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Anaerobic Digestion Process Modeling Under Uncertainty: A Narrative Review

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ABSTRACT

Growing concern about global climate change has led to considerable interest in investigating renewable energy sources such as the biological conversion of biomass to methane in an anaerobic environment. Through a series of complicated biochemical interactions, it uses various bacterial species to degrade biodegradable material in the feedstock. Due to the complex and interacting biochemical processes, anaerobic digestion has nonlinear dynamics. Anaerobic digestion is highly at risk of instabilities and uncertainties because of its dynamic and nonlinear behavior, uncertain feedstock quality, and sensitivity to the process's environmental conditions. Therefore, effectively operating a biogas production unit necessitates a thorough understanding of the system's uncertainties. The present study aims to identify and assess the sources and methods of coping with the uncertainties in anaerobic digestion processes through a narrative review. Moreover, the knowledge gap is also investigated to reveal the challenges and opportunities to have a robust model. The results indicate that the unpredictability of model parameters and input variables were the most significant source of uncertainty, and the Monte Carlo technique, confident interval, and interval observers, as well as sensitivity analysis were the most frequently used tools to cope with these uncertainties.

1. INTRODUCTION

Global population growth, industrialization, and a rising quality of living are all driving up energy demand [1]. Still, fossil fuels are the most common energy source, accounting for 79.9% of total demand [2]. Hence, alternative energy strategies for creating and using clean, renewable, dependable and sustainable energy sources are being sought. In contrast with the aerobic treatment of organic waste, anaerobic digestion (AD) can produce usable biogas utilized for energy production [3]. Biogas production by the AD process has been demonstrated to be a sustainable, renewable, and carbon-neutral energy source that can help reduce the world's reliance on fossil fuels and carbon footprint [4]. Being a multi-step biological process, AD degrades organic materials and converts them into biogas [5]. The main constituents of biogas are methane (50-70%) and CO2 (30-50%). It is a multi-step complex process that includes the following phases: hydrolysis, acidogenesis, acetogenesis, and methanogenesis [6]. Different groups of microorganisms mediate the different steps of the AD process, forming a complex microbial community [5].

Furthermore, changes in the feed composition are inherent to this process, and they can readily lead to the accumulation of intermediate products such as volatile fatty acids (VFAs), hydrogen, ammonia, and other chemicals [7]. This accumulation may inhibit microorganisms, resulting in process failure or reactor instability [8]. Additionally, various disturbances might be added to the process by raising the reactor's load. As a result, operating the AD reactors at modest feed rates is preferable to keep the operation stable [7] while maintaining optimum biogas production. Therefore, determining the ideal substrate feeding rate in the AD process is quite challenging [9].

As a result, modeling the biogas process is quite challenging. On the other hand, depending on the preferences, timing, and framing of the alternative scenarios, among other factors, designers might cope with the model uncertainty in a variety of ways [10]. A distinction must be made between sources of uncertainty, such as data, choices and relations, and types of uncertainty, such as data variability and inconsistency across alternatives [11]. There is uncertainty when there is a lack of information, either there is no data available or the data that are available is incorrect or vague. In contrast, variability may also be regarded as a necessary aspect of heterogeneity, which is the quality of data [12] or multiple values of the same quantity at different times, places, or instances [13]. Barahmand and Eikeland [14] provided a comprehensive overview of different types and sources of uncertainty. Uncertainty can be quantified in a variety of ways. Different techniques can be used depending on the type of model (mathematical, control, etc.). Barahmand et al. [14, 15] described the most used uncertainty modeling techniques. The key difference between these approaches is how they explain ambiguity in input parameters.

Among the most common methods for estimating uncertainty is the Monte Carlo technique [16]. Statistical modeling and random sampling are used in Monte Carlo simulations to estimate mathematical functions and simulate the behavior of complex systems [17]. The purpose of this technique is to develop probabilistic models for real-world processes to estimate specific average properties, such as mathematical expectations, variances, and correlations [16]. A Monte Carlo simulation involves generating random numbers, simulating the random values with a more complicated distribution and performing calculations [18]. In addition to being used directly for uncertainty quantification, the Monte Carlo approach can also be used indirectly in other methods, including global sensitivity analysis (GSA).

Even though sensitivity and uncertainty analysis are often thought of as one activity, they are actually two separate concepts, each with its own purpose, that is often explored in con- junction with one another. A sensitivity analysis (SA) attempts to determine the relationship between variations in input values and variations in outputs [19]. The SA technique is used in numerical models to estimate the effect of uncertainty on one or more input variables on output variables [20]. Additionally, SA can serve as a guide in conducting experimental analyses, reducing models, and estimating parameters [16]. SAs can be either local or global. A local SA examines how small perturbations affect the model's output. Conversely, a global SA is used to investigate the effects of large variations in model parameters on model outputs [21]. The critical aspect of a complex model (such as ADM1) with several input parameters and output parameters is identifying the most influential input parameter or variable on the model's outputs [22]. There is a significant fluctuation in the results when specific assumptions are changed when sensitivity is high; these assumptions must be extremely well established. Changing specific assumptions when sensitivity is high results in significant changes in the output; these assumptions should be extremely well established [15, 23].

