthCOD  (Nielfa et al., 2015; Raposo et al., 2011)	This model allows calculating the production of methane under specific temperature and pressure conditions. It depends on the volatile solid of the added substrate and the amount of molecular methane (mol); It gives a reasonable estimate because it assumes that all quantities of DOC are degradable. This model can be used to study the influence of COD on methane production.	Five input parameters: 1. Gas constant (R = 0,082 atm L/mol K). 2. Temperature of the glass bottle (308 K). 3. Atmospheric pressure (1 atm). 4. Volatile solids of the substrate (mol). 5. Amount of molecular methane (mol).	Assessment of the maximum potential of methane from COD; The model has the advantage of being applicable to several types of substrates; by optimizing the cost and calculation time. The model provides important information on the COD content in the substrate	The substrate is not fully biodegradability.
BMPthOFC  (Nielfa et al., 2015; Lesteur et al., 2010; Raposo et al., 2011)	In this model, the BMPthOFC is determined from the percentages of proteins, carbohydrates and lipids. The percentages of its monomers are multiplied by constant equivalent potentials; which gives unclear results. This model can be used to study the influence of the percentage of proteins, carbohydrates and lipids on the methane production.	Six input parameters, three of them are constants and others are variables: 1. Percentage of protein, 2. Percentage of carbohydrates 3. Percentage of lipids	The model has the advantage of being applicable to several types of substrates (animal waste, slaughterhouse waste and agro-food waste). The model allows obtaining important information on the concentration of various monomers existing in the substrate.	The model gives results with high lipid content. This high content may have an inhibitory effect on the biological process, thus no methane production.
BMPthAtC  (Nielfa et al., 2015; Raposo et al., 2011)	BMPthAtC model can be determined from the stoichiometric equation based on the atomic composition of substrates. This model assumes that N, C, O and H atoms are consumed by bacteria; this condition is difficult to reach because of unexpected inhibitors. It is possible to use this model to study the influence of the quantity of N, C, O and H on the methane production.	Four input parameters which are the equilibrium coefficients for the stoichiometric equation: 1. Percentage of nitrogen 2. Percentage of carbon 3. Percentage of oxygen 4. Percentage of hydrogen	The model has the advantage of being applicable to several types of substrate. The model also offers useful information on the atomic configuration of the substrate.	The model assumes that N, C, O and H atoms are consumed by bacteria, which is not the case in practice.

experimental data than those of Gompertz and Logistic. Manjula and Mahanta (2014) have focused on the effect of temperature on methane production from saw dust and cattle manure. Using five models (linear, exponential, Gaussiann, logistic and Gompertz) and three temperatures ranges (35, 45 and 55°C), it appeared that the exponential model calculates the better methane production. Gaussien model has a better coefficient of determination at 35°C. The logistic and Gompertz models provided similar results

and a better correlation of cumulative methane production. Moreover, Kafle and Chen (2016) have realized a comparative study in the case of batch feeding from five livestock wastes (farm manure, horse manure, goat manure and chicken manure). Three different models have been used: first order and Gompertz. The results show that the first order model agrees well with the experimental values, with a difference relatively less than 3%. Vijay et al. (2016) studied the performance of an anaerobic bioreactor

by determining the methane content (CH<sub>4</sub>) in the amount of biogas produced using ANN and the organic fraction of municipal solid waste. This study emphasized on the effects of various factors such as pH, moisture content, total volatile solids, volatile fatty acids and on methane production. The performance of the learning and validation dataset showed a high correlation coefficient and a very low mean squared error, which reflects a good performance of the model (Vijay et al., 2016). Table 3 presents different

