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REVIEW PAPER

Optimization of Wastewater Anaerobic Digestion Using Mechanistic and Meta-heuristic Methods: Current Limitations and Future Opportunities

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Abstract Anaerobic digestion is widely used to treat high-strength wastewater and produces methane as a by-product for power generation. Treatment and reuse of industrial effluent also contribute to water conservation efforts. Nevertheless, the sensitivity of anaerobic digestion system proves to be a challenge in ensuring consistent quality of treated wastewater and biogas production. Hence, it is essential to devise an effective model and control system that accurately represent the dynamics of anaerobic digestion and can respond to changes in process parameters with proper fault detection and output prediction. This article provides a comprehensive review on (1) the anaerobic digester technology and parameters governing its efficiency, (2) mechanistic and meta-heuristic models used to describe this process, and (3) the process control strategies. In this study, adaptive controller was found to be able to provide wider options in terms of controlled and manipulated variables. Nevertheless, an in-depth study is essential to determine the best controller to be applied for a particular system where further optimization can be done to achieve the best performance.

Keywords Anaerobic digestion · Wastewater treatment · Process control · Meta-heuristic · Modelling

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Introduction

Anaerobic digestion is widely used for the treatment of wastewater with high organic carbon content, as an alternative to aerobic digestion [1]. Utilization of anaerobic digestion for treatment of high-strength wastewater reduces the production of sludge while producing methane as a by-product that can be used for power generation [2]. Additionally, anaerobic digestion of wastewater is an effort to conserve water in many areas with arid conditions, where the treated effluent can be reused within the process plant to reduce freshwater consumption.

Biogas generated from anaerobic digestion could potentially offset the anthropogenic carbon dioxide emission from industries and reduce reliance on fossil fuel. Furthermore, industries could gain additional revenue by utilizing biogas produced from anaerobic digestion of wastewater. As an example, four palm oil mills in Malaysia were approved to connect electricity generated from utilization of biogas to national grid. It is expected that a typical palm oil mill processing 60 tonnes/h of fresh fruit bunch could gain a net profit of up to RM 3.8 million (1 million USD) annually from producing grid electricity [3].

Nevertheless, anaerobic digestion is a complex process, which involves the use of bacteria that are sensitive to changes in operating conditions [4]. The implementation of anaerobic digestion is further complicated as the characteristics and flow rate of wastewater into the treatment plant are rarely consistent—making it a challenge to maintain and control optimal operating conditions for the anaerobic bacteria [5].

There is therefore a need to devise an effective control system capable of responding to changes in wastewater characteristics and operating condition of the treatment plant. Implementation of an effective control system, within the plant, would also see improvement and stabilization in the composition of biogas. This improvement will increase efficiency of the internal combustion engines and minimizes corrosion to the pipeline and other equipment due to higher concentration of hydrogen sulfide [6].

Fault detection and output prediction are indispensable methods in process control. These methods are used to manage production rate of biogas and quality of treated wastewater from anaerobic digesters. The application of appropriate model and process control can maximize the process efficiency, improve sustainability of plant operation, and encourage more parties to adopt anaerobic wastewater treatment systems, eventually leading to a reduction in greenhouse gas emissions. Despite extensive studies in modelling and optimization of anaerobic digester [7–9], many recent developments on anaerobic digestion technology and process control were not thoroughly reviewed in recent years. These studies also did not discuss the use of several meta-heuristic approaches in modelling and control of the digester. Meta-heuristic started gaining traction in recent years and has been used in various applications. Hence, it is important to conduct a comprehensive review in this area to provide proper insight to decision makers for effective handling of wastewater processes to reduce operational costs. Therefore, this review serves to identify the advances in anaerobic digestion of wastewater, modelling, and process control of these systems from year 2000 onwards.

The subsequent section (“Anaerobic Digestion and Digester Technology” section) evaluates various high-rate anaerobic digesters that were utilized for wastewater treatment and latest developments involved. The mechanistic and meta-heuristic models that were used to describe anaerobic digestion are thoroughly discussed in “Process Parameters in Anaerobic Digestion” and “Mechanistic Model” sections. “Meta-heuristic Model” discusses the use of several control strategies to improve the performance of the system. Lastly, “Process Control of Anaerobic Digester” identifies the various challenges and opportunities for development of automated anaerobic digesters for industrial wastewater treatment. All these areas assessed by this review paper contribute to water conservation as the utilization of process control methods and automation of industrial wastewater treatment processes produce treated water with higher quality that can be used for recycle and reuse within the industry. In addition, the implementation of process control engineers a wastewater treatment system that can adapt with movable effluent discharge targets set by regulatory bodies.

Anaerobic Digestion and Digester Technology

Anaerobic digestion is a biological process which involves the use of microbes to degrade complex organic matters (i.e., carbohydrates, proteins, lipids) in the absence of oxygen to methane, carbon dioxide, and water. This process involves a sequence of reactions which includes hydrolysis, acidogenesis, acetogenesis, and methanogenesis using a mixed consortium of bacteria [10, 11]. Anaerobic digestion is often selected over aerobic digestion to treat high-strength industrial wastewater because it is less energy intensive and has higher pathogen inactivation rate. Furthermore, the by-product of this treatment, methane, can be used for power generation. These characteristics are beneficial for areas/countries with limited energy source. They can reduce fossil fuel for boilers and other energy-intensive equipment, hence, reducing overheads of industrial processes [3].

Conventional anaerobic digester (for wastewater) was conducted in anaerobic ponds complemented with facultative and aerobic ponds to ensure sufficient removal of organic materials and pathogens [4, 12, 13]. However, this method requires long retention time and large treatment area. As such, high-rate anaerobic reactors were introduced to provide high sludge retention and sufficient contact between bacteria and substrate (wastewater), which minimizes the duration of this treatment and space requirement [14].

Continuous stirred tank reactors (CSTRs) are the least efficient type of anaerobic reactors as they operate at longer hydraulic retention time (HRT) and similarly contribute to lower efficiency in the removal of contaminants. Though CSTR has a relatively simple design, the mechanical agitation can be the contributing factor to the reduced performance of the reactor. The shearing effect induced at rapid mixing can destroy the microbial cells. Additionally, more oxygen will be present in the reactor if the CSTR is not operated at a strict anaerobic condition [10]. Furthermore, it is difficult to ensure that wastewater is well mixed when it is implemented in large scale with larger volume of feed. As such, pilot or industrial scale CSTRs tend to operate at a lower efficiency as compared to laboratory scale CSTRs [15–17].

Upflow anaerobic sludge blanket (UASB) reactors can consistently remove contaminants from industrial wastewater and can achieve an efficiency of up to 97 % of chemical oxygen demand (COD) removal in addition to the production of biogas with at least 60 % of methane concentration. However, foaming, sludge floatation, and granulation inhibition can be present when system is operated at high organic loading rates (OLRs) or when the wastewater contains high concentration of volatile fatty acid (VFA) [18–20]. Besides, high concentration of fats, oil, and grease, phenolic compounds in certain industrial wastewaters, and residual antibiotics in pharmaceutical were reported to cause inhibition in anaerobic digestion [21–24]. This is apparent for the treatment of coal gasification wastewater (as shown in Table 1) where

Table 1 Performance of various anaerobic reactors for industrial wastewater treatment

Wastewater	Reactor type	Organic loading rate (OLR) (kg COD/m^3 day)	Hydraulic retention time (HRT) (days)	Maximum COD removal efficiency (%)	Methane concentration (%)	References
Slaughterhouse wastewater	Anaerobic baffled reactor	–	3.8	90	–	[25]
	Upflow anaerobic filters	10.05	0.5	79	46–56	[26]
	Anaerobic lagoons	–	5–10	96	–	[27]
	Upflow anaerobic sludge blanket/anaerobic sequencing batch reactor	1.82–12.79	1	94.31	–	[28]
Grease trap waste	3-stage packed bed upflow	21.2	1	81	81	[29]
Coal gasification wastewater	UASB	2.5	1	60	–	[24]
Swine wastewater	CSTR (pilot scale) UASB	2.5	20	65.3	–	[15]
		1.0	8	85.4	66	[30]
Pharmaceutical wastewater	Hybrid UASB reactor	9.0	1.5	75	70	[31]
Brewery wastewater	Fluidized bed	10.0	–	90	–	[32]
Wash water from virgin olive oil purification	CSTR -With biomass immobilized on bentonite	0.86–5.38	4–25	–	–	[33]
	-Suspended biomass	0.86–4.30	5–25			
Palm oil mill effluent (POME)	UASB-HCPB	27.65	2	90	60	[34]
	UASFF	8.74	3	97.5	74.2	[35]
	EGSB	2.9[a]	5	95.5	66	[36]

UASFF upflow anaerobic sludge fixed film, *UASB-HCPB* upflow anaerobic sludge blanket-hollow centered packed bed, *EGSB* expanded granular sludge bed

[a] Units are quoted in gram volatile solid per liter per day

the COD removal efficiency (60 %) is lower than any other wastewater treated using UASB reactor due to the presence of phenolic compounds. Thus, it is essential to consistently monitor the composition of wastewater entering the reactor and to implement appropriate control to ensure satisfactory removal of contaminants from wastewater.

