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Machine Learning Applications in Biogas and Methane Production: A Bibliometric Analysis

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ABSTRACT. Biogas processes play an important role in the disposal of organic waste. However, these processes are difficult to control because they are highly sensitive and variable. A lot of work has been done to date in order to eliminate this problem. With the development of technology and artificial intelligence, the spread of "Autonomous" systems has become widespread in the control of anaerobic processes as in many other fields. The Anaerobic Digestion Model No. 1 (ADM1) developed by the International Water Association (IWA) has been adopted as the standard model for the AD process since 2002. With the development of this model, Simple Regression Tree (SRT), Probabilistic Neural Networks (PNN), Artificial Neural Networks (ANN), Gradient Boosted Tree (GBT), Linear Regression (LR), Tree Ensemble Regression (TER), Random Forest Regression (RFR), Polynomial Regression (PR), Fuzzy Logic (FL), Adaptive Network-Based Fuzzy İnference System (ANFIS), Different ML algorithms such as Support Vector Machine (SVM), Particle Swarm Optimization (PSO), Genetic Algorithm (GA) Developing Data-Driven Models (DDDV), Deep neural network (DNN) have been used in various studies and tried to perform process optimization, real-time monitoring, disturbance detection and parameter estimation. In this study, the data obtained by using the Bibliometrix package and Biblioshiny package through the R programming language in the R-Studio programme were evaluated. For this purpose, a total of 80 articles in the field of 'Machine Learning' in the Web of Science (WoS) database between 2012-2024 in the fields of 'Biogas Production', 'Methane Production' and 'Anaerobic Digestion' processes were accessed and evaluated. As a result of the evaluations, the development of ML models in biogas processes was determined and recommendations were presented.

Keywords: Anaerobic digestion, ADM1, Autonomous, Bibliometric analiysis, Artifical neural networks

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1. INTRODUCTION

Globally, the primary energy supply still relies heavily on traditional sources such as oil, coal, natural gas, and nuclear energy [1]-[3]. However, due to the limited availability of these resources [4], as well as their contribution to greenhouse gas emissions and environmental pollution [5]-[8], renewable energy sources are increasingly being considered as sustainable alternatives to mitigate the impacts of non-renewable energy use. In recent years, there has been a significant increase in efforts to improve process stability, enhance specific methane yield, and boost economic efficiency [9]-[28]. Anaerobic digestion (AD), a process that converts organic waste into biogas, has gained attention for its ability to support waste-to-energy conversion, promote renewable energy use, and diversify energy supplies in rural areas [29], [30]. Accurate prediction of biogas yield and economic feasibility is essential for the effective implementation of AD systems. However, AD optimization is challenging due to the involvement of numerous physical, chemical, and biological variables [31]. Various approaches have been explored to address these complexities, among which multi-criteria decision-making (MCDM) methods stand out [32], [33]. These methods assign numerical values to alternatives and criteria and use pairwise comparisons to identify the most suitable option [33], [34]. In parallel, machine learning (ML) models have gained significant traction due to their ability to process large datasets, recognize patterns, and offer predictive solutions. ML techniques such as artificial neural networks (ANN) and deep learning (DL) have been widely and successfully applied to model AD processes because of their strong capacity to capture non-linear relationships [16]-[27], [35]-[37], [39]-[45]. This study investigates the development of ML applications in AD through bibliometric analysis and presents novel solution approaches. One of the key innovative aspects of this study is the lack of advanced research using ML to predict the effects of specific microorganisms and their enzyme production capacities on

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AD performance. Although many studies have explored genetically modified microorganisms (GMMs) with enhanced enzyme activity, none have used ML to predict their effects without experimental procedures, which marks another novel contribution of this work. Furthermore, with the rapid advancements in bioinformatics, this study suggests that ML can be used to identify gene regions suitable for intervention (e.g., through cloning) in hydrolytic bacteria and/or methanogenic archaea. This could pave the way for groundbreaking innovations in biogas production, enabling predictive, non-experimental approaches to genetic modifications in AD systems.