**Table 2.** Model Equations of BMPth.

S/N	Model names	Model equations	Description of the parameters
1	<i>BMPthCOD</i>	$BMPthCOD = \frac{nCH_4 * RT}{p * VS}$ $nCH_4 = \frac{COD}{64(g/mol)}$	BMPthCOD: Theoretical methane production from COD (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ) COD: chemical oxygen demand nCH <sub>4</sub> : amount of molecular methane (mol) R: gas constant (R = 0,082 atm L / mol K) T: temperature of the glass bottle (308 K) p: atmospheric pressure (1 atm), VS: volatile solid of the substrate (g)
2	<i>BMPthAtC</i>	$BMPthAtC = \frac{22,4 \left( \frac{n}{2} + \frac{a}{8} - \frac{b}{4} - \frac{3c}{8} \right)}{12n + a + 16b + 14c}$ $C_n H_a O_b N_c + \left( n - \frac{a}{4} - \frac{b}{2} + \frac{3c}{4} \right) H_2O \rightarrow \left( \frac{n}{2} + \frac{a}{8} - \frac{b}{4} - \frac{3c}{8} \right) CH_4 + \left( \frac{n}{2} - \frac{a}{8} + \frac{b}{4} + \frac{3c}{8} \right) CO_2 + NH_3$	BMPthAtC: theoretical production of methane from the stoichiometric equation (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ) n: percentage of carbon a: percentage of hydrogen b: percentage of oxygen c: percentage of nitrogen
3	<i>BMPthOFC</i>	$BMPthOFC = 415 * \% \text{carbohydrates} + 496 * \% \text{proteins} + 1014 * \% \text{lipids}$	BMPthOFC : Theoretical production of methane from the percentage of proteins, carbohydrates and lipids (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> )

**Table 3.** Description of models cumulative methane production.

Models	Model Description	Observation	Advantages	Disadvantages
Logistic (Ware and Power, 2017; Altas, 2009; Li et al., 2012; Kafle and Chen, 2016)	The logistic function corresponds to the global form of kinetic methane production, an initial exponential increase and a final stabilization at the maximum level of production. This model assumes that the rate of methane production is proportional to amount of methane produced. The model neglects some physicochemical parameters and gives an estimate of the phase delay. The use of this model depending on the optimal temperature or pH, allow reducing delay time.	Four input parameters of model: 1. Potential methane production 2. Specific rate of methane production 3. Phase delay time 4. Final digestion time	The model gives the potential methane production, maximum methane production and production delay time under various conditions, based on the cumulative methane production curve.	Difficult to implement using complex substrate.

Table 3. Contd.

Gompertz (Ware and Power, 2017; Altas, 2009; Jagadish et al., 2012; Kafle and Chen, 2016)	<p>The methane produced is a function of bacterial growth in discontinuous digesters. The modified Gompertz equation links cumulative methane production and digestion time by potential methane production, the maximum rate of methane production, and the duration of delay phase.</p> <p>This equation has been identified as a good experimental model of nonlinear regression and commonly used in the simulation of methane accumulation.</p> <p>This model has same input data as the logistic and presents same principle of utilization.</p>	<p>Four input parameters of model:</p> <ol style="list-style-type: none"> <li>1. Potential for methane production</li> <li>2. Specific rate of methane production</li> <li>3. Phase delay time</li> <li>4. Final digestion time</li> </ol>	<p>The model gives the potential for methane production, maximum methane production, and production delay time under various conditions, based on the cumulative methane production curve.</p>	<p>Difficult to implement using complex substrate.</p>
Richards (Ware and Power, 2017; Altas, 2009; Jagadish et al., 2012; Kafle and Chen, 2016)	<p>The model Richards is a generalization of the Logistic model. It introduces a fourth parameter, shape coefficient. For values: -1, 0 and 1, the Richards model is similar to Exponential, Gompertz and Logistic models.</p>	<p>This model uses same input data as Logistics and Gompertz by adding a fourth parameter (form constant) to improve curve of methane accumulation.</p>	<p>Has the advantage of being applicable for complex substrates.</p>	<p>Hard to implement.</p>
First ordre (Ware and Power, 2017; Altas, 2009)	<p>This simplified model assumes that gas production follows the first-order kinetic in which methane accumulation follows also an exponential increase to the maximum.</p> <p>The model introduces a new parameter, mass of substrate used in the assay.</p> <p>This model can be applied to optimization of mass flow rate of substrate.</p>	<p>Three input parameters for this model:</p> <ol style="list-style-type: none"> <li>1. Potential for methane production</li> <li>2. Dry mass of waste used in assay.</li> <li>3. Methane production rate</li> </ol>	<p>Equation easy to implement,</p>	<p>Do not use production delay time</p>
Transfert (Ware and Power, 2017; Li et al., 2012)	<p>The transfer model has same form that Gompertz; the only difference is the negative sign at the exponential level. We will find curves that have two-member distribution: negative and positive.</p>	<p>Four input parameters of the model:</p> <ol style="list-style-type: none"> <li>1. Potential for methane production</li> <li>2. Specific rate of methane production</li> <li>3. Phase delay time</li> <li>4. Final digestion time</li> </ol>	<p>The model calculates the potential methane production, the maximum methane production and the production delay time under various conditions, depending on the cumulative production curve of methane.</p>	<p>The transfer function predicts a maximum gas production based exclusively on CH<sub>4</sub> production, neglecting other gases that are form by methane.</p>
Artificial neuron network (Kurtgoz et al., 2018; Antwi et al., 2017; Vijay et al., 2016)	<p>The Artificial Neuron Network consists of neurons connected to each other, with connections having digital weights that can be adjusted during training. ANN structures include an input layers, a hidden layers, and an output layers, each with its own neurons.</p>	<p>Ability to operate with several input and output parameters.</p> <p>Their order is available on several software (Matlab, SPSS, etc).</p>	<p>Simple to implement. Adapted to study the influence of the operating parameters and to optimize the production of methane.</p>	<p>Requires a learning base.</p>