In order to counter operational issues due to foaming, washout of biomass, VFA, and toxic compound inhibition in anaerobic digestion and to simultaneously boost contaminant removal and biogas production, researchers have ventured into the development of hybrid anaerobic reactors, multistage anaerobic reactors, and anaerobic co-digestion [15, 23, 34, 35]. One of the reactors which is highly suitable for application in palm oil mill effluent (POME) treatment would be upflow anaerobic sludge blanket-hollow centered packed bed (UASB–HCPB) which has a COD removal efficiency of 90 %, suspended solid removal capability of 80 %, and a biogas production which consists of 60 % methane concentration when operated under thermophilic condition with an OLR of 27.65 g L^{-1} day^{-1} and an HRT of 2 days [34]. Another alternative would be the application of a hybrid anaerobic reactor (upflow anaerobic sludge fixed film (UASFF)) [35] for POME treatment which shows notable improvement in the COD removal efficiency and methane concentration (Table 1). Similar outcome was reported by Hunter et al. [37] and Ke et al. [38] where multi-staged anaerobic reactor showed superior performance over single-stage anaerobic reactor. However, these systems are more difficult to implement as they involve many different process parameters that can influence their performances [38].

Process Parameters in Anaerobic Digestion

Regardless of the type of anaerobic digester used for wastewater treatment, it is essential to understand various process parameters that can influence the operational performance of high-rate anaerobic reactors to ensure that proper control system can be devised based on the conditions of the process. In this review, the focus is on the process parameters that are highly influential towards the performance of high-rate anaerobic reactors. These parameters are commonly used variables when devising anaerobic digester models and control strategies to improve quality of treated wastewater and biogas production.

Temperature

Microbes can optimally operate at three different temperature ranges—psychrophilic (<20 °C), mesophilic (>25 °C), and thermophilic (50–60 °C). Temperature is an important parameter in maintaining performance of an anaerobic digester as it governs bacterial growth and activity [14]. Several studies conducted to investigate the effect of temperature found that digester operating at the thermophilic region (55 °C) has several advantages: higher substrate degradation, higher biogas production rate, and the ability to operate under higher OLRs at shorter HRTs [39–41]. Higher biogas production rate is crucial to the operation of anaerobic digester as it is able to reduce the return of investment [42].

Nevertheless, biomass washout with accumulation of VFA could occur if the digester is not controlled to operate at its optimal temperature [43]. This is due to the fact that methanogenesis reaction that consumes VFA proceeds at a lower rate in comparison to the acidogenic reaction that produces VFA. When the anaerobic digester is operated in the thermophilic region, the rate of VFA production will increase. When it is coupled with other conditions such as high OLR and HRT, the methanogens will not have sufficient time to multiply or to convert the accumulated VFA in the system, causing biomass washout. Therefore, temperature of the digester should be strictly maintained to ensure optimal performance during anaerobic digestion of wastewater.

pH and Volatile Fatty Acid Concentration

pH is another crucial parameter that needs to be monitored and controlled to maintain good performance of an anaerobic digester. This is attributed to the microbial community that is sensitive to pH changes. As such, most anaerobic digesters (except two/multiple-stage digesters) operate at an optimal pH of 6.8–7.2 as this range of pH is optimal for the growth of methanogens that produces methane as the main product. On the other hand, pH lower than 4 and higher than 9.5 is not advisable as methanogenesis can occur at a lower rate at lower pH, leading to the accumulation of VFA, which will eventually lead to failure of the anaerobic digester [11, 44]. Furthermore, reduction of pH (from alkaline to neutral region) was reported to be able to reduce ammonia toxicity within the digester, ensuring that VFA in the system could be properly utilized for the conversion to methane [2]. pH of anaerobic digester is commonly controlled to be below 10 as at higher pH (between 9 and 10) the treated effluent may not conform to the effluent discharge limit [10].

Organic Loading Rate (Dilution Rate) and Hydraulic Retention Time

OLR and dilution rate are interchangeable terms that represent the load of contaminants fed into the anaerobic digester. OLR is determined via the COD or volatile solid concentration per unit time, per volume of digester, while dilution rate represents the flow rate of contaminants per volume of culture in the digester. Values of OLR are generally dependent on the "strength" of wastewater. OLR and HRT are inter-related in the operation of an anaerobic digester. The operating HRT and concentration of organic substance can influence the OLR of a system. Anaerobic digesters have to be operated at high OLR if the wastewater fed into the reactor has high concentration of COD and is retained in the digester for a short period of time (short HRT).

Generally, it is desired to operate an anaerobic digester at high OLRs as the output of biogas from the system increases. Nevertheless, investigations on anaerobic treatment of various industrial wastewaters found that an increase in OLR was shown to cause the performance of anaerobic digesters to decline [12]. This is mainly due to the fact that microbial population in the anaerobic digester could not convert substrates on time, thus leading to lower COD removal efficiencies and accumulation of VFA. Therefore, wastewater concentration and the flow rate should be closely monitored and controlled to avoid reactor upsets. Despite understanding the relationship between OLR and HRT, it is not possible to suggest an optimum OLR for the anaerobic digestion of all types of wastewater as the tolerable OLR is very much dependent on the level of contamination of the wastewater, the inhibitory compounds, and other operating condition, e.g., temperature and rate of mixing that will affect the growth of the microbial population in the digester.

Other Parameters Influencing Anaerobic Digestion

There are several other parameters that could inhibit the operation of anaerobic digesters such as metal toxicity [45–47], presence of herbicides, pharmaceutical components, overloading of macronutrients [2, 48], and unconsumed hydrogen. These factors can result in high hydrogen partial pressure which inhibits acetogenesis phase, in particular the conversion of long chain fatty acids into acetate and propionate [49]. Therefore, it is extremely important that the wastewater is carefully characterized prior to the design of wastewater treatment system and development of the process control system so that proper operating conditions and operating set points can be devised.

Mechanistic Model

In order to develop an effective control system for anaerobic digester, suitable mathematical model that can describe the dynamics of continuous anaerobic digestion and the interaction between controlled parameters described in "Process Parameters in Anaerobic Digestion" is crucial. Several mechanistic models had been proposed to describe this process, including early models proposed by Bailey and Ollis [50], Pavlostathis et al. [51], and Denac et al. [52] and the popular mass balance model developed by Bernard et al. [53] and Anaerobic Digestion Model No. 1 (ADM-1) by Batstone [54].

Mass Balance Model

Various anaerobic digestion models were proposed and reported in literature—ranging from models with great complexity which can be difficult to be physically implemented to models with assumptions that are not necessarily present in practice [53]. This disparity can be attributed to the lack of phenomenological knowledge, nonlinearity, and complexity of the process itself. The mass balance model circumvented these limitations by modelling and focusing on the reaction rates and minimizing the number of assumptions. Bastin and Dochain [55] were pioneers in reporting the effectiveness of the mass balance model.