In biogas facilities, automation systems are already employed to monitor real-time data such as pH, electrical conductivity (EC), volatile fatty acids (VFA), and especially methane (CH_4) concentration. However, interpreting these data and taking the necessary actions often depend on the experience of the operational staff. In cases where experience is lacking, significant damage to the AD process may occur, leading to time loss, financial setbacks, and reputational damage. To prevent such issues, machine learning can be used to determine key operational parameters—such as hydraulic retention time (HRT), organic loading rate (OLR), and inoculum-to-substrate (I/S) ratio—based on real-time and historical data. This study contributes to the advancement of "Autonomous Biogas Plants" by integrating artificial intelligence into AD systems, aiming to maximize methane production and maintain high operational efficiency continuously.

2. MATERIALS AND METHODS

2.1 Bibliometric Method

Bibliometric studies are highly valuable in identifying new ideas and approaches on relevant topics, developing specific areas of knowledge, identifying gaps, providing an overview of topics, and evaluating publication impact [46]-[48]. In studies, it is possible to examine many factors such as the contributions of the authors, the number of citations, the authors conducting research, the journals in which the articles were published, the countries where the publications were made, and the distribution of keywords by years [47]-[50]. The aim of this study is to evaluate the bibliometric properties of the concept of “Machine Learning” in AD processes in the Web of Science (WoS) database. In this context, the studies on the concept of “Machine Learning” with the keywords “Biogas Production”, “Methane Production” and “Anaerobic Digestion” and published in the WoS database were analyzed according to the years, number of citations, authors and journals, keywords of the publications and the relations of the related keywords with each other. The distribution of the number of citations, categorical clustering analysis and country distributions of the publications on the concept of “Machine Learning” were visualized with the R program and the results of the analysis were evaluated according to the literature. In the research, no year limit was imposed while searching the WoS database. During the search, 3 separate searches were performed using other keywords while keeping “Machine Learning” constant. The 150 articles obtained as a result of the search were examined, and a total of 80 articles related to the subject were identified when the irrelevant and repetitive articles were removed. All other operations were carried out on these 80 articles.

2.2 Machine Learning (ML)

AD processes are very sensitive to changes in the environment. Therefore, monitoring, control and optimization of this process is very difficult [41]. To date, various studies have been carried out to overcome these difficulties in AD processes. However, due to the large number of unknown parameters in these processes, it has been very difficult to increase efficiency or optimize process efficiency. This situation has become even more difficult due to seasonal conditions, substrate variations, especially changes in microbial activities in AD processes due to these variations. This is especially difficult in plants with variable substrate inputs. Therefore, various statistical, mathematical, logical, etc., studies have been carried out to overcome these problems and to maintain the stability/yield of AD processes. However, these traditionally applied methods and mechanistic models have their own difficulties and pitfalls.

Typically, mechanistic models or machine learning (ML) are used to model the AD process [43]. Therefore, it has been proposed by many researchers to build robust data-driven models that facilitate the development of robust data-driven models that utilize and interpret the complex information required for AD processes to function properly. ML has been used in many studies as an alternative method to address these constraints, and as shown in this study, there have been many studies using ML. The first model developed as a product of these studies, the anaerobic digestion model No. 1 (ADM1), is a representative model that simulates AD based on mass balance and kinetics of multiple reactions [51]. The model has been widely used and subjected to some updates to adjust parameters for accurate simulation [52]. The updated ADM1s have been used for methane (CH_4) and volatile fatty acids (VFAs) [53] and digestion of agricultural wastes such as oranges and apples [54] and obtained accurate predictions. However, ADM1-based models have limitations for accurate simulation as the kinetic model depends only on the amount of biomass [42], [55]. Modeling AD plays an important role in monitoring processes and making some predictions.

One way to model the AD process is through a comprehensive mechanistic description of the AD process. Among mathematical models, the Anaerobic Digestion Model No. 1 (ADM1) [51] developed by the International Water Association (IWA) is by far the most comprehensive model used by many researchers [56]-[59]. This model has been adopted as the standard model for the AD process since 2002 [60]-[62]. Initial studies with ADM1, which has been developed into several different models [36], [63]-[66], used a calibrated simulation model of a full-scale biogas plant and showed that the anaerobic digestion process can be predicted with an overall accuracy of 90% [56].