**Table 4.** Equations of models of cumulative production of methane.

N°	Model name	Model equations	Parameter description
1	Logistic	$y = A / (1 + \exp[-\frac{\mu m}{A}(\lambda - t) + 2])$	y: Cumulative methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), A: potential for methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), $\mu m$ specific rate of methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> d <sup>-1</sup> ) $\lambda$ : phase delay time (j), t: incubation time (j),
2	Gompertz	$y = A \cdot \exp\left(-\exp\left[\frac{\mu m \cdot e}{A}(\lambda - t) + 1\right]\right)$	y: Cumulative methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), A: potential for methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), $\mu m$ : specific rate of methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> j <sup>-1</sup> ) e: exp (1) = 2,7182 $\lambda$ : phase delay time (j), t: incubation time (j),
3	Richards	$y = A \left(1 + d \cdot \exp(1 + d) \cdot \exp\left[\frac{\mu m}{A}(1 + d)\left(1 + \frac{1}{d}\right)(\lambda - t)\right]\right)^{\left(\frac{1}{d}\right)}$	y: Cumulative methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), A: potential for methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), $\mu m$ : specific rate of methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> j <sup>-1</sup> ) e: exp (1) = 2,7182 $\lambda$ phase delay time (j), t: incubation time (j), d: shape coefficient of the curve
4	First ordre	$y = A(1 - \exp[-kt])$	y: Cumulative methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), k: kinetic parameter without dimension A: potential for methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> )
5	Transfert	$y = A \cdot \exp\left(-\exp\left[1 - \frac{\mu m \cdot e}{A}(\lambda - t)\right]\right)$	y: Cumulative methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), A: potential for methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> ), $\mu m$ : specific rate of methane production (mLCH <sub>4</sub> g <sup>-1</sup> VS <sup>-1</sup> j <sup>-1</sup> ) e: exp (1) = 2,7182 $\lambda$ : phase delay time (j) t: incubation time (j)

models of cumulative methane production for a substrate. These models are used at laboratory level in different countries to evaluate the productivity of a substrate (Gioannis et al., 2009; Lo et al., 2010; Pavlostathis and Giraldo, 1991). The equations of the cumulative methane production model (Table 4) given by different authors show a wide variety of analytical representation of methane productivity for different substrates. These models provide important information on the characterization of substrate productivity

that helps determine the most appropriate model.

#### Daily production

Daily production is the volume flow rate of methane produced by a biogas plant. In order to evaluate the contribution of the digester to the daily household energy needs of a family, a bibliographic synthesis was conducted

on several models. As such, several models of methane production used at bio-digester plant were examined (La Farge, 1995; Executive Board-CDM, 2008; Chen and Hashimoto, 1978).