Mass balance model proposed and validated by Bernard et al. [53] is one of the widely accepted models to simulate anaerobic digesters. Their model was devised from several variables such as concentration of biomass, total organic carbon (TOC), COD, VFA, and alkalinity. It was developed with the following assumptions: (i) α was introduced to consider the process heterogeneity. $\alpha = 1$ describes the dynamics of the classical CSTR where the biomass is completely suspended in the liquid phase. $0 < \alpha < 1$ describes the dynamics of fluidized-bed reactors or fixed-bed reactors (FBRs); (ii) it is considered that the alkalinity is mainly due to the concentration of bicarbonate and VFA; and (iii) it is assumed that the anaerobic digestion operates under isothermal condition. Other than being validated in their own experimental study, the Bernard et al. [53] model was seen to be consistent with a wider range of experimental verifications too [56–60].

The mass balance model is derived from a macroscopic mass balance of key variables of the process, and details of the model are presented in Bernard et al. [53] as shown in Table 2. In order to derive the control scheme for mass balance models, destabilization criteria were considered. The destabilization of anaerobic digestion processes primarily involves the development of unbalanced microbial consortia leading to a high concentration of VFA and eventually a total system failure. Therefore, VFA concentration has been proposed to be one of the reliable indicators of system's operation and performance. Choosing VFA as the variable to be controlled would result in the basic dynamical model of Eq. 1

Variations to the Bernard et al. [53] model were proposed by Mendez-Acosta et al. [61], Rincon et al. [60], and Flores-Estella et al. [5]. Mendez-Acosta et al. [61] sought to control anaerobic digestion by regulating VFA and total alkalinity (TA) as these were deemed to be the main parameters that led to washout. To achieve this, they used different assumptions to control the inlet parameters. This view was also shared by Rincon et al. [60], where the authors reported a mass balance model seeking to regulate VFA to avoid total system failure. However, the ability of the model to perform in dynamic conditions (destabilization phases) cannot be concluded as both studies were based on simulation and mathematical prediction with no physical verification being conducted. Another mass balance model specifically for the winery industry was reported by Flores-Estrella et al. [5]. In this model, Flores-Estrella et al. [5] sought to control the COD as it was

Table 2 Mass balance equation

	Mass balance equation	Prefix
1	$X_1 = X_1(\mu_1 - \alpha D)$	X_1 = concentration of acidogenic biomass (g/L) μ_1 = model for acidogenic bacteria kinetics (day^{-1}) α = proportion rate of dilution for bacteria (mmol/L) D = dilution rate (day^{-1})
	$X_2 = X_2(\mu_2 - \alpha D)$	X_2 = concentration of methanogenic biomass (g/L) μ_2 = model for methanogenic bacteria kinetics (day^{-1})
	$S_1 = \left(S_1^{in} - S_1\right)D - k_1\mu_1X_1$	S_1 = organic substrate characterized by its COD (g COD/L) k_1 = yield for substrate degradation (unitless)
	$S_2 = \left(S_2^{in} - S_2\right)D - k_2\mu_1X_1 - k_3\mu_2X_2$	$S_2(t)$ represents the concentration of VFA (mmol/L) k_2 yield for VFA production (mmol/g) k_3 yield for VFA consumption (mmol/g)
	$\mu_1 = \mu_{1max}\frac{S_1}{S_1 + K_{s1}}$	μ_{1max} = maximum bacterial growth rate (day^{-1}) K_{s1} = half saturation constant which depends on the substrate, S_1 (g/L)
2	$\mu_2 = \mu_{2max}\frac{S_2}{S_2 + K_{s2} + \left(\frac{1}{K_{I2}}\right)S_2^2}$	μ_{2max} = growth rate of bacteria at its maximum without inhibition (day^{-1}) K_{s2} = saturation constant which depends on the substrate S_2 (mmol/L) K_{I2} = inhibition constant which depends on substrate S_2 (mmol/L)

argued to be the fundamental objective in water treatment plants.

The monitoring of anaerobic digestion is admittedly difficult and complex, as it is a multivariate process. This is further complicated with limited reliable online sensors for the measurement of all required parameters and substances involved [62]. The mass balance model, however, is mainly interested in monitoring one or all of the following (1) COD, (2) VFA, and the (3) reduction of model complexity. This is where this model is advantageous, by limiting the number of parameters required and assumptions made. Moreover, it ensures reliable and extended time periods of useful operations.

Anaerobic Digestion Model No. 1

Apart from the mass balance model, ADM-1 is also commonly incorporated to develop model-based control for anaerobic digestion systems. ADM-1 is a mechanistic model developed with the purpose of creating a common platform for anaerobic process modelling and simulation that could encourage greater utilization of anaerobic process technologies in the future [54]. It can also be used to develop operational strategies and evaluate controllers [63]. The ADM-1 model incorporates all three biochemical steps (i.e., hydrolysis, acidogenesis, acetogenesis, and methanogenesis) and physico-chemical steps such as ion association/dissociation and gas–liquid transfer.

ADM-1 is modelled after a CSTR of 32 dynamic state concentration variables, where 24 of them are described using first-order Monod kinetics with a general form as shown in the equation below, where S_i is the component concentration (kg COD m^{-3}), q is the flow (m^3 day^{-1}), V_{liq} is the volume of the reactor (m), and the kinetic rates ρ_j for process j (kg COD m^{-3} day^{-1}) multiplied by the stoichiometric biochemical rate coefficients $v_{i,j}$:

$$\frac{dS_{\mathrm{liq},i}}{dt} = \frac{q_{\mathrm{in}} \cdot S_{\mathrm{in},i}}{V_{\mathrm{liq}}} - \frac{q_{\mathrm{out}} \cdot S_{\mathrm{liq},i}}{V_{\mathrm{liq}}} + \sum_{j=1-19} \rho_j \cdot V_{i,j} \tag{1}$$

(Accumulation = Input–Output + Reaction)

ADM-1 has been applied to simulate and control UASB reactor [64], to devise fuzzy-based controller of anaerobic reactor [65], and to develop multi-objective cascade controllers for anaerobic digester [66]. This model has become available in simulation software, such as MATLAB, Simulink, WEST, BioWin, and Aquasim [67] to ease its application. In some cases, ADM-1 was also modified to extend the application of this model to simulate anaerobic digestion involving ethanol degradation pathways [68, 69], anaerobic digestions which involve precipitation of $CaCO_3$ [70] and modifications which focus on hydrolysis kinetics [71].

ADM-1 is undeniably the most robust model that has been applied to develop control schemes for anaerobic digestion. However, for its implementation, it is crucial to have a comprehensive characterization of the substrate. This can be difficult for anaerobic digestion with significant variation in feed characteristics throughout the year, especially in wastewater treatment processes. For example, the olive mill wastewater (OMW) characteristics would vary greatly between mills [72, 73], and in the case of POME, it would vary according to season and type of fruits processed in the mill [73]. This could reduce the robustness of the control systems developed for such systems, and hence future development should be focused on the modification of ADM-1 to cater for wastewaters with varying characteristics.

Meta-Heuristic Model

Other than mechanistic models, researchers have also attempted to design and develop models based on meta-heuristic approaches, such as fuzzy logic, artificial neural network (ANN), particle swarm optimization (PSO), and their combinations.

Fuzzy Logic Model

Fuzzy logic modelling represents a linguistic model approach in describing domain knowledge (Fig. 1) [74]. Fuzzy logic models are superior in terms of the ease in increasing the number of input parameters it can monitor. This is because each input parameter will be modelled into a fuzzy set, simplifying the real-world representation by eliminating the need for crisp set theory. The basic idea of the fuzzy set theory is that an element belongs to a fuzzy set with a certain degree of membership. For example, a proposition is not either just true or false but may be partly true (or partly false) to any degree (membership function). Such approach allows for knowledge to be represented efficiently on a computer as a model. The membership functions of the input parameters will then be analyzed via a set of "if-then" rules to determine an appropriate output. Precision of the information evaluated can be improved through alteration of membership function which would provide a higher degree of accuracy in addition to alteration done on the "if-then" rules. The ability of the fuzzy logic model to handle ambiguity via membership functions and "if-then" rules make fuzzy logic ideal for bioprocesses and chemical engineering processes which are very dynamic in nature [29, 75, 76].

