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RESEARCH ARTICLE

Fuzzy approach to predict methane production in full-scale bioreactor landfills

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ABSTRACT

Bioreactor landfills (BRLs) aim to increase moisture content of municipal solid waste to enhance the biodegradation kinetics of the organic fraction and biogas production. Prediction of biogas production is a key tool to design an appropriate energy recovery system from BRLs. In this paper, a fuzzy-based model to predict methane generation in full scale BRLs is proposed. Eleven deterministic inputs (pH, RedOx potential, chemical oxygen demand, volatile fatty acids, ammonium content, age of the waste, temperature, moisture content, organic fraction concentration, particle size and recirculation flow rate) were identified as antecedent variables. Two outputs, or consequents, were chosen: methane production rate and methane fraction in the biogas. Antecedents and consequents were transported in the fuzzy domain by a fuzzyfication procedure and then linked by 84 IF-THEN rules, which stated the effects of the input parameters in a linguistic form. The fuzzy model was built and tested on seven lab-scale studies, representing different operational conditions and waste qualities. The fuzzy model showed good performances in the prediction of methane generation, although lab-scale studies depicted ideal conditions that can be hardly reached in real BRLs. In order to deal with higher heterogeneities and lower data availability typical of full-scale landfills, new antecedents and rules were added to the proposed model. With few adjustments based on the available information, the fuzzy model could be applied to a retrofit BRLs located in Northern Italy. The results confirmed that fuzzy macro-approach can be a powerful and flexible tool able to model the complex processes taking place in BRLs.

Keywords: Bioreactor landfill, fuzzy logic, landfill gas, methane, modeling

1. INTRODUCTION

The concept of bioreactor landfill (BRL) has been introduced in the last few decades with the aim of a more rapid degradation of the organic fraction of municipal solid waste (MSW) [1]. BRLs have been suggested as a more sustainable alternative to conventional “dry tomb” landfills [2]. The main advantages of this technology can be achieved thanks to moisture increase of waste through leachate recirculation as the processes are strongly dependent on moisture content. The liquid injected into the landfill body stimulates microbial activity by promoting higher distribution of substrates, nutrients and From the pioneering work of Pohland [4], a number of studies have shown the positive effects of leachate recirculation on MSW degradation, either at laboratory scale [5]-[10] or on- site applications [11]-[16]. The main advantage of bioreactor landfills is the rapid stabilization of organic fraction, which can be reached in 5-10 years instead of 30-50 years of the conventional landfill [17]. Biogas production can be therefore increased with more volumes in less time, improving the efficiency of the energy recover. Moreover, long-term environmental impact and post-closure care costs can be reduced [11]. The major initial investments and costs related to the liquid injection system and operations can be offset by a number of economic benefits arising from the management of the BRL, including lower costs for treatment and disposal of leachate and the use of biogas for electric energy generation [18]. Although they represent a more sustainable alternative to conventional landfills, BRLs alone are not sufficient. In the perspective of sustainable landfilling, also the amount of biodegradable MSW destined to disposal should be reduced with appropriate pretreatments. The emission potential of waste can be reduced to large extent during pretreatments so that, compared to un-pretreated waste, significantly reduced emissions occur [19]. Mechanical-biological treatment

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(MBT) represents a widespread option for the stabilization of the biodegradable fraction in the residual MSW. MBTs combine mechanical processes, such as shredding and sorting, with biodrying and biostabilization in order to obtain a more homogeneous and less biodegradable waste [20]-[22]. MBT waste still contains at least 5-20% of the organic biodegradable fraction, which can be finally treated in the landfill body. The combination of MBT and BRL technologies represent an emerging choice in those Italian districts without incineration facilities, aiming to reduce the amount of landfilled organic waste and to optimize energy recovery [23], [25]. In such emerging scenarios with lower organic content and different landfill configurations, where few and sometimes controversial data are available from previous studies [20], [23], [25] it becomes challenging to predict methane production without introducing high uncertainties. The prediction of biogas production in the landfill is commonly affected by uncertainties, due to the heterogeneity of the system, whose properties are changing both spatially and temporally during the landfill life. A landfill is a complex system in which different and interconnected processes take place. Biological processes play the main role in waste degradation, but they are strictly related to others of different nature such as physico-chemical, hydrological and geotechnical processes [26]. The description of all the processes involved become more challenging in case of BRLs, due to additional liquid injections and moisture distribution into the landfill body. Generally, biogas generation rates are estimated using mathematical models dependent upon poorly defined factors, thus introducing significant uncertainty in the modelling process and therefore in the its estimations [27]. In the literature, the most used model is the first-order [28]-[31], described by Equation (1):