Up to this point, all the uncertainties and models mentioned above belonged to mathematical models. Physical systems cannot be fully represented by a single mathematical model, and there may be uncertainties in the system as a result of disturbance signals or changes in system parameters [24]. A good control system in such a scenario should be robust and pro- vide consistent results. In order to cope with the uncertainty of the system, different observers and controllers have been developed. A system observer is a digital algorithm that combines sensor outputs with knowledge of the system to provide results that are superior to those provided by traditional structures, which are entirely dependent on sensors [25]. For example, an interval observer's task is to estimate the system states at each instant in time within certain intervals (upper and lower estimates) to deal with the uncertainty and disturbances that are large but bounded [26].

Modeling the biogas production process mathematically can be very complex, and the digestion process is usually modeled as a black box due to its complexity [27]. By analyzing big data and extracting internal information, machine learning (ML) models can solve non- linear classification and regression tasks [28, 29]. It should be noted that this method is entirely dependent on readily available online data or historical recordings of the process itself [30]. ML involves a cycle of three steps [31, 32]:

- Training: feeding the algorithm with training datasets to allow the model to learn un- noticed patterns in the data;
- Validation: a different dataset is used to improve the performance of the model by fine- tuning the hyperparameters of the classifier;
- Testing: a different sample of data is used to determine the final accuracy of the model.

As much as ML algorithms are capable of managing complex multivariate data, predicting nonlinear connections and managing missing data, choosing the most appropriate algorithm for a given task is critical for achieving the best results [33, 34].

Through a narrative review, the present study aims to identify the primary sources of uncertainty in the AD process and assess the tools and methods used to cope with them to reveal the challenges and opportunities to have a robust model. The present literature review provides a comprehensive, critical, and objective assessment of the current state of knowledge regarding the topic [35]. A narrative review takes a less formal approach than a systematic review [36]. Due to the limited number of sources in the literature, this method was chosen. The study's proposed research questions among the recent studies are:

(1) What are the sources and types of uncertainty in these processes?

(2) What are the tools and frameworks for dealing with uncertainties?

What is the most critical knowledge gap in the research?

2. ANAEROBIC DIGESTION

2.1 AD: Global status

In large piles of organic waste, combustible gas is generated. This fact has been known for centuries. AD technology developed during the previous century was predominantly used to stabilize putrescible solids in domestic wastewater [37]. As a result, heated, fully mixed reactors were developed, which are still widely used for the digestion of sewage sludge and animal manure. As fossil fuel prices declined and their accessibility increased, biogas pro- duction gained popularity during the first half of the twentieth century. However, it declined after the 1950s as a result of the low cost of fossil fuels. In the 1970s, AD regained popularity as a renewable energy source [37]. However, implementation slowed down due to high costs, ineffective management, and high failure rates of the digesters as a result of limited knowledge, design issues, and a lack of appropriate management [38]. At present, most biogas is produced in Europe and the United States, but Asia has installed the largest number of digesters, which are mostly small scale [39]. As opposed to other technologies, AD is possible at a wide range of scales, ranging from small-scale digesters making just enough biogas to power a single household to large centralized biogas plants with digesters capable of producing several thousand cubic meters of biogas per day [38, 40, 41].

2.2 ADM1 theoretical background

2.2.1 Description and basic concept

Developed by the International Water Association (IWA), the Anaerobic Digestion Model No.1 (ADM1) [42] is the most common platform for the modeling and simulation of AD processes [43]. The ADM1 is a structured mathematical model, which covers complex processes involved in converting organic substrates into (biogas) methane, CO_2, and inert byproducts [44]. Although the ADM1 does not cover all of the processes that take place during the AD process (such as precipitation of solids and sulfate reduction), the goal of ADM1 is to be a tool to provide as accurate predictions as possible that can be used in all phases of AD plants such as process development, operation, and optimization [45].

ADM1 includes several steps: Disintegrating complex solids into soluble and particulate inerts, carbohydrates, proteins, lipids, and inert substances, a nonbiological step, is the first step in ADM1 [46]. Next, the products of disintegration are hydrolyzed in the enzymatic step. The products are sugars, amino acids, and long-chain fatty acids. Then, in the acidogenesis process, sugars and amino acids are fermented to produce VFA, H2, and CO_2. Finally, in both hydrogenotrophic (cleavage of acetate to methane) and acetoclastic (reduction of CO_2 by molecular hydrogen to produce methane) methanogenesis processes, methane is produced [47]. Figure 1 shows the reaction path in ADM1 [42].

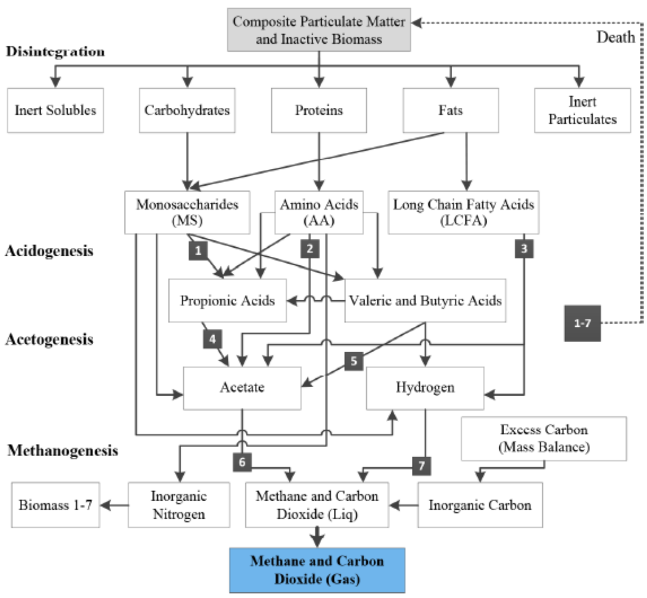

Figure 1. The reaction paths described in Batstone et al. [42]

2.2.2 Growth kinetics

Many kinetic expressions that define substrate conversion rates in terms of substrate concen- trations and rate constants explain substrate conversion processes [42]. First-order kinetics explain the disintegration of influent substrates as well as the hydrolysis of carbohydrates, proteins, and lipids [46]. All inter-cell biochemical processes of substrate uptake in acido- genic and acetogenic steps are based on Monod-type growth kinetic expressions with pH inhibition and noncompetitive inhibition by total volatile fatty acids (TVFAs), free ammonia, and hydrogen [47]. Dead biomass is retained in the system as composite particulate material, and again first-order kinetics describe endogenous decay processes. The metabolism of biomass to preserve its life is known as endogenous decay [48].