Application of fuzzy logic in AD can be seen in works presented in Giraldo-Gomez and Duque [21], Boscolo et al. [77], Mingzhi et al. [78], and Steyer et al. [79], Turkdogan-Aydınol and Yetilmezsoy [80], and Varne and Macwan [81]. In recent publications, Turkdogan-Aydınol and Yetilmezsoy

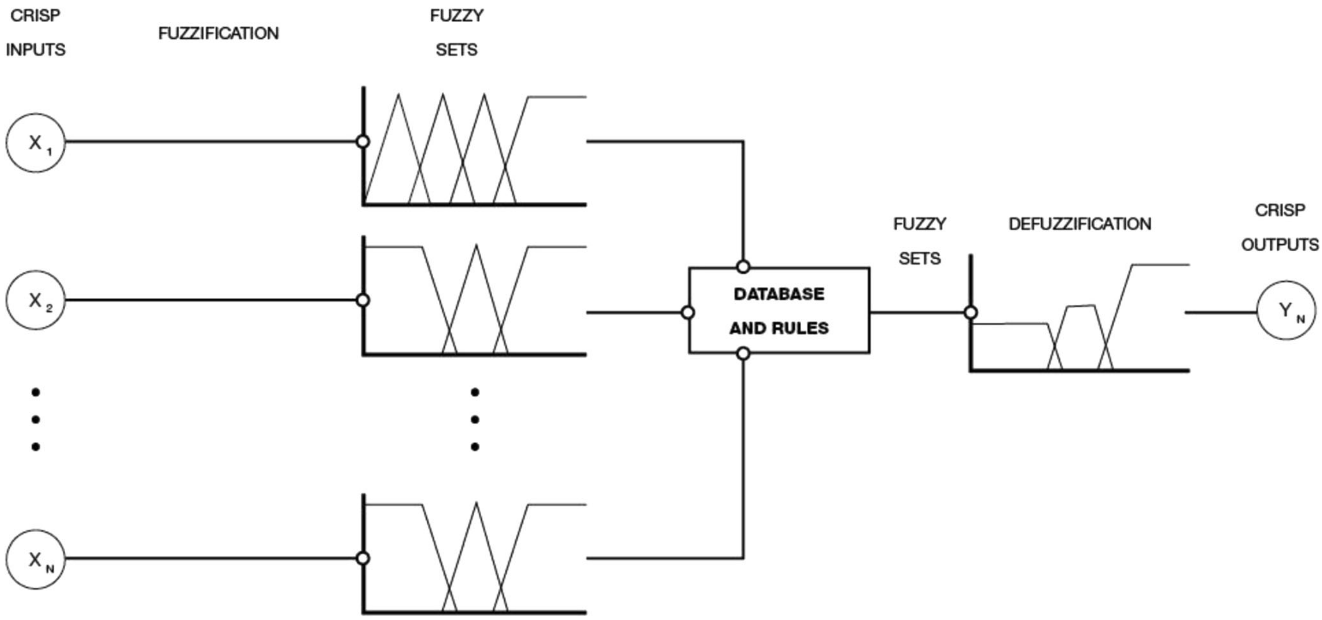


Fig. 1 Mamdani fuzzy logic model

[80] developed fuzzy model to predict biogas and methane production rates in molasses wastewater treatment. They used Mamdani's fuzzy inference method with five input variables, i.e., volumetric OLR, volumetric COD, removal rate, influent alkalinity, and influent and effluent pH. On the other hand, Varne and Macwan [81] developed fuzzy model to predict COD reduction and biogas production rate using flow rate, influent COD, pH, and temperature.

Use of fuzzy logic in AD brings several advantages.

1. Fuzzy logic can handle a large number of inputs allowing optimum operational condition to be attained without the need to rely solely on the experience of operators.
2. Fuzzy logic can rationally quantify uncertainty in systems and qualitative behavior of the system.
3. Fuzzy logic can handle greater sensitivity and instability poised by AD [82].
4. Fuzzy logic allows consistent generation of biogas [13].

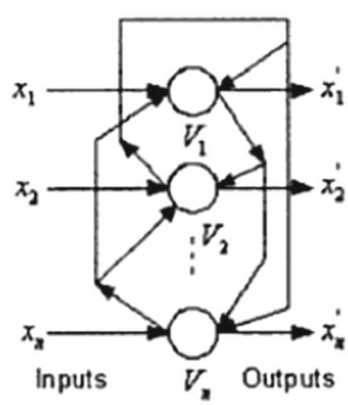
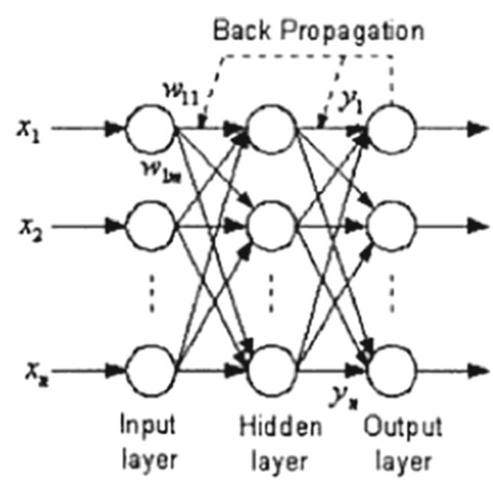
One of the main concerns in implementing a fuzzy logic model is that it evaluates relationship between the parameters defined in the system (inputs and output) via a set of "if-then" rules, which may be seen to oversimplify the dynamics of the digestion system. However, in terms of physiochemical and biological changes, it is important that biomass activity occurring during anaerobic digestion is taken into account during the analysis [5, 75]. The other concern is the nonsystematic initial tuning approach [29]. Trial and error tuning has to be continuously done as a fuzzy logic model can be compared to a black box model which is nontransparent and highly complex. The tuning procedure may vary depending on the type of bacteria, temperature, and the phase of the reaction. However, once a general model is established, future tuning is simple as it uses normal human language that is easily understandable for the operators.

ANN

ANN is a collection of "neurons," and the properties of the network are determined by its topology and the properties of the neurons. Being inspired by the human nervous system, ANN was developed by interconnecting models which would give similar behavior to biological neurons. Instead of depending on the prior knowledge or the need to list the correlations between parameters, ANN is a self-learning model which allows prediction of output that is considerably of higher versatility compared to other logical operation system. The abstract properties of ANN, such as their ability to perform distributed computation, to tolerate noisy inputs, and to learn, have attracted the interest of researchers in various problem domains, including anaerobic digestion of wastewater [83]. Structures of ANN can be divided into two main categories, namely the recurrent or feedback networks and feedforward or multi-layer network. The main characteristics of these networks are presented in Table 3.

Training on ANN is executed by three types of learning algorithm, namely supervised, unsupervised, and reinforcement learning. Supervised learning requires supervision in the form of desired outputs to be stated where the weights of interconnectivity between neurons will be adjusted based on the difference between actual and desired output with reference to the input provided. Unsupervised training on the other hand only requires input to be given whereby input patterns with similar features will

Table 3 Characteristic of recurrent and feedforward network [84]

Network	Recurrent (Feedback)	Feedforward (Multilayer)
Connectivity between neurons	An interconnecting network is organized by the interconnection of multiple neurons	Multiple layers with a hierarchical structure where interconnection among neurons in the same layer are absent in some layers
Signal flow	• Both directions: forward and backward • Weights in neurons are constantly adjusted until a steady state is reached or the system exhibits oscillation or chaotic behavior. Thus, application on rapidly changing of input neurons is not favored due to unwanted response and time wastage • Response of given input depends on initial stage (supports short-term memory)	• Unidirectional connections whereby signals flow from input to output layers • No loops present • Each neuron consists of only information of the adjusted weights from input to output neurons
Figure		
Examples of ANN	• Hopfield network • Elman network • Jordan network	• Multi-layer perceptron • Learning method quantization • Cerebellar model articulation control

be clustered into groups through adaptability of connections between weights. For reinforcement learning, targeted output is not sought after but instead accuracy of neural network output based on the given input is evaluated instead.

ANN has several advantages. Among them is its processing speed and greater fault tolerance. It has a highly parallel structure that is suitable for real-time dynamic control. Moreover, it also allows implementation of nonlinear control problems. Highly adaptable and integrative is another advantage of the ANN. It permits handling of large scale, complex, and system with multivariable. Besides, ANN is not only limited to handling qualitative data but also quantitative data. Lastly, ANN is able to generalize data through training of past data records which is highly useful for processes that are difficult to be handled by descriptive rules or of complicated mathematical models.