$$Q = ML_0ke^{-(t-t_i)} \tag{1}$$

where Q is the methane production (m^3 yr^{-1}), M is the disposed waste (ton), L_0 is the biochemical methane potential (BMP) (m^3 ton^{-1}), t is the time after waste placement in the landfill (yr), t_i is the lag phase between the placement and the start of production, k is the first-order rate constant (yr^{-1}). Models like Equation (1) are intended for single batches or single years; every batch has to be integrated along the year the landfill was in service in order to build the whole gas generation curve, valid for the entire landfill. The first-order model is the most reliable model since the outcomes of the zero-order model present relatively high errors while higher order models have more complicated procedures in order to estimate the parameters, which are not justified by the increase in accuracy [27]. First-order model has two main adjustable parameters: the BMP (L_0), and the methane generation rate constant k. Both of them can be defined through lab-experimentations, pilot-scale cells or from ranges of the literature, in order to obtain a best-fit on field data and minimize the residual errors between the predicted and the experienced methane production [26]. In the pilot-scale study by Bilgili [30], BMP test was used to determine initial and remaining L_0 during the landfilling operations. However, it is often challenging to obtain accurate field-scale data in order to calculate and validate the model parameters [27], [29], [32], [33]. In attempt to solve the limitations of deterministic approaches, artificial intelligence based models, such as fuzzy logic, have recently been conducted in the modeling of complex systems, thanks to their predictive capabilities by handling a large number of parameters of non-linear nature [34]-[36]. As reported in the pioneering work of Ruggeri and Sassi on fuzzy modeling of bioreactors [37], if the complexity of a system increases, its quantitative information become more and more incomplete. The use of macro-approach based on qualitative knowledge about BRLs behavior can offer an easier alternative in CH_4 production modeling. Fuzzy approach is a macro-approach that is able to consider numerous aspects affecting a specific process, without the necessity to handle differential equation models with high computational efforts. In its knowledge-based structure different sources of information can be combined, not only experimental data but also literature, theoretical findings and expertise. As reported by Turkdogan-Aydinol and Yetilmezsoy [34], in the prediction of biogas and methane production rates of a pilot-scale anaerobic digester treating molasses wastewater, the applicability of fuzzy logic is very simple and there is no need to define the complex reactions and their mathematical description or accurate biochemical pathways. To date, few studies have proposed the application of fuzzy logic in the estimation of methane production from BRLs. Garg [33] proposed a multilevel fuzzy composite programming method to combine various parameters affecting landfill gas extraction into a biogas potential index. In addition, a fuzzy logic controller was developed to identify the operational phase of a BRL [36]. Another artificial intelligence based model, that is artificial neural networks, was used to predict methane fraction in biogas by considering leachate components from a BRL [38].In this paper, we propose the use of a fuzzy-logic- based model to estimate methane generation from BRLs at different operating conditions and waste qualities [3], [7]-[9], [24]. Methane production rate and methane concentration in the biogas were predicted from 11 input parameters describing (*i*) leachate quality, such as pH, RedOx potential (*ORP*), chemical oxygen demand (*COD*), volatile fatty acids (*VFA*), ammonium content; (*ii*) waste quality, such as age, moisture content (*MC*), organic fraction concentration, particle size; (*iii*) operational conditions, such as temperature and leachate recirculation flow rate. In a first step, the fuzzy model was developed using experimental data from seven lab-scale studies simulating BRLs. The seven studies were selected because they were representative of BRLs with different properties and operating conditions. In this way it was possible to develop a model that could be applied in a wide range of scenarios. The second step consisted in modeling the full-scale case study of Cerro Tanaro (CT) landfill, a retrofit BRLs for MBT waste located in Northern Italy. Using the previously developed model as a basis, new inputs and rules were added in order to adjust the model for the prediction of CH_4 generation from a single gas extraction well. Finally, the modeling was extended to the entire volume of CT landfill and an estimation of its heterogeneity could be made by comparing the model results to the actual landfill data. The main aims of this study were to confirm the potential use of fuzzy macro-approach for complex processes taking place in BRLs and to offer a valid basis of a biogas prediction tool for BRLs, which can be easily adapted to various site-specific conditions.