Table 5 presents the analysis effectuated through observations, advantages and disadvantages of the various models presented. Table 6 show the equations and parameters used in each model. In the present state, due to lack of experimental data in the scientific

**Table 5.** Description of daily biogas production models.

Models	Model Description	Observation	Advantages	Disadvantages
La Farge (La Farge, 1995)	<p>La Farge have developed a model that estimates the methane production multiplying the substrate's methanogen potential by the amount of oxidizable material.</p> <p>The amount of oxidizable material represents 60% of COD.</p> <p>This model allows simulation of the flow of methane with respect to methanogen potential. It also allows analyzing the influence of the quantity of DOC used on production.</p>	<p>Two input parameters:</p> <ol style="list-style-type: none"> <li>1. Methanogen potential of substrate</li> <li>2. Amount of oxidizable material.</li> </ol>	<p>Easy to use with two input parameters. It can use this model to test the model which determines the methanogen potential of substrate presented in the previous section.</p>	<p>The model requires several tests at the laboratory to determine its input parameters, with parameters to optimize the performance of digester.</p>
Vedrenne (Vedrenne, 2007)	<p>This model is similar to La Farge, adding two constant parameters to optimize the production of methane flow.</p> <p>These two parameters depend on the temperature and the hydraulic retention time</p>	<p>Four input parameters:</p> <ol style="list-style-type: none"> <li>1. Potential for methane production;</li> <li>2. oxidizable material;</li> <li>3. Fraction of manure directed towards a management system;</li> <li>4. Methane conversion factor;</li> </ol>	<p>Easy to use with two input parameters</p>	<p>The determination of its parameters requires several tests at the laboratory.</p>
Executive Board-CDM (Board-CDM, 2008)	<p>This model allows estimating the volume of daily methane produced according to COD mas.</p> <p>The model assumes a deterioration of the DOC quantity, a difficult condition to reach, because it requires the optimization of all parameters influencing the digestion at the same time.</p> <p>Measurement of DOC mass for a feed substrate is realized on a single sample. As a result, a failure in the DOC analysis can lead to an over-dimensioning of methane flow produced.</p>	<p>Six input parameters:</p> <ol style="list-style-type: none"> <li>1. Volume of feed waste;</li> <li>2. Fraction of degradable organic matter;</li> <li>3. Methane conversion factor;</li> <li>4. Fraction of COD converts to methane;</li> <li>5. Methane fraction in landfill gas (0.5, IPCC, 2006);</li> <li>6. Coefficient of carbon conversion to methane.</li> </ol>	<p>Easy to handle template with input parameters. These parameters allow make a statistical analysis and to compare with the other models.</p>	<p>Evaluating its input parameters requires a lot of analysis and time.</p>
Hashimoto (Chen and Hashimoto, 1978)	<p>This model determines the volume of methane produced as a function of substrate temperature, hydraulic retention time and the volume of digester. Sizing with these models optimizes the gross mass of substrate, digestion temperature and the hydraulic retention time.</p>	<p>Six input parameters:</p> <ol style="list-style-type: none"> <li>1. Volume of biodigester and specific production;</li> <li>2. Oxidizable material;</li> <li>3. Hydraulic retention time;</li> <li>4. Potential for methane production;</li> <li>5. Operating temperature of the digester</li> </ol>	<p>Easy to use with parameters that can be identified. This model allows optimizing the operating temperature of digester, hydraulic retention time and the mass required to feed the digester.</p>	<p>The percentage of organic matter varies exponentially, so a small variation during determination of this parameter may oversize the flow rate of methane produced.</p>