Application of ANN on anaerobic digestion modelling is deemed effective [85] as ANN is highly adaptable. This can be viewed in terms of parameter adjustment employed on the system through the design of a cognitive which enables effective changes to be made. In addition, ANN is commonly applied in energy industry. With reference to this observation, it can be inferred that application of ANN in anaerobic digestion is rather efficient as biogas recovery can be considered as a form of renewable energy salvation from waste. Moreover, based on current trend which illustrates the effectiveness of ANN to predict and demonstrate models dealing with unclear mechanistic [71], the efficacy of ANN can be further deduced when utilized in anaerobic digestion system.

A successful application of ANN in control system is the modelling and prediction of bioethanol production [21] which shows a relatively good prediction as the coefficient of determination (R^2 value) ranges from 0.800 to 0.999. This indirectly demonstrates the effectiveness of ANN to be used as a predictive model for anaerobic digestion. The only downside is the need to vary the number of weights to improve R^2 value. In addition, use of ANN for anaerobic digestion depends on the input and output variables and the type of network used. Holubar et al. [86] trained feedforward back propagation (FFBP) ANN to model and subsequently control methane production in anaerobic digester. They used gas composition, methane production rate, VFA concentration, pH, redox potential, volatile suspended solids, and COD of feed and effluent as the input variables. The output from the network is fed into a decision support system to find out the best feeding profile for the next time steps in advance. Rangasamy et al. [87] used maximum OLR, HRT, and the efficiency of the reactor to determine the effluent COD and pH, biogas production, VFA, and alkalinity. They proposed the use of multilayer perceptron ANN which has two input neurons, five output neurons, and two hidden layers. Holubar et al. [86] and Rangasamy et al. [87] successfully demonstrated the viability of ANN to model anaerobic digestion. Other issues faced by ANN, summarized in Table 4, are mainly poor generalization of models leading to over fitting.

Particle Swarm Optimization

PSO has a working principle illustrated in Fig. 2. In contrast to fuzzy logic and ANN, PSO is mainly used to optimize processes instead of direct application as a control process. Implemented on complex nonlinear and multidimensional functions, the main aim of PSO is to attain global optimum value via convergence [91]. Solutions acquired by particles are differentiated into two main types. In terms of particle basis, a comparison will be made and personal best value will be obtained, whereas global optimum solution is gained in terms of PSO process by global optimization. Speed of convergence relies closely to the size of search space, population size of the swarm, and the number of generations. Representation of the initial population of PSO can be further improved by introducing some rule of thumb or constraints to reduce the search space. Perturbation, such as crossover [92], can also be carried out within PSO to speed up the convergence speed of the algorithm. Rate of change in position of particles is regarded as apparent velocity of the particle which changes according to the translation velocity shown below at each iteration.

$$v_{Nk}^{i+1} = \omega v_{Nk}^{i} + A_1 \mathrm{rand}(0,1)(P_{Nk} - X_{Nk}) + A_2 \mathrm{rand}(0,1)(G_N - X_{Nk}) \tag{2}$$

where

K	Number of particles
$X_k = \{X_{k1}, X_{k2}, \ldots, X_{kN}\}$	Position of kth particles
$P_k = \{P_{k1}, P_{k2}, \ldots, P_{kN}\}$	Best visited position of the kth particles
$G = \{G_1, G_2, \ldots, G_N\}$	Best result of all particles in PSO algorithm
$v_p = \{v_{p1}, v_{p2}, \ldots, v_{pN}\}$	Apparent velocity of particle p
A_1 and A_2	Constant {learning factors; acceleration of particles towards the best position over the search space}
ω	Inertia weight

ω continuously changes over each iteration according to the equation below:

$$\omega_{\mathrm{i}} = \omega_{\max} - \frac{\omega_{\min}}{i_{\max}} \times i \tag{3}$$

where

ω_i	Inertia weight
$i_{\max}$	Maximum steps of iteration
$\omega_{\max}$	Maximum value of inertia weight
$\omega_{\min}$	Minimum value of inertia weight

Based on empirical studies, acceptable values of $\omega_{\min} = 0.4$ while $\omega_{\max} = 0.9$ [93].

In compliance with the equations stated above, further fine tuning of PSO is compulsory similar to fuzzy logic. For PSO, algorithmic performance is greatly influenced by the tuning parameter known as exploration and exploitation. Locating a good optimum and more favorably a global optimum solution

Table 4 Overview of meta-heuristic model [88–90]

Meta-heuristic model	Fuzzy logic	Artificial neural network (ANN)	Particle swarm optimization (PSO)
Basis	Derivation of rules	Empirical risk minimization	Population-based strategy
Strengths	• Does not require mathematical model • Flexible • Implementation and interpretation is relatively easy, low complexity • Simple fuzzy sets and inference rules via linguistic terms	• No mathematical model is necessary • Adaptation ability towards minor environment changes • Able to handle multiple variables with multitude functions • Scalable • Able to handle multiple constraints imposed on the system evaluated • Possess forward propagation mode once satisfactory trained level of network is attained that can be used as an analytical tool on other data • Minimal data is required	• Calculation required in PSO is relatively simple • Adoption of real number code allowing direct application by solution whereby dimension number is equivalent to the solution constant • Have the capability to store memory • No overlapping or mutation calculation where only the most optimist particle can transmit info to other particles which fasten the research speed
Weakness	• Require rule derivation • Highly dependent on inference rules that affect accuracy • Relied on relevancy of rules and the features	• Requires training data and prior knowledge of environment • Training speed is affected by network size • Subjected to over-train leading to output respond which depends solely only on one input • Developed model which is not the general representation of the system may lead to overfitting • Local minima may provide multiple solutions which is not robust for different samples	• Problems of scattering cannot be solved • Optimization process may only be completed partially • Problem of noncoordinate system also could not be solved • Clustering of data may happen when the load of data handled is too large
Challenges	• Derivation of rules must be determined accurately which requires experts' knowledge during initial stage • Fine tuning is relatively difficult as standard procedure is absent and requires trial and error method • Every possibility for the system process must be listed in order to acquire higher accuracy	• Clean and task relevant data is necessary during the training phase • Data and parameters chosen must be appropriate as training performance speed are dependent on it	• Weak theoretical foundation where stable movement of particle is rather limited • Suitability of topologies of different ranges which gives a better function can be researched on • Application area of PSO has yet to be widely used and combination of PSO with other optimization algorithm is proposed to give a better result

through various region testing is exploration, while concentration of search at specific particles for precise location of optimum is known as exploitation. Although both parameters are favorable and hope to be acquired, a tradeoff is usually necessary among the two as complete theoretical analysis on the two indicates the involvement of mathematical complexity whereby simplified derivation is yet to be found [82].

However, PSO is considered an effective algorithm to be implemented on fuzzy logic or ANN for optimization of anaerobic digestion modelling. This is in line with previous reports which indicated effectiveness of PSO when coupled with ANN. The main advantage of PSO is the ability of each particle to record their best position despite the change in population samples over time. Hence, based on this plus point, high load of data can be handled by PSO and best solution to attain the optimum condition for anaerobic digestion can be found as the best trajectory paths of particles to achieving the global are kept tracked allowing the optimum control condition to be acquired. Smith [94] demonstrated the applicability of PSO in determining the pressure of seven different types of gases present in anaerobic digester: ammonia, carbon dioxide, hydrogen, hydrogen sulfide, methane, nitrogen, and oxygen.