2.2.3 Basic equations

The original ADM1 consists of 108 different equations, which can be classified into differential equations, algebraic equations, process rates, and process inhibition equations [49]. The outputs of ADM1 are the solutions to the 35 differential algebraic equations (DAEs) to model the concentration rate of various species in the liquid and gas phases. Table 1 provides a simple classification of these equations [50].

Jeppsson and Rosen [49] implemented ADM1's ordinary differential equation model. Barahmand [50] grouped these 35 DAEs into five classes. As seen in the following, all the DAEs are nonlinear with order and degree of unity. For soluble matters, the general form of the differential Eqns. (1)-(12) can be written as:

$$\frac{dS_z}{dt} = \frac{q_{in}}{V_{lia}}\left(S_{z,\,in} - S_z\right) + \mathcal{F}\left(\rho_a, f_{product\,,\,substrate}, N_c, Y_d, C_e\right) \tag{1}$$

where, S_z is the soluble substrate concentrations in kg.COD.m^{-3}), q_{in} is the influent volumetric flow rate in m^{3}d^{-1}, V_{liq} is the volume of the liquid in m^3, $S_{z,in}$ is the concentration of the influent soluble substrate in kg.COD.m^{-3}, $\mathcal{F}$ represents different functions and variables defined in [49], and ρ_a represents 19 biochemical process rates, 6 acid-based rates, and 3 gas transfer rates in d^{-1}. $f_{product,substrate}$ is the yield (catabolism only) of the product on a substrate in kg.COD. (kg.COD)$^{-1}$, N_c is the nitrogen content of component c in, k.mole.N. (kg.COD)$^{-1}$, Y_d is the yield of biomass on a substrate in kg.COD. (kg.COD)$^{-1}$, and C_e is the carbon content of component e in k.mole.C. (kg.COD)$^{-1}$.

Table 1. Classification of the ADM1 equations (Source: Jeppsson and Rosen, 2006)

Model equations	No. of equations	Model equations	No. of equations
Process rates	**28**	*Process inhibition equations*	**15**
Biochemical process rates	19	*Differential equations*	**35**
Acid-base rates	6	Water-phase equations	32
Gas transfer rates	3	*Soluble matter*	*12*
Algebraic equations	**30**	*Particulate matter*	*12*
Soluble matter	14	*Cations and anions*	*2*
Inhibition	5	*Ion states*	*6*
Ion states	4	Gas-phase equations	3
Gas-phase equations	7		

The general form of differential Eqns. (13)-(24) associated with particulate matters is:

$$\frac{dX_z}{dt} = \frac{q_{in}}{V_{liq}}\left(X_{z,\,in} - X_z\right) + \mathcal{F}\left(\rho_a, f_{product,substrate}, Y_d\right) \tag{2}$$

where, X_z is the concentration of particulate component (biomass) z in kg.COD.m^{-3}, and $X_{z,in}$ is the concentration of influent biomass z in kg.COD.m^{-3}. The general form of differential Eqns. (25)-(26), cations and anions, does not include $\mathcal{F}$ term.

$$\frac{dS_{cat^+/an^-}}{dt} = \frac{q_{in}}{V_{liq}}\left(S_{cat^+/an^-,in} - S_{cat^+/an^-}\right) \tag{3}$$

where, S_{cat+} is the concentration of cation, S_{an-} is the concentration of anion, and $S_{cat+,in}$ and $S_{an-,in}$ are input cation and anion all in k.mole.m^{-3} Moreover, there are six differential Eqns. (26)-(32) for ion states. Their general form is:

$$\frac{dS_w}{dt} = -\rho_{A,i} \tag{4}$$

where, S is the concentration, ρ is the acid-base rates, and w and i are defined in Table 2.

The last three differential Eqns. (33)-(35) are related to the gas phase with the general form of:

$$\frac{dS_{\text{gas.u}}}{dt} = -\frac{S_{\text{gas.u}}\, q_{\text{gas}}}{V_{\text{gas}}} + \rho_{T,l}\frac{V_{\text{liq}}}{V_{\text{gas}}} \tag{5}$$

where $S_{gas.u}$ is the concentration of gases (H_2. CH_4. CO_2) in kg.COD.m^{-3}, $\rho_{T,l}$ is the gas trans- fer rates in d^{-1}, and q_{gas} is the gas flow in Nm3 d^{-1}, and V_{gas} is the gas volume in m^3. Except for these differential equations, there are numerous intermediate equations such as biochemical processes, acid-based and gas transfer rates, inhibition-related equations, and algebraic equations.

2.2.4 Inhibition functions

Different functions were proposed, emphasizing modeling the effects of pH, hydrogen, inad- equate nitrogen inhibition, and free ammonia inhibitions [42]. Continuing this way, Jeppsson and Rosen [49] implemented and updated inhibition functions.