2. MATERIALS AND METHODS

2.1. Fuzzy-Logic-Based Model from Lab-Scale Studies Input and Output Parameters

Eleven input parameters were selected among the main factors influencing methane production in BRLs (Table 1). Methane production rate and methane concentration in biogas were the two desired outputs (Table 1). The input parameters describing the leachate quality were chosen because they provide information about waste decomposition phase and waste stabilization [36], [38]: anaerobic digestion is stable for pH in the range 6.5-7.5; ORP shows if a reducing environment is present to support methanogenesis; COD is and indirect measurement of the total oxydable organic content; VFAs is an indication of how the acidogenic and methanogenic microorganisms interactions are well balanced, in fact if acidogenic phase prevails high amount of VFAs causes a decrease of pH with the inhibition of CH_4 production; accumulation of NH_4^+ due to recirculation can lead the concentrations of NH_4^+ in the inhibition range [7]. Waste quality parameters such as waste age and percentage of organic fraction are indexes of how much biodegradable matter can be converted into methane. In the most of laboratory experimental works, the waste was previously shredded, because lower particle size increases the available surface for microorganisms and nutrients distribution, hence decreasing mass transfer phenomena always present in such systems. Due to the difficulties in taking into account this kind of phenomena by a deterministic approach, mean particle size of waste was selected as macro parameter able to give indication of the amplitude of the mass transfer phenomena. Optimized moisture content provides an aqueous environment containing the necessary nutrients and microbes able to improve micro/macro convective phenomena in the waste [39]. Regarding the operational conditions, most of the landfills operate in the mesophilic field, in the range 30-35 °C, depending on climate conditions. A proper flow rate for leachate recirculation should increase MC and liquid distribution, without causing flushing of organic matter and methanogens bacteria [26]. Methane generation can be estimated through the two outputs methane production rate and methane concentration in the biogas. The fuzzy logic based model thus offers a tool to predict an efficient energy recovery strategy of BRLs. The cumulative methane production was calculated from the methane production rate with Equation (2):

$$Q_{CH_4} = \sum_{i=0}^{n} R_i \Delta t_i \tag{2}$$

where Q_{CH4} is the cumulative CH_4 production (L kg^{-1}), R_i is the CH_4 production rate at day i (L kg^{-1} day^{-1}), Δt is the time interval with rate R_i (days), n is the total time of operation (days).

Table 1. Input and output parameters of the fuzzy-logic-based model for laboratory BRL

	Parameters
	INPUTS
Leachate quality	pH
	ORP (mV)
	COD (mg O_2 L^{-1})
	VFA (g CH_3COOH L^{-1})
	NH_4^+ (mg L^{-1})
Waste quality	Age (yr)
	Moisture content (% *w/w*)
	Organic Fraction (% *w/w*)
	Particle size (cm)
Operational conditions	Temperature (°C)
	Recirculation flow rate (% V water/V waste day^{-1})
	OUTPUTS
Methane generation	CH_4 production rate (L kg^{-1} day^{-1})
	CH_4 concentration in biogas (% *v/v*)

2.2. Fuzzy Model Development of Lab-Scale BRLs

The fuzzy logic based model of BRLs was developed using data from different literature sources, all at lab-scale, working in different operating conditions and different initial waste compositions. The implementation of the model was carried out by using the Fuzzy Logic Toolbox present in MATLAB (MATLAB® V8.3). Here only a brief introduction on fuzzy logic is reported, major details can be found in [40], its application in bioreactor engineering is presented in [41] while a model for biogas estimation in anaerobic digestion in described in [34]. A general fuzzy model has basically four steps: (*i*) fuzzification which permits to move from the deterministic to the fuzzy dominion, (*ii*) fuzzy rules definition in order to describe the reality to be modeled, (*iii*) fuzzy inference engine which handle fuzzy variable inputs to obtain fuzzy outputs, and (*iv*) defuzzification procedure to convert the fuzzy output back to the deterministic dominion.