**Table 6.** Equation of daily production models of biogas.

S/N	Model name	Model equations	Parameter description
1	Vedrenne	$Q_{CH_4} = Bo * Mo * MCF * Sg$	$Q_{methane}$ : Daily methane volume ( $m^3CH_4/day$ ) Bo: Potential for methane production ( $m^3CH_4/kg$ ) Mo: oxidizable material per day (kg/day) MCF: Methane conversion factor. Sg: Fraction of manure oriented towards a management system
2	La Farge	$Q_{CH_4} = Bo * Mo$ $Mo = 0.6 * COD$	$Q_{methane}$ : Daily methane volume ( $m^3CH_4/day$ ) Bo: Potential for methane production ( $m^3CH_4/kg$ ) Mo: Oxidizable material per day (kg/day) COD: Chemical oxygen demand per day (kg/day)
3	Executive Board-CDM	$Q_{CH_4} = Sy * COD * FCM * CODf * F * \frac{16}{12}$	$Q_{methane}$ : Daily methane volume ( $m^3CH_4/day$ ) Sy: Volume of waste feeding the digester ( $m^3$ ) COD: Chemical oxygen demand per day (kg/day) FCM: Methane conversion factor DCOF: Fraction of DOC converted to biogas F: Fraction of methane in landfill gas. 16/12: Coefficient of conversion of carbon to methane
4	Hashimoto	$Q_{CH_4} = B * V * \frac{Mo}{HRT}$ $B = Bo \frac{1-K}{Mm * HRT + K - 1}$ $K = 0.6 + 0.021 * 10^{0.05 * Mo}$ $Mm = 0.013 * T - 0.129$	$Q_{methane}$ : Daily methane volume ( $m^3CH_4/day$ ) B: Methane production per kg of feedstock per day ( $m^3CH_4/kg/day$ ). V: Volume of the biodigester ( $m^3$ ) Bo: Potential for methane production ( $m^3CH_4/kg$ ) Mo: oxidizable material per day (kg/day) HRT: Hydraulic retention time (days) T = Digestion temperature ( $^{\circ}C$ ). K: Inhibit factor related to the value of MB Mm: Kinetic growth coefficient of bacteria, per day, as a function of temperature

literature, these models have been rarely used.

## ANALYSIS AND DISCUSSION

The first types of models studied allow evaluation of theoretical bio-methane productivity (BMPth). This methane potential obtained by BMP test is an essential input parameter and it is widely used in several models of cumulative methane production. This experimental test provides a lot of data such as methane potential, incubation time, etc. The

implementation of BMPth requires the characterization of materials by realizing a database that contains stoichiometric compositions (percentage of hydrogen, carbon, oxygen and nitrogen) and the organic fraction compositions (percentage lipids, proteins and carbohydrates). BMPth results give higher theoretical values than those observed experimentally, because the models assume that the material is totally digested while it is difficult to completely degrade lignocellulosic material. The difference remains below 15%, which shows that these models are a

good precision (Nielfa et al., 2015; Raposo et al., 2011). On the basis of tests realized for different substrates, BMPthOFC model presents the best result (error between 4 and 7%) than BMPthAtC and BMPthCOD models, respectively (error between 5 and 15%) (Nielfa et al., 2015; Raposo et al., 2011). The use of these models requires the characterization of substrate, and presents advantage of being applicable to all kinds of waste, optimizing the cost. The second category is related to kinetic models of cumulative methane production. A review of seven models used to



model the cumulative methane production during anaerobic digestion was effectuated. These models can be used for homogeneous or heterogeneous substrates; majority of the models neglect some important physicochemical parameters (temperature, pH, etc) of the substrate.

Gompertz, logistic and transfert equations present same input data that relates cumulative methane production and digestion time to methane potential, the maximum rate of methane production and the duration of delay phase. Richards model is a generalization of Logistic model, it introduces a fourth parameter, shape coefficient which allows better approach towards experimental curve. For -1, 0 and 1 values of this coefficient, Richards model merges with exponential models of Gompertz and Logistic, respectively. The models used either underestimate or overestimate of the cumulative methane production depending substrate used (Nielfa et al., 2015; Ware and Power, 2017; Kafle and Chen, 2016). The model of artificial neuron networks presents the possibility to predict the production of methane, taking into account, different input parameters. The model is characterized by a high correlation coefficient and a very low mean squared error, which is consistent with the results of several studies in the literature (Kurtgoz et al., 2018; Antwi et al., 2017; Nair et al., 2016). The third category of models determines the daily methane production of a biogas plant. These models have different input data depending on the authors. Only Hashimoto model (Table 6 and Equation 6) takes into account, kinetic of methane production by introducing hydraulic retention time and the temperature of digestion. The Hashimoto model is suitable for sizing a biogas plant. Indeed, from the cumulative methane production model, another model of sizing has been developed, which was not realized by the other models.

## CONCLUSION

This study is a literature review on three categories of methane production calculation models: the methane productivity of substrates, kinetic of production and the daily production. In the first category, the possibility of determining methane productivity was analyzed through three models (BMPthCOD, BMPthAtC and BMPthOFC). The BMPthCOD model is the easiest to use because the amount of volatile solid of the substrate (easy determination), is the only input parameter; on the other hand, it is less powerful because its relative error is higher. However, the BMPthAtC and BMPthOFC models that require characterization of substrate consist of determining several physicochemical parameters (percentage proteins, lipids, etc.). These models are more precise.