Table 2. Definitions of w and i in (4)

W	i
va^-	4
bu^-	5
pro^-	6
pro^-	7
ac^-	10
nh_3	11

2.3 Sources of uncertainty

AD is extremely vulnerable to instabilities and uncertainty due to its dynamic and nonlinear behavior. ADM1 model consists of numerous parameters and input state variables directly affecting the process performance. Table 3 provides a classification of these based on [49].

Table 3. Classification and number of parameters and variables in ADM1

Parameters	
Stoichiometry	41
Biochemical	36
Physiochemical	23
Physical	2
State variables	
Input state variables	28

Among over 100 parameters, although most of them have crisp and deterministic values, several are uncertain, such as the influent substrate composition (uncertain feedstock qual- ity). On the other hand, input state variables also suffer considerable ambiguity in real-life applications. Therefore, effectively operating a biogas production unit necessitates a thor- ough understanding of the system's uncertainties.

3. RESEARCH METHODOLOGY

An article review entails locating, reading, understanding, and presenting the published research and theory in an organized manner [51]. Literature reviews can be classified into different types depending on their purpose and methodology. Grant and Booth [52] reviewed the 14 most com- mon literature review methods. Narrative or traditional review, scoping review (i.e. [14, 16, 22, 53]), systematic review, critical review, rapid review, and umbrella review are among com- monly used methods. To address specific research questions, a narrative literature review was conducted. The goal is to find a few pieces of research that describe a particular problem. There is no preconceived research question or search technique in narrative reviews compared with scoring or systematic reviews, and it is less formal than them [54]. A narrative literature review was conducted in three phases and nine steps to address the review question [55]. The three phases are planning, conducting, and reporting. The planning phase covers topic selection, forming the research questions and defining the objectives, the development and validation of a review protocol, and searching the literature and selecting the literature. The conducting phase includes analyzing and synthesizing; the reporting phase consists of concluding and reporting [56]. Following is a step-by-step description of how this review was conducted.

Step 1: topic selection-the topic selected for this study is the application of uncertainty modeling in biogas production through AD.

Step 2: forming the research questions and defining the objectives-the objective of this study was to explore and describe the sources of uncertainty in the AD process and methods to cope with them. The purpose of this study was to address the following review question:

Q1) What are the sources and types of uncertainty in these processes?

Q2) What are the tools and frameworks for dealing with uncertainties?

Q3) What is the most critical knowledge gap in the research?

Table 4. Search string in different databases

Database	String
Scopus and WoS	((anaerobic AND digestion) OR ADM1 OR WWTP) AND (uncertain* OR robust*)
Google Scholar and ScienceDirect	((anaerobic AND digestion) OR ADM1 OR WWTP) AND (uncertain OR uncertainty OR robust OR robustness)

Step 3: the development and validation of a review protocol -similar to research design in empirical research, this step consists of a predetermined plan for how all other steps of the research process would be conducted.

Step 4: search the literature - to search for relevant literature, four online databases were selected based on a purposive sampling method [57], namely Google Scholar, ScienceDirect, Scopus, and Web of Science (WoS). The strings used in the databases are listed in Table 4.

On the one hand, this study focused primarily on AD. ADM1, on the other hand, is a very popular and well-known method, and according to the authors' experience, many studies included only ADM1 in the title. As a result, ADM1 has been added to the string with the "OR." Similarly, the search string has been amended to include WWTP, which is stand for wastewater treatment plant. The asterisk (*) can be used with word stems to get different versions of a phrase with less typing. For example, uncert* can find uncertain, uncertainty, uncertainties, etc. For Scopus, WoS, and ScienceDirect, the strings were applied to the titles only with no other limitation on the year or type of the publications.

Step 5: selecting the literature-the purpose of this step is to determine which articles will be included in the analysis or excluded [55]. For Scopus, WoS, and ScienceDirect, the strings were applied to the titles only. Moreover, this search was limited to studies in English. No other limitations were applied to the year or type of publication.

Step 6: content analysis and synthesis reading selected articles and analyzing them is part of this step. Furthermore, the step involves categorizing and grouping similar data following concepts and themes. Synthesizing allows the grouped data to be arranged into a specific form.

Step 7: conclusion and reporting - a demonstration of how this study extends existing research findings is included in this step.

4. RESULTS

A total of 56 documents were found to be relevant after completing steps 3-5 in Section 3. By applying the search strings in Table 4, Scopus, WoS, and ScienceDirect were able to locate 25, 32, and 12 documents, respectively. In order to eliminate duplicates, Microsoft Excel® was used and 36 documents remained. A further 20 relevant documents were added from Google Scholar, bringing the total number of studies to 56. In the final step and after a full-text screening of all studies, five studies were found to be nonrelevant. As a result, this literature review continued with 51 selected documents (Table 5).

4.1 Year-wise analysis

The year-wise analysis gives an overall picture of the research progress. The present study examined 51 studies that were published between 2000 and 2022 (with no limit on year). An overview of the number of publications and the overall trend is shown in Figure 2. In 2012, the highest number of publications was recorded with eight publications, whereas in some years, such as 2006 and 2007, no studies were recorded. Meanwhile, the overall trend shows a steady increase in interest and the number of studies. Despite the large number of uncertain- ties associated with AD modeling, a limited number of studies have been conducted on this topic. Among the reasons for this would be the challenges associated with modeling uncer- tainty in complex systems.