In the first step, the numerical values of inputs and outputs from [3], [7]-[9], [24] were converted into linguistic terms, fuzzy sets, thus defining the antecedents and consequents of the system. The degree of truth of a fuzzy set A (verbal variables such as low, medium, high etc.) is defined by a value of membership function (MF), μ_A, in the interval [0 1], differently from conventional deterministic numerical sets where an element either belongs or does not belong to a particular set (μ_A= 0 or μ_A=1). Abdallah [36] reported that this distinctive feature is advantageous in case of controlling a landfill where the change in input variables does not cause the controlled process to shift abruptly from one state to another. MFs can be represented in different shapes such as triangular, trapezoidal, Gaussian or Sigmoid, depending on the system under study. Among them, triangular and trapezoidal are the most used, due to their simple handling and implementation [35]. In our case, all the MFs for both antecedents and consequents presented trapezoidal shape, as shown in Equation (3):

$$A(x)=\begin{cases}0, & x\leq a\\ \dfrac{x-a}{b-a}, & a\leq x\leq b\\ 1, & b\leq x\leq c\\ \dfrac{a-x}{a-c}, & c\leq x\leq d\\ 0, & x\geq d\end{cases} \tag{3}$$

where μA is the MF of a vector x, and *a, b, c, d* are four scalar parameters. As example, the MFs of two of the eleven antecedents inputs are showed in Fig. 1 with their shape and linguistic labels: very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H) and very high (VH); the same linguistics variable were adopted for the two consequents. The second step, concerning the definition of fuzzy relations between antecedents and consequents, resulted in 84 rules in the form of IF-THEN statements, which were established through the experience and the experimental data sets. Approximately 70% of the available crisp data were used to train the model and build the corresponding fuzzy rules with the Fuzzy IF-THEN Rule Editor on the MATLAB® environment. An example of one of the IF-THEN rules is presented below:

IF 'PH' is 'M' & 'ORP' is 'M' & 'COD' is 'VL' & 'VFA' is 'VL' & 'NH_4' is 'VL' &

'MC' is 'L' & 'T' is 'M' & 'ORG' is 'M' & 'SIZE' is 'M' & 'FLOWRATE' is 'VL'

THEN 'CH_4 RATE' is 'VL' & 'CH_4%' is 'VL'.

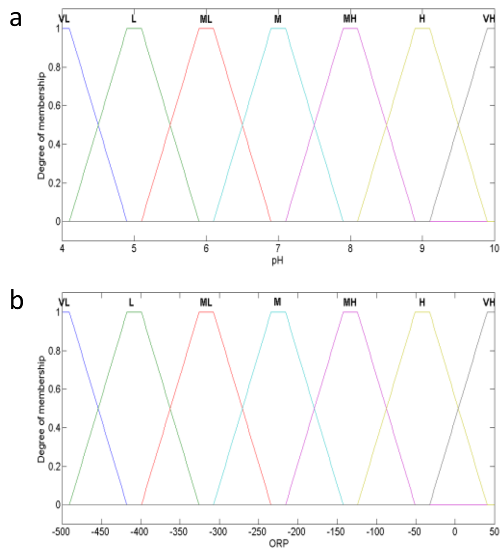

Fig 1. Membership functions of the fuzzyfied inputs: a) "pH" and b) "ORP" (mV).

Once the MFs and the rules had been built, it was possible to enter the fuzzy model with a set of inputs and obtain the corresponding outputs. The experimental data of laboratory tests of different Authors under different operational conditions were used as inputs, Table 2 reports the main characteristics of experimental tests. The model was tested on the total number of available inputs from the chosen lab-scale studies. The fuzzy outputs were calculated through the fuzzy inference engine that processes the fuzzy inputs based on their relevant fuzzy rules. Mamdani-type fuzzy inference method was chosen, as it is the most commonly applied fuzzy methodology [34]. The last step is the defuzzification procedure, which incorporates different fuzzy sets to give a single crisp value in the deterministic domain for the two outputs. The defuzzification method here used was the centroid or center of gravity method which is the most popular among different defuzzification methods [42],[43]:

$$(yi)d=\frac{\sum_i \mu(yi)yi}{\sum_i^r \mu(yi)} \tag{4}$$

Where $(yi)_d$ is the defuzzified output, *r* is the number of fired rules for the specific situation, y_i is the output value in the *i* subset and μ_i is the MF value of y_i.

Table 2. Summary of the different characteristics of the seven lab-scale studies used.