ADM1, which can make accurate predictions of some AD variables such as biogas production and waste concentration [67], [68], describes, with the help of rate equations and model parameters, the main known chemical pathways from the hydrolysis of polymers and monomers to the formation of organic acids, acetic acid, hydrogen and biogas. In addition, ADM1 includes conditions that inhibit the process, such as those related to pH, hydrogen, ammonia and inorganic nitrogen [43]. Besides these advantages, adapting and calibrating ADM1 to various variants of AD processes is a challenge due to limitations in knowledge of microbial consortium composition and complex strain-specific metabolic pathways that require extensive measurements and analyses [51].

Due to these challenges, the development of machine learning (ML) algorithms has become imperative. With the help of ML, process optimization, real-time monitoring, disturbance detection and parameter estimation can be performed [42]. In this context; Simple Regression Tree (SRT), Probabilistic Neural Networks (PNN), Artificial Neural Networks (ANN), Gradient Boosted Tree (GBT), Linear Regression (LR), Tree Ensemble Regression (TER), Random Forest Regression (RFR), Polynomial Regression (PR), fuzzy logic (FL), Different machine learning algorithms such as adaptive network-based fuzzy inference system (ANFIS), support vector machine (SVM), genetic algorithm (GA) and particle swarm optimization (PSO), developing data-driven models (DDDV), Deep neural network (DNN) are used in various studies [17], [23]-[27], [39], [40], [42], [43], [59], [69]-[74]. Such modern machine learning models have the ability to accurately predict the necessary but missing data for AD. For this, model training is first performed with the help of datasets. Then, the resulting model is tested [75] and after these processes, the missing data is predicted [76].

3. RESULT and DISCUSSION

When the data obtained by using the Bibliometrix package and Biblioshiny package through the R programming language in R-Studio were evaluated, a total of 80 articles were reached between 2012-2024 in the field of “Machine Learning” in the “Biogas Production”, “Methane Production” and “Anaerobic Digestion” processes. The 80 articles were written in 35 different journals, by 387 different authors and using a total of 311 keywords. 4708 references were used in the articles. International co-authorship was 45%. No single author was found on the subject and it was determined that the other articles were written by approximately 6 authors (5.51). The top 4 journals in which the articles were published were Chemical Engineering Journal (n:9), Science of The Total Environment (n:8), Journal of Cleaner Production (n:7), Environmental Science and Pollution Research (n:6). Bioresource Technology (n:393) was the most cited journal due to the high number of ML and AD studies, despite not publishing articles directly related to the topic. The most cited country was China with 328 citations and it was found that 9 of the 22 studies prepared by Chinese authors were prepared with the participation of authors from more than one country, and the most cited documents (n:104) were Kim et al., (2020) [77] and De Clercq et al., (2020) [63]. The institution that publishes the most on the subject is Univ Nottingham Malaysia (n:11).

Figure 1 shows the three domain graphs. Through this graph, the 15 authors with the highest number of publications in the field of “Machine Learning” with the keywords “Biogas Production”, “Methane Production” and “Anaerobic Digestion”, the 15 frequently repeated keywords (in the abstracts) and the 15 journals that were most frequently used (most cited) while preparing the studies were visualized. This graph provides information about which keywords the authors use the most and the most influential authors in these studies. The figure shows that Chan yj (impact factor: 145), Zhang y (impact factor: 103) and Wang l (impact factor: 81) are the most influential authors and these three authors were found to be the most influential authors and Bioresource Technology (impact factor: 296), Water Research (impact factor: 296) and Renewable and Sustainable Energy Reviews (impact factor: 296) are the most relevant journals. As a result of the examinations, various methods (ANN, XGBoost, kNN, RF, etc.) were used in studies using machine learning,), various wastes and additives were added (wood waste, microplastics, poultry manure, food waste, Fe_3O_4 additive, animal manure, palm oil wastewater, ZVI (Zero valent iron), Biochar, various predictions (UYA, biogas yield, odor gases, biogas plant operating cost, AD liquid level prediction, ML benchmarking) and microorganism interactions and effects, gene and genome sequences were examined.