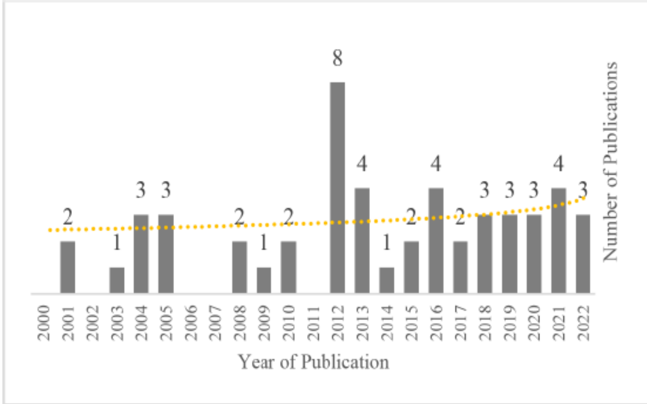

Figure 2. Number of selected studies and overall trend between 2000-2021

Table 5. Selection of the related studies

	No. of documents
Result of search in titles: Scopus	25
Result of search in titles: WoS	32
Result of search in titles: ScienceDirect	12
After deleting duplicates:	36
Adding 20 document from Google Scholar	56
Removing five documents after full-text screening	(5)
Number of final selected files	51

4.2 Co-occurrence analysis

Analysis of co-occurrences within a collection of units consists of counting the number of objects that occur together [58]. Based on extracted keywords from the citation context, VOSviewer® was employed to generate keyword co-occurrence networks using the full count- ing method. In this analysis, the minimum number of occurrences of the keyword was set to five, and from 473 keywords in 51 selected studies, 14 keywords met the threshold (see Figure 3).

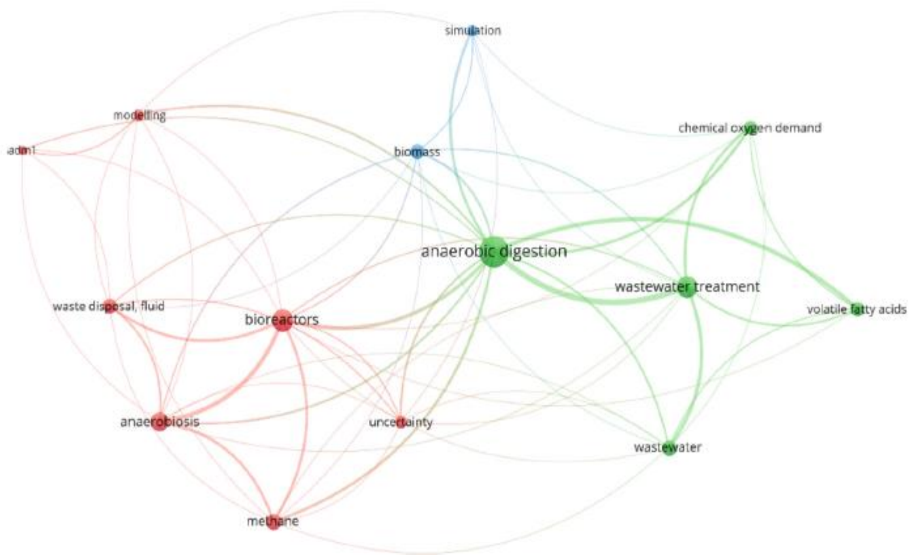

Figure 3. Co-occurrence analysis of the selected studies using VOSviewer®

5. DISCUSSION

5.1 Content-based study

To address the research questions, this section investigates the selected 51 studies to reveal the sources of uncertainty, methods to cope with the model uncertainties, and their applications. Moreover, by identifying the knowledge gap, the present study provides some suggestions for further studies. In the following, the selected studies were reviewed and categorized based on frequently used methods and tools to deal with the system uncertainty. Table 6 summarizes different tools and their frequencies among selected studies. As seen among 16 different tools, the Monte Carlo simulation dominates and has the highest contri- bution. Few of the articles used several methods in combination.

Table 6. Tools and methods to deal with the system uncertainties in selected documents

Tools/Methods	Freq.	References
Monte Carlo Simulation (MCS)	14	[3, 59-71]
Confidence Interval / Interval Observer (CI/IO)	11	[72-82]
Global Sensitivity Analysis (GSA)	3	[62, 65, 83]
Morris Screening (MS)	3	[62, 65, 83]
Artificial Neural Network (ANN)	3	[84-86]
Luenberger Observer (LO)	3	[87-89]
Local Sensitivity Analysis (LSA)	3	[63, 65, 90]
Standardized Regression Coefficients (SRC)	2	[62, 65]
Random Forest (RF)	2	[85, 86]
Bifurcation Analysis (BA)	1	[91]
Detrended Fluctuation Analysis (DFA)	1	[92]
Min-Max Method (MMM)	1	[93]
Scenario Analysis (ScA)	1	[94]
Fuzzy Decision-Making (FDM)	1	[7]
Expected Utility Theory (EUT)	1	[66]
Multi-Criteria Analysis (MCA)	1	[67]
Uncertainty Quantification (UQ)	1	[83]
Dempster-Shafer Theory of evidence (DST)	1	[95]
Support Vector Regression (SVR)	1	[86]
Simple Observer (SO)	1	[96]
Deep Deterministic Policy Gradient (DDPG)	1	[97]
Neural Network Sliding Mode Control (NNSMC)	1	[98]
Variance-Based Sensitivity Analysis (VSA)	1	[99]
Nonlinear State Observers (NSO)	1	[100]
Gramian based Fixed-time Convergent Observer (GFCO)	1	[101]
Asymptotic Observer (AO)	1	[101]
Super-Twisting Observer (STO)	1	[101]
External validation of Near-infrared (NIR) calibrations	1	[102]
Robust H Theory (RHT)	1	[103]
Output Feedback Observer (OFO)	1	[104]
Extreme Learning Machine (ELM)	1	[85]
Support Vector Machine (SVM)	1	[85]
Genetic Programming (GP)	1	[85]
Multiplicative White Noise (MWN)	1	[105]