Ref. Study	Main characteristic
[7]	29% organic content; low initial MC; constant low leachate recirculation rate
[7]	8 years old waste; 29% organic content; low initial MC; constant low leachate recirculation rate
[3]	tropical climate; 55% organic content; recirculation rate of leachate + water increasing with time
[3]	tropical climate; 55% organic content; recirculation rate of only leachate increasing with time
[9]	aerobically pretreated waste; 40% organic content; constant low leachate recirculation rate
[8]	synthetic waste; 45% organic content; constant leachate recirculation rate
[24]	MBT waste, low biodegradable waste, leachate recirculation rate decreasing with time

2.3. *Extension of Fuzzy Model to CT Landfill Case Study*

The case study of CT landfill depicts a scenario typical of small/medium Italian waste management facilities without incineration plants. CT landfill had been originally built as a conventional landfill for non-hazardous pretreated wastes. After source segregation, the residual MSW was pretreated in a MBT plant in order to reduce considerably the amount of organic waste destined to landfilling, according to the EU Landfill Directive (Directive 1999/31/EC). Low water content and lack of rapidly degradable matter implied slow biogas production and long post-management period. With the Bio.Lea.R. Project [47] financed by EU Life+ Program, part of CT landfill was equipped with a leachate recirculation system, in order to optimize the moisture content and the energy recovery with a retrofit BRL technology. The landfilled MSW was hence characterized by a low organic content, which had been pretreated by means of aerobic MBT and partially bio-decomposed in the conventional landfill operations. The peculiarity of this case study made it difficult to predict biogas production with conventional deterministic biogas models, due to the lack of information regarding the kinetics of methane generation from that specific low biodegradable waste. Moreover, the amount of moisture increase into the landfill body under leachate recirculation could not be quantified. Although experimental tests were conducted at lab-scale and pilot-scale to investigate the behavior of CT landfill [24], they represented an ideal scenario with very little spatial heterogeneities, which is very difficult to obtain at full scale. The up-scaling of the laboratory results to the full-scale BRLs is not an easy task due to the different scale of heterogeneity of the mass of waste and the spatial/temporal changes of the leachate properties that cannot be controlled. These were the main reasons why the use of fuzzy logic seemed to be a proper choice to model methane generation from CT landfill. However, the fuzzy-logic-based model developed on lab-scale studies had to be adjusted to obtain a better fitting of the different conditions and the lower data availability encountered in the full scale plant of CT. The extension of the fuzzy-model based on the laboratory results to full scale landfill was reached by two steps: first a cylindrical volume, around a single biogas extraction well, was modeled introducing additional antecedents able to depict the heterogeneities of the well behavior calibrated on the quality and the quantity of biogas experimentally evaluated, and then the extension to the entire volume of the landfill by considering the total experimentally evaluated biogas produced, as described in the following sections.

2.4. *Fuzzy-Logic-Based Model for a Single Well of CT Landfill*

The leachate recirculation system of CT landfill mainly consists of 8 sub-irrigation rings of 20 m diameter, located at the top of 8 gas extraction wells, under the final waste capping, as shown in Fig 2. Leachate recirculation was initially conducted on three injection rings, chosen because their relative wells gave the worse performances in term of methane generation. At the beginning of the experimentation, the injection was performed on one ring at a time, in order to monitor if some liquid leakage could occur, with a flow rate in the range 5-2.5 $m^3\ h^{-1}$, 8 hours per day. In particular, the gas extraction well named CTB110 (Fig 2.) had the longest injection time and its data on methane production were used for the fuzzy-logic modeling. In order to apply the fuzzy model on CT landfill, a cylindrical volume around one biogas extraction well was chosen as control volume. Taking into consideration that a depression at the head of the well of around 15-20 cm H_20 generates a depression which propagates till around 10 m in the landfill body of usual compaction (0.5-0.7 ton m^3) [48], the dimensions of the control volume were assumed to be cylindrical with 10 m radius and 13 m height, that is the actual height of CT landfill. The control volume consisted in approximately 3,500 ton of pretreated waste. 20 sets of crisp experimental data from the monitoring of leachate and biogas quality, along 1.5 years (January 2014 to July 2015), were used to develop the fuzzy model. The first problem encountered dealt with the data of monitoring of leachate, since they were representative of the leachate of the entire landfill and did not depict the specific conditions of the control volume alone. Moreover, in contrast to what happened in lab-scale, where temperature was maintained constant, at full-scale local changes of the leachate temperature occurred depending on the seasonal variation (10 – 30 °C). Although temperature inside the CT landfill body could not be monitored, by analyzing the available data, it was noticed that during the summer an increase of methane generation was registered from CTB110 under leachate recirculation.

In order to fuzzy model the biogas production from the well two new antecedents were added to the lab fuzzy based model. The first originated by the observation of behaviors under seasonal temperature variation above reported; antecedent called "*season*" was used. Another important parameter is the moisture content of the landfill body that could not be monitored at the full-scale plant.