The choice of the model is effectuated as a function of time and parameters characterization cost and model precision.

In the second category, the analysis is devoted to descriptive models of kinetic of methane production. According to results of analysis, Gompertz and Logistic models have the best coefficient of determination as compared to other functions (transfert, first ordre and Richard). In addition, the input data (methanogen potential, specific rate of production and phase delay time) for these models are accessible.

Finally, the third part of this study presented a comparative analysis between several models of daily methane production. Hashimoto model has been identified as the only model suitable for biogas plant sizing. In the end, this analysis reveals the following:

1. For the evaluation of methanogen potential, the choice of the optimum model depends on the context.
2. Regarding the cumulative methane production, ANN models are more appropriate.
3. Finally, for the sizing of a biodigester, Hashimoto model is more efficient.

In perspective, the use of current models allows prediction of the methane production and characterization of methanogen potentials of substrates, in order to evaluate, subsequently, the methanogen potential of a discharge. A good prediction of methane production contributes to a good sizing and better monitoring of biogas plants. As a result, a systematic use of predictive models is a major element for the development of biogas technology and its wide dissemination, which necessarily contributes to sustainable local and sub-regional development. Under these conditions, it is very suitable to use ANN models in order to ensure a better prediction and optimization of the potential of methane production and a better sizing of the biogas plants.

## CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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**Nomenclature.**

$\lambda$	Phase delay time	d
$\mu m$	Specific rate of methane production	$\text{mL CH}_4\text{g}^{-1}\text{VS}^{-1} \text{d}^{-1}$
A	Potential for methane production	$\text{mLCH}_4\text{g}^{-1}\text{VS}^{-1}$
B	Daily production of methane per kg of feedstock	$\text{m}^3 \text{CH}_4\text{kg}^{-1}\text{d}^{-1}$
BMP	Biochemical methane potential	$\text{mL CH}_4\text{g}^{-1}\text{VS}^{-1}$
BMPth	Theoretical BMP	$\text{mL CH}_4\text{g}^{-1}\text{VS}^{-1}$
BMPthAtC	Theoretical BMP determined from atomic compositions	$\text{mL CH}_4\text{g}^{-1}\text{VS}^{-1}$
BMPthCOD	Theoretical BMP determined from the concentration of DOC	$\text{mL CH}_4\text{g}^{-1}\text{VS}^{-1}$
BMPthOFC	Theoretical BMP determined from fractions of organic composition	$\text{mL CH}_4\text{g}^{-1}\text{VS}^{-1}$
Bo	Potential for methane production	$\text{m}^3\text{CH}_4/\text{kg}$
COD	Chemical oxygen demand	kg
COD <sub>reduced</sub>	Chemical oxygen demand eliminated per day	$\text{kg d}^{-1}$
DCOf	Fraction of DOC converted to biogas	
d	Shape coefficient of the curve	
F	Fraction of methane in landfill gas	
FCM	Methane conversion factor	
HRT	Hydraulic retention time	d
K	Inhibition factor related to the value of Mo	
k	kinetic parameter without dimension	
MCF	Methane conversion factor	
Mm	Kinetic growth coefficient of bacteria, as a function of temperature	
Mo	Oxidizable material	kg
nCH <sub>4</sub>	Amount of molecular methane	mol
p	Atmospheric pressure	atm
Q <sub>biogaz</sub>	Daily biogas volume	$\text{m}^3\text{d}^{-1}$
Q <sub>méthane</sub>	Daily methane volume	$\text{m}^3\text{CH}_4\text{d}^{-1}$
R	Gas constant	$\text{atm L mol}^{-1}\text{K}^{-1}$
Sg	Fraction of manure oriented towards a management system	
Sy	Volume of waste feeding the digester	$\text{m}^3$
T	Temperature	°C
t	Incubation time	d
$\mu m$	Specific rate of methane production	$\text{mLCH}_4\text{g}^{-1}\text{VS}^{-1}\text{d}^{-1}$
V	Volume of the biodigester	$\text{m}^3$
VS	Volatile solid	g
y	Cumulative methane production	$\text{mLCH}_4\text{g}^{-1}\text{VS}^{-1}$

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