When the “Trending Topics” words in the abstract sections of the 80 articles analyzed were examined, it was seen that the first studies with ML started across “biogas plants”. Then, it was determined that especially since 2021, researches were conducted on “biogas production”, “methane yield” and “anaerobic digestion”. In today's studies, it was observed that the keywords “cod removal”, “importance analysis” and “feature importance” were widely used, and studies in which various ML models were tested on AD were emphasized. As can be seen in Figure 2, studies on ML in biogas processes are quite diverse. With the help of interdisciplinary studies, it is aimed to overcome the problems experienced in biogas processes. However, the applicability of ML models in AD processes is still one of the biggest problems today due to access to accurate and sufficient data. In order to overcome these problems, a network should be created and accessibility to “accurate and sufficient” data should be increased by making this information available. In this way, a big step will be taken in the fight against climate change, which is a global problem, regarding the disposal of organic wastes.

With the realization that machine learning (ML) should be applied to improve the efficiency, sustainability and profitability of biogas processes [78], many models have been created and used to control and support AD processes [79], [80].

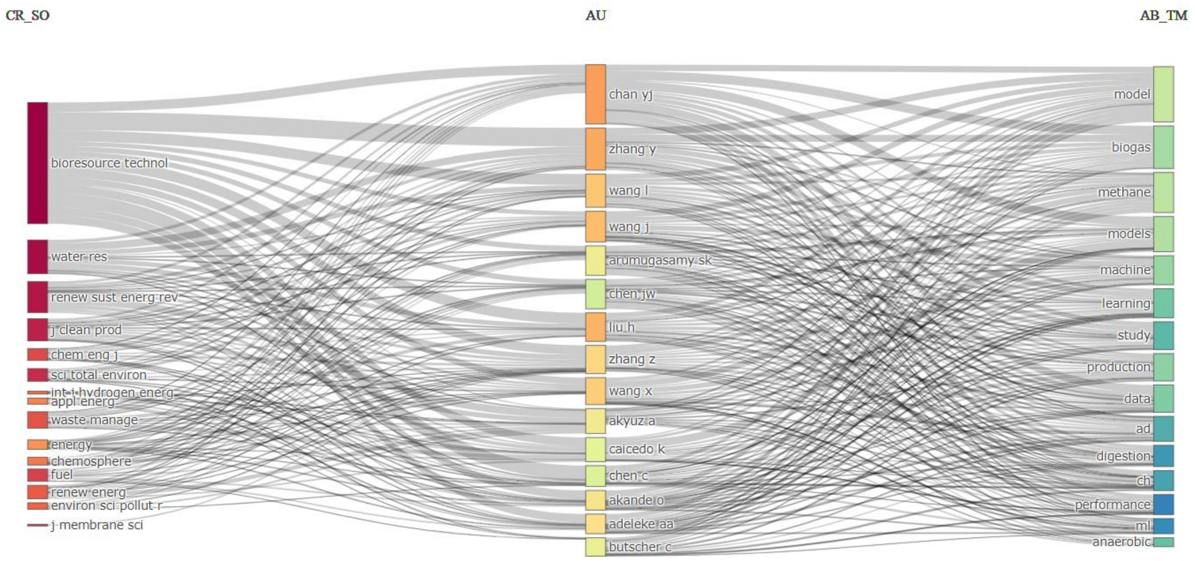

Fig. 1. Three Field Graph

However, early models did not reflect the reality as important parameters such as hydraulic retention time (HRT) [81] and temperature [82] were considered as "constant values" [23]. Many publications cannot provide data on the ten variables (inoculum types, volume (mL), temperature (℃), particle size (mm), inoculum-substrate ratio (according to VS), cellulose content (%), hemicellulose content (%), lignin content (%), digestion time (g), climate and process conditions) selected to create the ML dataset [83], [84]. Therefore, there is a great danger that the data obtained may not reflect the reality.