Considering that the moisture is dependent on the quantity of recirculated leachate, another antecedent was added "*Vrec*", which is the volume of leachate re-added in the landfill; this is considered an index able to give information of the moisture present in the landfill.

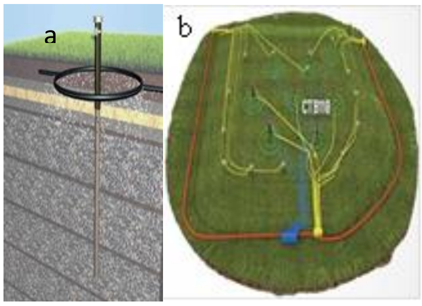

Fig 2. Illustrations of the sub-irrigation system in CT landfill: a) detail of a sub-irrigation ring around one gas extraction well; b) landfill surface showing, gas extraction system (yellow lines), and leachate injection system (blue lines) with the 8 sub-irrigation rings [47].

The final adjustment made on the lab fuzzy-logic-based model regarded the addition of a membership function named very very low, "VVL", in the output variable of CH_4 production rate. This was necessary in order to capture the changes in methane production at the very lower rates recorded on the full-scale, compared to the ranges obtained at lab-scales.Thanks to the above described adjustments, whose MFs are reported in Fig 3, on the model developed from lab-scale studies, it was possible to build 20 new IF-THEN rules, able to simulate the behavior of CTB110. In order to avoid overfitting, the fuzzy model was then tested on other 10 sets of data, in addition to the 20 sets used to develop the model.

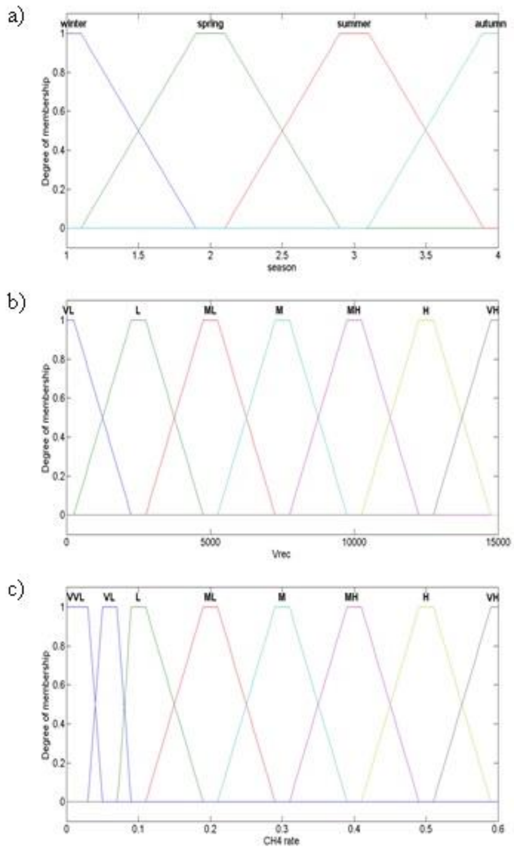

Fig 3. Extension of fuzzy model to biogas capture well: MFs of the new antecedents a) "season" and b) cumulative volume of leachate recirculated "*Vrec*" (m^3) and the modified label of output c) "CH_4 rate" (L kg^{-1} day^{-1}).

2.5. Extension of the Fuzzy-Logic-Based Model on the Entire CT Landfill Volume

The fuzzy-logic-based model of a single gas extraction was used to simulate the entire volume of CT landfill. It was assumed that each of the 26 vertical wells behaved following the IF-THEN rules developed for the well CTB110, as if the waste properties were homogeneously distributed on the entire volume. By comparing the fuzzy model results on biogas production with the actual biogas data of all the 26 wells, it was possible to evaluate the spatial heterogeneity via a Heterogeneity Index (*HI*), expressed as discrepancy between the predicted and the observed data of the total biogas production rate from CT landfill:

$$HI = \left| 1 - \frac{\sum_{i=1}^{n} {P_{RATE\,i}}/{P_{\%\,i}}}{\sum_{i=1}^{n} {Q_{RATE\,i}}/{Q_{\%\,i}}} \right| \tag{5}$$

where P and O are the predicted and the observed values, respectively, of methane production rate (RATE) and methane fraction (%) of the i_{th} well.