In addition, as the solution is independent of population sample changes, variation in data collected over time can be continuously added to the system to attain the best optimum solution at that point of time. This is highly favored in anaerobic

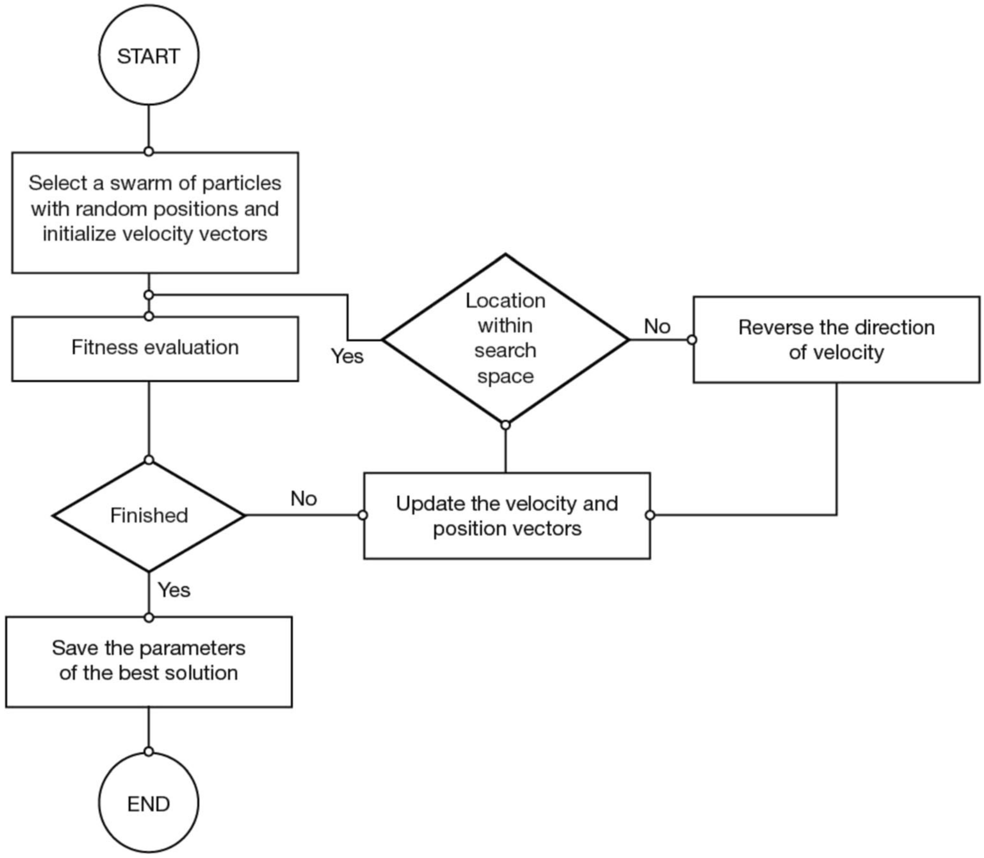


Fig. 2 Particle swarm optimization

digestion modelling due to variation of characteristic and composition of feed to the anaerobic digestion process. Moreover, PSO shows great control of balance during the search of local and global solution which is indicated during convergence besides having a relatively competent search ability.

But, as every particle is moving in a random direction, population of particles has a tendency to cluster together. Hence, further hybridization between genetic algorithm and PSO is proposed for enhancement of performance before the incorporation of PSO into other artificial intelligence such as recurrent fuzzy and recurrent neural network [91].

Hybrid Meta-heuristics

In order to further improve the process control models developed, combination and coupling of models have been proposed and implemented in order to complement the disadvantage and drawbacks of individual meta-heuristic models as shown in Table 4. Hybrid meta-heuristics combines two or more other meta-heuristics to solve the same problem. The meta-heuristics can be either combined or switched one after the other over the course of the meta-heuristic. The hybridization is done to combine the desired features of each meta-heuristics in order to improve the convergence speed or quality of the solution from the hybridized meta-heuristics. Since the three main models discuss earlier are fuzzy logic, ANN, and PSO, coupling of meta-heuristic models will be focused on these three.

First is the combination of fuzzy logic and ANN as shown in Fig. 3. These two models can be combined to form two different hybrid models, namely cooperative fuzzy neural network and hybrid fuzzy neural network. Fuzzy logic and ANN complements each other as the downside of fuzzy logic includes the lack of systematic method for the conversion of experience and knowledge in the form of if-then rules to be entered into the system as the basis for the prediction

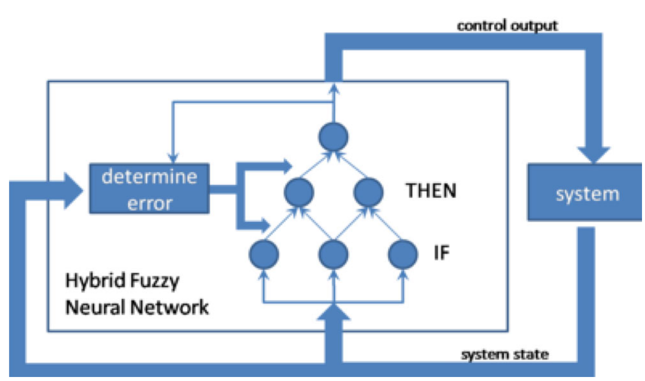


Fig. 3 Hybrid fuzzy neural network [95]

model to determine the outputs. Besides, to ensure that the results produced are within the acceptable error range, adaptability of fuzzy logic has to be raised which can be in the form of the addition of learning algorithm. ANN in contrast is subjected to the drawback of difficulty in extraction of knowledge attained either from the configuration or weights of ANN. By grouping these two methods together, a control system of faster convergence rate and of higher robustness can be developed [96].

For cooperative fuzzy neural network, fuzzy logic and ANN work independently whereby parameters acquired from fuzzy logic are learnt by ANN. There are four main categories of cooperative fuzzy neural network which are indicated in Table 5.

Hybrid fuzzy neural network on the other hand resembles ANN where communications between fuzzy logic and ANN are no longer necessary as they are considered as a whole unit. Rules of fuzzy logic are taken to be the network, membership function as weights, whereas input and output variables are taken to be neurons. This hybrid model allows the full complementation of drawbacks which exist in individual models. With the fusing of neural network with fuzzy logic, it allows optimization of membership functions in fuzzy logic via generalization of data.

Another possible fusion is the combination of ANN with PSO where the process is summarized as shown in Fig. 4. Since ANN is heavily dependent on training process and accuracy of model developed is mainly caused by lack in training process, PSO is suggested for weight training as an alternative to use of fuzzy logic. The other reason which contributes to the favoritism of PSO to be coupled with ANN is to acquire faster convergence so that speed of process can be heightened especially for multilayer feedforward network [93]. Initially, PSO will be used to determine the best solution inside the “search” space [91]. The search space is the boundary where the inputs are randomly distributed according to initial condition. Best solution will be first searched from within the boundary prior to further search in accordance to the boundary set, while ANN is used to initiate a suitable population size where ANN weight is represented by each particle. Continuous iteration is performed until the stopping criterion is fulfilled, global solution is attained, and prediction of network is the output results wanted. New ANN function will be decided based on updated particle weights, and process is only completed when the error standard is satisfied by the trained ANN function. Summary of the process is as shown in Fig. 3.

At present, application of hybrid meta-heuristics in both modelling and control of anaerobic digestion is promising. This is due to the fact that high process stability and great reactor performance are observed when fuzzy neural network is applied to the anaerobic system. For future work, further optimization and fine tuning of fuzzy neural network can be achieved such as introduction of adaptive controllers which will be described in detailed in “Process Control of Anaerobic Digester.” Examples of hybrid PSO with ANN can be found in works presented by Juang and Manshad [91, 93] which shows a reduction in absolute relative errors as compared to the use of other models. Other hybrid meta-heuristics in anaerobic digestion can be found in works presented by Tay and Zhang [97], Abu Qdais et al. [98], and Rajagopal and Radha [99].

Tay and Zhang [97] proposed the combination of ANN and fuzzy logic to determine the response of high-rate anaerobic digester 1 h in advance on FBR, anaerobic filter, and UASB. Abu Qdais et al. [98] predicted the methane production using multi-layer ANN and GA by considering the effect of temperature, total solids, total volatile solids, and pH on the biogas yield.