5.2 Monte Carlo simulation

In a Monte Carlo simulation, random sampling and statistical modeling are used to estimate mathematical functions and simulate the behavior of complex systems [106]. This technique develops probabilistic models for real-world processes to estimate specific average proper- ties, such as mathematical expectations, variance, and covariance. The main steps to performing a Monte Carlo simulation are random number generation; simulation of the ran- dom values with more complicated distribution and calculations [107]. As seen in the following, the Monte Carlo approach was used directly for uncertainty quantification or indi- rectly in other methods such as GSA.

Neba et al. [60] presented a systematic technique to establish the process performance objectives by combining practical identifiability, uncertainty quantification, and attainable region principles, which are particularly useful when exact kinetic coefficients are unknown. A Monte Carlo simulation was used to assess the uncertainty bands on the model states and attainable regions to construct high degrees of uncertainty for the case of the modified Hill model. Asadi and McPhedran [59] employed different uncertainty modeling tools to maximize biogas production. This study used a Genetic Algorithm (GA) combined with data-driven modeling and uncertainty analysis to determine the optimal operating parameter values for a municipality waste treatment plant's AD process. This study utilized an Artificial Neural Network (ANN), Adaptive Network-based Fuzzy Inference System (ANFIS) using Monte Carlo Simulation for uncertainty analysis and nonlinear regression models. Sharara et al. [61] employed the Monte Carlo simulation methodology to establish manure AD systems in the face of uncertainty. In this probabilistic approach, parameters were sampled repeatedly from their respective distributions.

Ramin et al. [62, 108] applied a GSA using the Benchmark Simulation Model No. 2 (BSM2) platform for a secondary settling tank in a wastewater treatment plant. Two methods were employed to apply this SA: (1) standardized regression coefficients method using linear regression of Monte Carlo simulations and (2) Morris screening. The Monte Carlo simulation was employed to examine the impact of parameter uncertainty on the stated plant perfor- mance criteria. Kil et al. [3], based on ADM1, explored and calculated the links between the influent components' concentrations and the process's steady-state using process output information to estimate waste characteristics. The system uncertainty was evaluated using the Monte Carlo simulation. Xu [63] developed a method for calibrating parameters to optimize ADM1 for an industrial-scale plant. With a series of Monte Carlo simulations, local SA and a multivariate regression technique, Xu proposed a partial least square method to validate the calibrated parameter set. Gehring et al. [64] examined the substrate characterization uncer- tainty influence on the system results. The Monte Carlo simulation with a 20% uncertainty range for the recorded feedstock data was used in AMD1 to mathematically model the ther- mophilic mono-fermentation of maize silage.

Solon et al. [65] utilized a GSA to analyze the impact of uncertainty in substrate composi- tion, kinetics, stoichiometry, and mass transfer parameters in ADM1. Two methods (Morris screening method and standardized regression coefficients) were employed to perform the GSA. The Monte Carlo simulations were used in the standardized regression coefficients approach, with Latin Hypercube Sampling [109], which randomly selected a set of parame- ters for each simulation. Južnič-Zonta et al. [66] provided a multi-criteria assessment technique for establishing biochemical wastewater treatment plant operating strategies based on an ADM1 and under an uncertain environment. The Monte Carlo simulation and the Expected Utility Theory (EUT) [110] were used to cope with the alternatives among risky operating methods with multi-dimensional outcomes. Since World War II, EUT has been regarded as the preeminent paradigm in decision-making.

EU theory remains the leading method for modeling risky decision-making [111]. Benedetti et al. [67] conducted a scenario analysis based on an open-loop version of BSM2 using Monte Carlo simulations and mul- ti-criteria analysis. Even though MCSs were not an iterative optimization approach, the parameter space was investigated in great depth with potentially fewer simulations than a multi-objective genetic algorithm [112].

This review revealed that the Monte Carlo simulation was the most frequently used tech- nique (almost 28 percent of the methods) to address the uncertainty in the AD process.

5.3 Confidence interval

Confidence intervals are used to determine a range of possible values for a target parameter, and a confidence factor indicates that the real value is included within that interval [113].

Using a confidence interval observer, Alcaraz-Gonzalez et al. [77] demonstrated how to manage an AD pilot plant for treating wine vinasses using a novel Single-Input-Single-Output (SIMO) control approach. In these studies, three primary sources of uncertainty have been introduced to develop a robust control observer. These sources include poorly known kinetics, a lack of sensors to measure all the online variables and unknown influent composition. Girault et al. [72] developed a procedure for degradation kinetics to divide a substrate's total Chemical Oxygen Demand (COD) into each ADM1's input state variables. A confidence range of 95% and an F distribution on the primary source of uncertainty were used. The primary source of uncertainty in COD fractionation was reported as temporal variability in substrate properties. Montiel-Escobar et al. [78] proposed a robust state estimation technique for AD processes described by ADM1 to approximate important variables under uncertain scenarios. The interval observers were used to cope with the uncertainty of the process inputs, unknown specific growth rates, and reaction kinetics were considered.