3. RESULTS AND DISCUSSION

3.1. Lab-Scale BRL Fuzzy Model

The outputs of the fuzzy-logic-based model were compared with the experimental data from [3], [7]-[9], [24]. The proposed model could fit reasonably well the experimental data from 7 lab-scale studies simulating BRLs working at different conditions and with different MSW qualities (Table 2). Fig 4 and Fig 5 show a good agreement between observed and predicted data from two of the selected lab-scale study, while Fig 6 illustrates the goodness of fit with the performance indicators R2 for all the laboratory data. The fuzzy model fitted the experimental methane production data reasonably well, with small deviations and coefficient of determination of 0.96 and 0.95 for cumulative and fraction of CH_4, respectively. The results suggested that the approach chosen, although applied on lab-scale studies, could be a valid basis to predict landfill gas production from BRLs with a wide range of operational conditions and it paved the way for the application of fuzzy modeling on the full-scale.

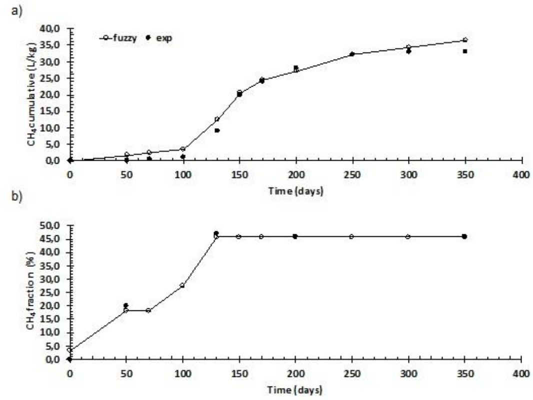

Fig 4. Comparison of experimental data and fuzzy modelling results of a) cumulative methane production and b) methane fraction from [7].

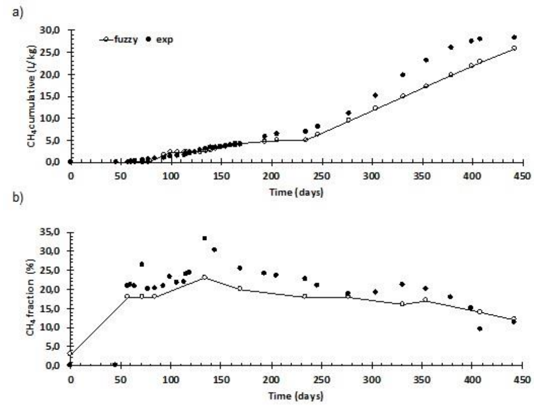

Fig 5. Comparison of experimental data and fuzzy modelling results of a) cumulative methane production and b) methane fraction from [24]

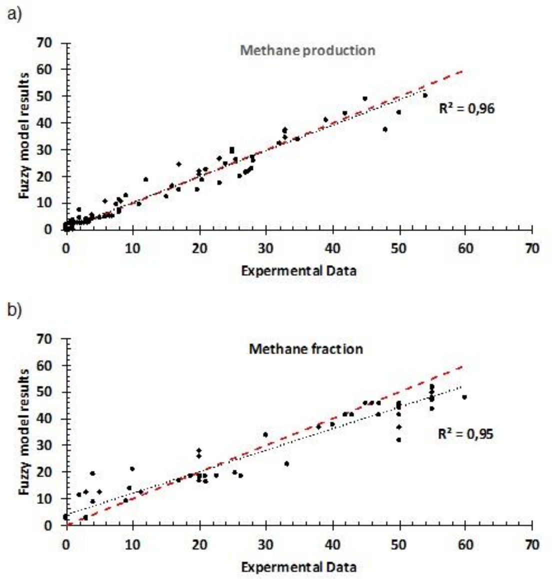

Fig 6. Linear regression between the fuzzy model outputs and the corresponding lab experimental data with the resulting R2 for a) cumulative methane production and b) methane fraction in the biogas.

3.2. Full-Scale BRL Fuzzy Model

On the basis of the data available on the full-scale plant of CT landfill, the proposed lab fuzzy-logic-model was adjusted in order to predict methane and biogas production from pretreated MSW under leachate recirculation. Although this case study was characterized by lack of information from the previous literature, fuzzy modelling represented a valid tool which could be easily adapted to the specific system under study. The prediction of methane generation from well CTB110 gave good results. Fig 7 shows the comparison of predicted and detected results. The performance indicator R2 of 0.99 and 0.66 for cumulative methane production and methane percentage, respectively confirmed a good agreement between the predicted and the actual data, especially for the first output.