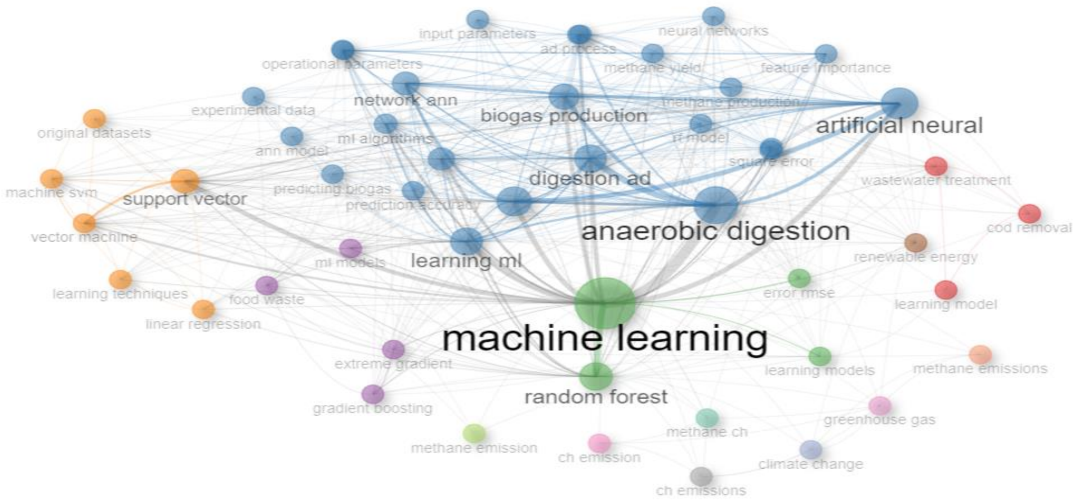

Fig. 2. Co-occurrence Network

In order to optimize the AD process, ML-based models have been applied to many types of wastes and additives [wood waste; [31], microplastic; [89]-[92], poultry manure; [93], food waste; [94], Fe_3O_4 additive [71], animal manure; [40], palm oil wastewater; [25], ZVI (Zero valent iron) [87], Biochar [95], [96], [132], microorganism interactions and effects, gene and genome sequences [33], [36], [52], [65], [88], [92], [97], [105] and various estimates UYA; [52], [106], methane emissions; [73], [74], [107], hydrogen production; [108], biogas/methane yield/production; [13]-[15], [17]-[24], [26], odor gases; [38], biogas plant operating cost; [16], [29], [31], AD liquid level prediction; [41], ML benchmarking; Ling et al., 2024 [42], methane solubility in aqueous phase; [109].

It is understood that for the estimation of biogas production potentials, substrate properties (pH, EC, OM, etc.) are usually estimated with the help of physical and chemical properties such as process temperatures, hydraulic retention times, organic loading rate (Appendix A). The first article identified within the scope of this study was published by Gaida et al. (2012) [56] in 2012. In this article, ADM1 was used and predictions were developed for a full-scale biogas plant with 90% accuracy. Subsequently, Jones and Salter (2013) [79] and Anderson et al. (2013) [80] performed profit/loss analyses of biogas units assuming some values as constant. Pioneered by these studies, other studies have been carried out on AD processes using various wastes and methods. Microorganism, gene and genome studies have accelerated with the advancement of technology and firstly, Vendruscolo et al. (2020) [99] investigated the microbial community structure changes in two biodigesters using metagenome analysis. Subsequently, Long et al. (2021) [36] conducted studies and Yao et al. (2022) [98] developed the “Genomics-enable hybrid” model. In later studies, various studies were carried out using improved ML models and more data. In these studies, 80% of the data were generally used in the training phase and 20% in the testing phase. However, in some studies [13], [16], [76], [96], [108], some of the data were used for “validation”. R^2 values were found to be quite high in most of the studies. In some studies, the large amount of data used caused decreases in R^2 values [24], [30], [107]. This proves that it is more important to have appropriate and consistent data rather than a large number of data. The most comprehensive study for Turkey is the study conducted by Pence et al. (2023) [40] in which the animal manure-based biogas potentials of Antalya, Isparta and Burdur provinces located in the Western Mediterranean Region of Turkey were calculated. However, while there are many studies using genetically modified microorganisms (GMMs) whose enzyme production yields are increased by mutations [39], [110]-[131], no study was found to predict the effects of these GMMs with ML without experimentation.