Batstone et al. [73] used an interval observer to evaluate the degradability extent, the lumped apparent first-order coefficient values and their uncertainties based on nonlinear parameter approximation. The observed parameter confidence regions were quite nonlinear, especially for continuous systems, implying that estimating genuine parameter uncertainty requires iterative or sampling approaches. Lübken et al. [74] modified the ADM1 and estimated kinetic parameters to simulate the performance of a mono-substrate two-stage agricultural biogas plant. The model's uncertainty was approximated using confidence intervals of parameter estimates. The same procedure was done by Batstone et al. [75] for parameter estimation in modeling AD.

This technique was the second most frequently used method to cover the process uncer- tainty. Almost 18 percent of the methods belonged to this technique.

5.4 Other tools

Ghanavati et al. [7] maximized the ADM1-based process and combined a fuzzy supervisory control methodology with an Adaptive Model Predictive Controller (AMPC). The AMPC was based on the Auto-Regressive Moving Average (ARMA) model, which updates its parameters at each sample period to make the controller more resilient to uncertainties and external stresses. Restrepo et al. [91] performed a comparative performance analysis of types of controllers applied to an Upflow Anaerobic Sludge Blanket (UASB). By employing bifurcation analysis (BA) to discover and compare the stability regions and the impact of identification uncertainty over these regions in the process parameter space, these controllers were applied to a bioreactor. López-Pérez et al. [93] used a Min-Max method ($\pm$7% of the nominal values) to design a software sensor based on the state observer for a continuous bioreactor in a heavy metal removal application. They analyzed the system's observability properties at a local level, taking parametric uncertainties into account. Lardon et al. [95] offered a methodological framework based on Dempster-Shafer's theory of evidence to use a pilot size fixed-bed AD reactor to explore how different faults may be controlled efficiently in an experimental setting. The evidence theory's key benefit is that it may also be used to discover inconsistencies in the expert rules related to each module. Das *et al.* developed a novel index to evaluate the performance of state estimation tech- niques. Hurst exponent [114], a dimensionless estimator for a time series' self-similarity, was calculated using the Detrended Fluctuation Analysis (DFA) approach to estimate the internal variables from a nonlinear AD model and available measurements. There were different methods such as SA, Morris screening standardizes regression coefficient, scenario analysis, fuzzy logic, and multicriteria analysis, among others. SA (global and local) accounted for almost 15 percent of the methods.

More information about sources, methods, and applications of the uncertainty in AD processes can be found in Tables 7 and 8.

There are several sources of uncertainty, such as uncertainty in input variables, kinetic coefficients, parameter estimation, model parameters, reaction, and specific growth rates, substrate composition, controller proportional constant, gain and temporal parameters, among others. As found in this review, Monte Carlo simulation was the most frequently used technique (nearly 28 percent of the methods) to address the uncertainty associated with the AD process. The Confident Interval technique and SA were the second and third most frequently used methods for addressing the uncertainty of processes, and they accounted for almost 18 and 15 percent of the methods. According to the results, the most significant source of uncertainty was the unpredictability of model parameters and input variables. As a result of the knowledge gap and mathematical sense, fuzzy set theory is an important technique that eliminates costly and time-consuming simulations such as Monte Carlo or GSA.

Finding the sources of uncertainty, defining appropriate fuzzy values and conducting SA are the most important steps in modeling uncertainty using fuzzy set theory to have a robust model.

6. CONCLUSION

The current study identifies and analyzes uncertainty caused by AD processes and tools and strategies to cope with the uncertainties through a narrative review. Four databases have been selected and were used for the search (Scopus, Web of Science, ScienceDirect, and Google Scholar). After the full-text screening, this number dropped to 51 articles as the final selected studies. Among different methods and tools to cope with the uncertainty, 34 different methods have been addressed in selected studies. The highest contribution belongs to Monte

Carlo simulation, followed by a statistical approach using confidence intervals/ interval observer and GSA. Uncertainty in model parameters such as reaction kinetics, substrate composition, and parameter estimates are the primary sources of uncertainty in biogas modeling processes. Based on this review, the following approaches have been sug- gested. These suggestions are associated with quantifying the uncertainty in AD process methodologies. It is recommended that all published AD studies contain a comprehensive uncertainty study. More attention should be paid to uncertainty in all model parameters. Finally, as a knowledge gap, it is suggested to use powerful mathematical tools such as the fuzzy set theory to quantify the model uncertainties. In comparison with Monte Carlo simulations, this method is much less costly.

Table 7. Sources of uncertainties and methods to cope with them in the selected studies