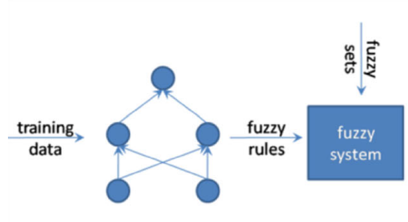
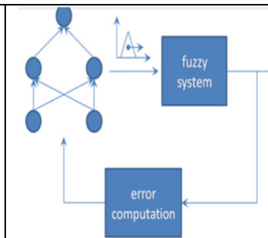
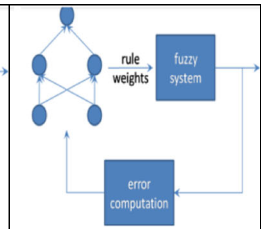
Rajagopal and Radha [99] developed adaptive neuro-fuzzy inference system (ANFIS) and PSO with spectral projected gradient (SPG2) algorithm to determine the effluent COD of a full-scale anaerobic wastewater treatment plant. These works demonstrated the applicability of hybrid meta-heuristic approach. Combining desired features of each meta-heuristics can improve the convergence speed and quality of the solution. However, doing so requires in-depth knowledge and experience. If both algorithms are distinctly different, the tuning of parameters involved has to be carefully adjusted; else, it may trap in the local optimal solution and delay the convergence speed.

In conformity with the two hybrid models discussed earlier, it can be deduced that suitability of the application of a model is highly dependent on the control system to be modelled and controlling parameters which are to be taken into studies. As anaerobic digestion is highly sensitive and a suitable model has yet to be developed, ANN and fuzzy logic is proposed where fine tuning and further improvements are proposed to be attainable by the implementation of hybrid models. But, all these have yet to be confirmed. Hence, more work and research on this area and practical application should be tested in order to verify the proposal.

Improvements Towards Wastewater Treatment System Through Introduction of Mechanistic and Meta-heuristic Models

Based on the models discussed in “Mechanistic Models” and “Meta-Heuristic Models,” it can be inferred that improvements towards implementation on industrial wastewater treatment can be observed in the form of improved prediction. For mechanistic model, improvements are observed via the inclusion of physiochemical and biochemical reaction that occurs during anaerobic digestion through the introduction of ADM-1. This allows better prediction as reactions occurring within

Table 5 Types of cooperative fuzzy neural networks [95]

Type				
Operating principle	• Based on given training data, fuzzy neural network learns from fuzzy logic • Membership functions are fitted to a neural network	• Based on training data from neural network, fuzzy rules are determined • Neural network performed before fuzzy logic initialization	Membership function parameters are learnt by the system while applying fuzzy logic	Neural network determines rule weights for fuzzy logic rules
Performed	Offline	Offline	Online	Online or Offline
Determination of rules	Data attained/ learnt parameters are then fed to fuzzy logic via formation of rules	Rule learnt via: • Self-organizing feature map clustering • Application of fuzzy clustering method	• Membership functions and fuzzy logic rules are derived earlier • Error measurement is compulsory for improvement and guidance on learning step	Rule weight is equivalent to the rule influence which are multiplied with rule output

the reactor are accounted for. On the other hand, plus point for the mass balance model would be the fact that everything entering and leaving the reactor are taken into consideration, allowing improved deduction based on mass balance equations. The mass balance model allows for optimization to be performed as the influence of each parameter in and out is

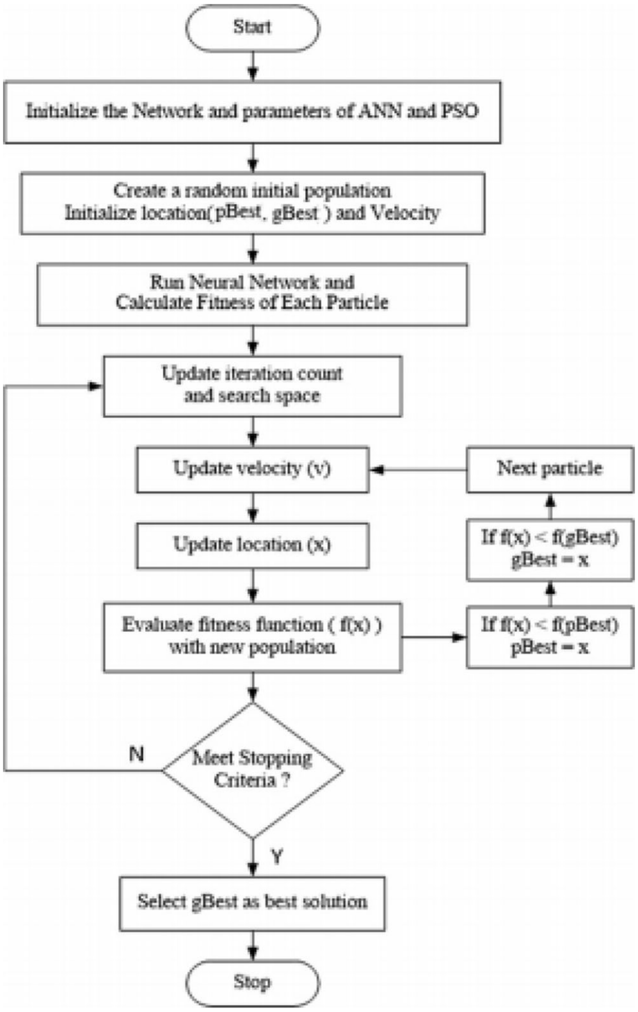


Fig. 4 Summary of the hybrid ANN and PSO process [93]

known. Therefore, it reduces the dependence of AD performance on the number of microbial consortia or unsteadiness of the system which leads to destabilization.

In terms of meta-heuristic models, better control on process parameters can be viewed through study of patterns of the system which allows earlier prediction on how the reactor would performed. This allows proper adjustment to be made for optimization of wastewater treatment process. Besides, ANN is able to study and learn the patterns of the system via the information feed to the model which would further improve the overall system performance. The challenges to be overcome include the need for in-depth understanding including characterization and experimental studies via pilot scale plant. But, in overall, it can be deduced that the implementation of mechanistic and meta-heuristics models allows improved control as parameters or condition that causes failure of system can be detected and corrected beforehand. Hence, destabilization of anaerobic digestion that would lead to system failures can be avoided/minimized.

Process Control of Anaerobic Digester

Despite its significance in anaerobic wastewater treatment, little attention has been paid over the years to compare the use of various control strategies. One of the first surveys was done by Heinzle et al. [100] with 15 control applications were referenced in this article and six of them were done in simulations (without any experimental validation). In recent years, development and improvement of bioreactor controllers have demonstrated that bioprocesses can be optimized and controlled efficiently. However, process control of anaerobic digester is still difficult and intrinsically unstable. Following are the factors typically considered when designing a controller for anaerobic digester [58, 79]:

- Nonlinear nature of the process
- Modelling errors induced by its complicated kinetics
- Load disturbances in the inlet composition
- Constraints in the control input due to practical operation conditions or restrictions in the actuators

The main purpose of anaerobic digester is the complete digestion of the influent to carbon dioxide and methane and/or reduction of COD level of the effluent. Therefore, its control objective(s) also departs from the same notion and varies according to the nature of its application. In wastewater treatment plant, anaerobic digester is commonly used to maintain output flow pollution level below a certain value [101].

Several control strategies have been proposed and implemented. These control strategies can be generalized into two main categories. The first category uses mechanistic model to develop a control mechanism for anaerobic digester and consists of PID-like controllers and adaptive controllers. The second category uses meta-heuristic model(s) and consists of control mechanism that uses one or more meta-heuristics to achieve the predetermined control objectives. A list of control strategies used in anaerobic digesters for wastewater treatment is displayed in Table 6 where further discussions on individual controller types can be found in the subsections below.