In order to extend the model on the entire volume of BRL, the modified fuzzy model developed on the single well CTB110 was applied to all the 26 wells present in CT landfill. By comparing the total biogas generation rate observed and predicted on one day, it was possible to quantify approximately the spatial heterogeneity of the system with the calculation of the index HI through Equation (8), which resulted of 9.7%. It means that approximately 90.3% of the total volume of CT landfill behaved as the modelled control volume around well CTB110 in terms of biogas production rate, expressed as fraction between the two outputs CH_4 rate and CH_4 fraction. The HI index is a corrective index of the fuzzy model output in the simulation of other full scale BRL landfill with similar quality of refuses and under similar environmental condition of CT landfill. For different situations the above procedure permits to evaluate analogous HI index.

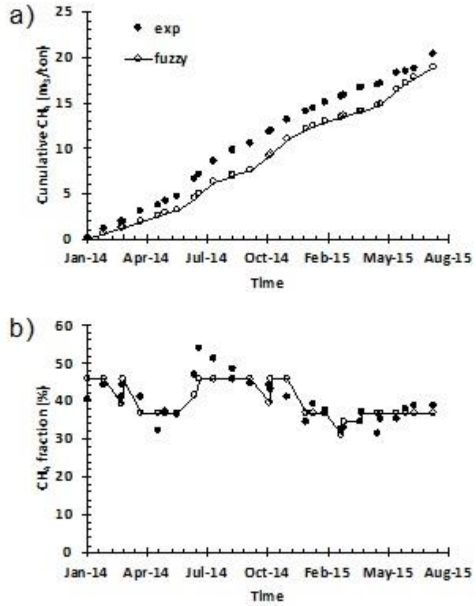

Fig 7. Comparison of one well of Cerro Tanaro full plant experimental data and prediction from modified fuzzy-logic-based model for a) cumulative methane production and b) methane fraction from one gas extraction of CT landfill.

The results obtained by applying the fuzzy-logic-based model on the full-scale confirmed the flexibility of fuzzy modelling, thanks to its learning structure able to represent complex systems with any kind of available information. Without formulating complicated mathematical equations, it was possible to adapt the model to the specific scenario represented by CT landfill. This approach can be further applied on a number of different BRL technologies, with no need of detailed data, which are often difficult to collect and manage in the case of full-scale facilities.

4. CONCLUSION

A fuzzy-logic-based model was developed for the evaluation of methane production rate and methane fraction in landfills under leachate recirculation, using experimental data of literature of lab-scale studies simulating BRLs. In new generation landfills, aiming at more sustainable waste management, biogas generation estimation is a key tool to run an efficient energy recover and to evaluate energetic and environmental sustainability. In complex and heterogeneous system, such as a BRL, the existing models are often affected by high uncertainties due to the difficulty in identifying all the interconnected processes and in collecting all the necessary data. The fuzzy-logic-based model proposed can be a simpler alternative to the deterministic approaches, which need complex and tedious mathematical formulations with difficult tuning parameters. The fuzzy model showed good performances in the prediction of methane generation for different lab-scale BRLs. The results showed good agreement between the observed and the predicted data, suggesting that the approach chosen, although applied on lab-scale studies, could be a valid basis to predict landfill gas production from BRLs with a wide range of operational conditions.

The proposed fuzzy model was then applied on the full-scale case study of CT landfill, a retrofit BRL treating MBT waste. Although this case study was characterized by lack of information from the previous literature, fuzzy modeling represented a valid tool which could be easily adapted to the specific system under study. Few adjustments were made on the model in order to better fit the data of methane generation, based on the available inputs. Additionally, by applying the model on a smaller control volume of landfill and extending the results on the entire landfill volume, it was possible to quantify approximately a mean value of the spatial heterogeneity of CT landfill. It resulted that the proposed fuzzy model was able to predict 90.3% of the total biogas production rate, suggesting that 9.7% of the waste volume had a different behavior of the selected control volume of landfill due to its heterogeneities.

Finally, the results obtained both on lab-scale and the extension to full-scale confirmed that fuzzy approach is a powerful and flexible tool that, thanks to its learning structure, is able to model the complex processes taking place in BRLs, with no need of sophisticated mathematical modeling and accurate value of parameters, but simply the necessity of accurate as much as possible, of the site-specific information.

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