4. CONCLUSION and SUGGESTIONS

Bibliometric analysis is an important convenience in terms of giving researchers an idea about the subject to be analyzed by selecting appropriate keywords. However, when searching the WoS database, if the settings and restrictions are not fully defined, some publications cannot be accessed and some publications that are not related to the subject may be found in the analysis. Therefore, care should be taken when conducting the review. As a result of the reviews, various methods (ANN, XGBoost, kNN, RF, etc.) are used in studies using machine learning,), various wastes and additives were added (wood waste, microplastics, poultry manure, food waste, Fe_3O_4 additive, animal manure, palm oil wastewater, ZVI (Zero valent iron), Biochar, various predictions (UYA, biogas yield, odor gases, biogas plant operating cost, AD liquid level prediction, ML benchmarking) and microorganism interactions and effects, gene and genome sequences were examined. It is also recognized that microorganisms are highly determinant parameters related to AD processes. Although it is known that the enzymes secreted by microorganisms in the hydrolysis, acetogenesis, acidogenesis and methanogenesis stages of AD processes are of vital importance for biogas processes, there is no advanced study on ML to predict the effects of specific microorganisms on AD processes and the positive / negative effects of enzyme production capacity of microorganisms on AD.

One of the other shortcomings is the lack of understanding regarding which physical and/or chemical mutagen affects which gene region, thereby increasing enzyme production capacity (lipase, cellulase, amylase, protease, etc.). Finally, in an era where bioinformatics studies are advancing day by day, monitoring developments in AD processes through cloning studies will allow groundbreaking innovations in biogas processes by enabling the prediction of which gene regions need to be targeted through ML, without the need for experimental studies on controlled changes (cloning, etc.) in the gene regions of hydrolytic bacteria and/or methanogenic archaea.

Using automation systems for real-time monitoring of AD systems, parameters such as pH, EC, TAN, and especially CH_4 can be used to determine HRT, OLR, and I/S ratios via ML [133]-[135]. This allows AI to propose solutions based on real-time data and historical information (obtained through training), thereby maximizing efficiency in AD processes. In "dual systems" where hydrolysis and methane production stages are in separate reactors, monitoring parameters like pH, EC, and TAN of the hydrolysis reactor can help determine the substrate amount (OLR) and hydraulic retention times (HRT) prior to hydrolysis. This ensures that the substrate used in the methane production stage is of high quality and suitable for the highly sensitive methanogenesis stage (with more monomers due to decomposition processes). This will be highly beneficial for sustainable AD processes, maintaining high biogas yields. In reactors where the methanogenesis stage is sustained, the required post-hydrolysis substrate amount can be determined by continuous or intermittent measurements of biogas volume and methane content. Consequently, interventions can be made in the Hydrolysis and Methanogenesis stages based on the information provided by AI trained with ML.

After establishing this system, it is essential to have a deeper understanding of the microorganisms involved for a more sustainable AD process. Metagenomic analyses carried out at certain intervals can closely examine the changes of microorganisms involved in AD processes from a microbiological point of view. Using the data obtained, ML-based predictive models can be developed. This will allow the dosing of hydrolytic bacteria and methanogenic archaea - previously identified and isolated with high enzyme production efficiencies (lipase, cellulase, protease, amylase, etc.) - into AD processes in desired quantities. Consequently, methane yield from AD processes can be maintained at consistently optimal levels, giving rise to the concept of "Autonomous Biogas Plants" empowered by artificial intelligence.

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