Tools	Sources of Uncertainty	Ref
MCS	Input variables	[59]
MCS	Kinetic coefficients and parameter estimation	[60]
MCS	Model parameters	[61]
BA	Controller proportional constant and gain-temporal parameter	[91]
DFA	State estimation	[92]
MMM	Parametric uncertainties	[93]
DFT	Poor online data	[95]
CI	Lack of adequate sensors, poorly known kinetics, and uncertain influent	[76]
CI	Poorly known kinetics and substrate composition	[77]
GSA: MCS + SRC + MS	Model parameters	[62]
MCS	Component composition	[3]
CI	Model parameters	[47]
MCS + LSA	Model parameters	[63]
MCS	Substrate composition	[64]
CI	Process inputs, reactions, and specific growth rates	[78]
ScA	Model parameters	[94]
FL	External disturbances in feed composition and model uncertainty	[7]
GSA: MCS + SRC + MS + LSA	Model parameters	[65]
CI	Model parameters	[73]
MCS + EUT	Model parameters	[66]
MCS + MCA	Model parameters	[67]
ANN	Model parameters	[84]
CI	Model parameters	[74]
GSA: QU + MS	Model parameters	[83]
MCS	Model parameters	[68]
CI	Model parameters	[75]
LO	Process kinetics and variations in the influent composition	[87]
MWN	Model’s biological uncertainty	[105]
LO	Input constraints, parameter uncertainty, and load disturbances	[88]
IO	Uncertainties of the inputs, load disturbances, and nonlinearity of the system	[79]
IO	Unknown inputs, disturbances in the state, and COD of the input, as well as parametric uncertainties	[76]
RF + ANN + ELM, SVM, and GP	Sensor noise and delay	[85]
OFO	Several load disturbances, severe uncertainties, and typical operational failures.	[104]
RHT	Feedstock conditions, time lags, and the lack of reliable measurements	[103]
IO	Parameter uncertainty and load disturbances	[80]
IO	Disturbances, the dynamics of the main state variables, lack of reliable and cheap sensors of the key process variables	[81]
NIR	Model parameters	[102]
LO	Unmeasured variables (such as VFA) and unknown microbial growth kinetics	[89]
GFCO + AO + STO	Uncertainties in inlet chemical oxygen demand (COD) and the acidogenic bacteria population, methanogenic bacteria population, and time-varying parameters to estimate the inlet volatile fatty acid (VFA) concentration	[101]
NSO	Differences in the rate of biochemical reactions, process uncertainties, and the consequences of interconnection between the two bioreactors	[100]
NNSMC	Model parameters	[98]
DDPG	External perturbations and parametric model uncertainty	[97]
SO	Noise and variations of the COD influent concentration	[96]
MCS	Model parameters	[69]
MCS	Input data, model structure, and parameter values	[70]
SVR + ANN + RF	Regression model uncertainties	[86]
MCS	Stoichiometric, bio-kinetic, and influent parameters, hydraulic behavior of the plant and mass transfer parameters, and the combination of them	[71]
VSA	Subsampling, i.e., taking subsets of the database of WWTPs and evaluating the potential changes in the overall index	[99]
CI	Influent data	[82]
LCA	External disturbances in the influent and kinetic/stoichiometric model parameters	[90]
Literature review		[115]

Table 8. Applications and year of publication of the selected studies

Ref	Application	Year
[59]	Maximizing biogas production	2018
[60]	Self-optimizing operation of anaerobic digesters	2016
[61]	A techno-economic optimization	2004
[91]	UASB controller	2018
[92]	Optimal anaerobic digestion processes monitoring	2017
[93]	Cadmium removal in an anaerobic process	2016
[95]	Online diagnosis in biological processes	2004
[76]	Anaerobic digester with highly nonlinear dynamics	2001
[77]	Interval-based regulation for anaerobic digestion processes	2005
[62]	Importance of secondary settling tank models	2012
[3]	Continuous anaerobic digestion based on ADM1	2017
[47]	Degradation kinetics	2012
[63]	Optimizing ADM1	2019
[64]	Mathematical simulation of maize silage	2013
[78]	state estimation scheme for ADM1	2012
[94]	A biodegradability and modeling	2013
[7]	Control of an anaerobic bioreactor on the ADM1-based virtual plant.	2021
[65]	Modeling of anaerobic digesters (ADM1)	2015
[73]	Estimation of Parameters in Anaerobic Digesters	2008
[66]	Multi-criteria analyses of bio-processes (ADM1)	2012
[67]	Wastewater treatment plant design and control	2010
[84]	Two Stages Anaerobic Digestion Process (ADM1)	2018
[74]	Simulation of a biogas reactor (ADM1)	2015
[83]	ADM1-based AD Model	2021
[68]	Wastewater treatment plant (WWTP) control strategies	2012
[75]	Anaerobic sequencing batch reactor	2004
[87]	The control scheme for the stability of continuous anaerobic digestion processes	2010
[105]	Controlling anaerobic digestion processes at an industrial scale	2003
[88]	A pilot plant up-flow fixed-bed reactor that is treating industrial wine distillery wastewater	2008
[79]	Chemical and biochemical processes	2005
[76]	Industrial wine distillery wastewater	2005
[85]	Monitoring of volatile fatty acids in anaerobic digestion processes	2020
[104]	Control of an anaerobic digestion pilot plant	2016
[103]	Anaerobic digestion stable operation	2019
[80]	Operational stability in anaerobic digestion processes	2013
[81]	Highly uncertain anaerobic digestion processes	2012
[102]	Estimation of process parameters of anaerobic digestion	2012
[89]	Highly uncertain continuous anaerobic digestion processes	2021
[101]	Monitoring anaerobic digestion	2022
[100]	A two-stage anaerobic digestion process	2022
[98]	A biomass anaerobic digestion	2019
[97]	Digestion systems of tequila vinasses	2022
[96]	Stabilization in anaerobic digestion process	2001
[69]	Eindhoven wastewater treatment plant upgrade	2013
[70]	WWTP model	2020
[86]	Energy benchmarking to compare WWTPs, identify targets, and improve their performance	2016
[71]	Model-based design of a wastewater treatment plant	2009
[99]	44 different wastewater treatment plants	2020
[82]	Activated sludge models to full-scale wastewater treatment plants	2012
[90]	Activated sludge model 2D calibration with full-scale WWTP data	2014
[115]	Literature review	2021

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