PID-Like Controllers

These controllers are commonly used to achieve substrate regulation. They are easier to be developed and can be implemented in wide-plant level [112]. PID-like controllers are dominant in the process industry and probably will remain so for a long time. There are several reasons that support the

Table 6 Control strategies used in anaerobic digesters for wastewater treatment group in accordance to control method

Control method	Authors	Year	Model/data	Variable	
				Controlled	Manipulated
Adaptive controller	Hilgert et al. [102]	2000	Experimental data	Biogas flow rate	Influent flow rate
	Alcaraz-González et al. [103]	2000	Mass balance model [53]	COD and VFA	Dilution rate
	Alcaraz-Gonzalez et al. [104]	2001	Mass balance model [53]	COD	Dilution rate
	Antonelli et al. [105]	2003	Mass balance model [53]	Methane gas flow rate	Dilution rate
	Seok [106]	2003	Seok's model (2001)	Propionate concentration	Dilution rate
	Mailleret et al. [107]	2004	Bailey and Ollis's model (1986)	Outlet pollutant concentration	Influent pollutant concentration
	Alcaraz-Gonzalez et al. [56]	2005	Mass balance model [53]	COD	Dilution rate
	Mendez-Acosta et al. [58]	2007	Mass balance model [53]	TOC and VFA	Influent flow rate
	Garcia-Sandoval et al. [108]	2008	Mass balance model [53]	COD	Dilution rate
	Rincon et al. [59]	2009	Mass balance model [53]	VFA concentration	Dilution rate (flow rate)
	Mendez-Acosta et al. [61]	2010	Mass balance model [53]	VFA and TA	Influent flow rate
	Mendez-Acosta et al. [109]	2011	Mass balance model [53]	COD	Dilution rate
	Rincon et al. [60]	2012	Mass balance model [53]	VFA and TA	Influent VFA and COD concentrations
	Flores-Estrella et al. [5]	2013	Mass balance model [53]	COD	Dilution rate
	Petre and Selisteanu [110]	2013	ADM-1	COD	Dilution rate
Proportional-integral-derivative (PID)-like controller	Harmand et al. [111]	2000	Linear model (experimental data)	Gas flow rate	Influent flow rate
	Alvarez-Ramirez et al. [112]	2002	Pavlostathis et al. model [51]	COD	Dilution rate
Proportional-integral (PI) controller	Alvarez-Ramirez et al. [112]	2002	Pavlostathis et al. model [51]	COD	Dilution rate
Output feedback control	Mendez-Acosta et al. [113]	2008	Mass balance model [53]	VFA concentration	Dilution rate
Multi-objective cascade controller	García-Diégueza et al. [69]	2011	ADM-1	Methane flow rate, VFA	COD concentration
Fuzzy controller	Polit et al. [114]	2002	Denac et al. model [52]	Gas flow rate	Influent flow rate
	Punal et al. [115]	2003	Experimental data	VFA	Influent flow rate
	Yordanova [116]	2004	Mass balance model [53]	Biogas output flow rate and pH	Dilution rate
Linear control with feedforward/feedback structure	Mendez-Acosta et al. [117]	2005	Mass balance model [53]	COD of output	Inlet COD concentration

use of these controllers. Among them are their long history of proven operation, well understood by operational staffs, and have automatic and manual switching, set point tracking, and emergency manual modes.

Despite their wide adoptions in the industry, the performances of PID-like controllers have several limitations. One of the limitations is the narrow range of the operating conditions [102]. Moreover, the cost of implementation can increase due to the number of instrumentations and only restricted operation can be assured. PID-like controllers also have difficulty in considering various parameters that influence and characterize the growth of microorganisms [78], and they neglect the nonlinearities inherent in most biological processes [105]. Lastly, this method is susceptible to disturbances in the input variable(s) and significant set point changes [61, 112]. Due to these limitations, PID-like controllers are becoming obsolete—with three papers proposing PID controllers in a decade ago (Table 6) and none in recent years.

Adaptive Controllers

Adaptive controllers were designed and developed to address limitations posed by PID-like controllers. Unlike the former approaches, adaptive controllers consider the nonlinearity and nonstationary features of the anaerobic digestion processes [55, 118, 119]. These controllers are typically derived from a physical model of the digester (mass balance model or ADM-1), and they also feature an online estimation of physically related unknown variables and parameters [53]. The online estimators or observers commonly used in biological processes include asymptotic observers [110], disturbance decoupled observer [120], Luenberger observer [58, 61], state observer [60], and interval observer [76]. Despite their reported satisfactory results, these observers require the total knowledge of the process variables, which are rarely available in practice. If the whole system does not have the details of these variables, it will become nonobservable and consequently rendering it impossible to design online estimators. This limitation has prevented the wide adoptions of the observer schemes and the nonlinear controllers at the industrial scale.

Nevertheless, adaptive controller offers its own merits and demerits compared to the conventional PID-like controllers. One of the merits of this approach is its variation of the model parameters, which allow it to have good disturbance rejection capability [102, 121]. It is also able to handle actuator constraints and provides soft control actions while handling process nonlinearities [105]. Lastly, it is able provide online estimation of several unknown variables and parameters, allowing adaptive controllers to only require simple sensors to work with [79]. The main disadvantage of this approach is its complexity. As mentioned earlier, anaerobic digestion is complex and nonlinear; hence, they are difficult to model. Moreover, it also requires linear parameterization to implement parameter estimator [101], which typically obtained by putting together a large set of kinetic and yield parameters. Therefore, the use of adaptive controllers might not be suitable for anaerobic digestion of complex wastewater, where the kinetics and yield parameters of these processes are not readily available.

Meta-heuristic-Based Controllers

Meta-heuristics are not only used to model anaerobic digester but they are also used as basis to minimize the pollution level of the treated wastewater and to control biogas production rate [122]. However, among all meta-heuristics, only fuzzy controllers were found controlling certain output variables of anaerobic digesters [115, 116].

Punal et al. [115] developed set of rules (control law) based on Mamdani's fuzzy inference method to handle VFA concentration of anaerobic digester. These rules were developed based on the acquired knowledge from the process. Variables used are the input flow rate of the raw wastewater, while the output was the degree of modification required for the influent flow rate in order to lead the system to achieve the desired set point.

Yordanova et al. [116] developed a two-stage fuzzy logic to control biogas production rate of an anaerobic digester with controlled variable to be the production rate of biogas and manipulated variable to be the dilution rate. Validation was performed through PI controller construction. This comparison demonstrated the effectiveness of fuzzy logic-based controller in providing faster responses to reference changes and disturbances with less overshoot.

Identified Gaps and Suggestions for Improvements

Despite its wide adoption, anaerobic digestion is difficult to model, especially when the biological systems are generally ill-defined [116]. Moreover, the reproducibility of the experiment is low as the microbial activity is highly dependent on the physiological state of the microorganisms and its environment, especially in case of mixed cultures where interaction between different microorganisms is fairly complex. This is also hindered by the lack of available measurements to monitor the activity of microorganisms. Moreover, the experiment data tend to be noisy and the characteristics of the noise are difficult to define. Systematic errors may also present and accumulate since anaerobic digestion processes occur sequentially.

These issues pose several challenges in controlling anaerobic digester. Despite the different control strategies that have been applied in the face of incomplete system knowledge, the task of designing a control law to ensure robustness against load disturbances and parameter variations is, in general, still difficult. Wen and Vassiliadis [85] and Boger [123] characterized the ability to monitor and control the effluent from wastewater treatment process as "primitive" and "notoriously difficult." Lindberg [124] further defined wastewater treatment to be a complex multivariate process with highly variable inputs, nonlinear time varying dynamics, and a time series structure with autocorrelation that is subject to large disturbances.

Nevertheless, there were several success stories in monitoring and controlling anaerobic digesters. Among them are works reported by Harmand et al. [111], Seok [106], Mailleret et al. [107], Mendez-Acosta et al. [58], and Garcia-Dieguez et al. [69]. Harmand et al. [111] proposed disturbance accommodating controller to fluidized-bed anaerobic digester. This method is not only robust to large internal and external disturbances, but it is also robust to expected and unexpected disturbances. Seok's [106] controller has been tested on an anaerobic fluidized-bed bioreactor for 200 h. Despite sudden increase in the feed concentration of up to 50 %, this method can maintain the propionate concentration at 700 mg H Prl^{-1}. Mendez-Acosta et al. [58] implemented and validated robust-adaptive controller to regulate VFA in an upflow fixed-bed reactor of an anaerobic digester for 36 days under different set point values and different scenarios. Their methods successfully demonstrated the use of an observer to control VFA even in the presence of noisy measurements and control input saturations. Garcia-Dieguez et al. [69] implemented multi-objective cascade controller based on VFA concentration in the effluent and methane production rate in an upflow sludge bed filter (USBF) reactor (anaerobic treatment of winery wastewater)

There were also several control schemes that performed well in their simulation studies such as the Rincon et al. method [60] that can handle the uncertainty in the kinetic function, biomass concentration, biological yield coefficients, kinetic parameters, and the effect of input saturation. Petre and Selisteanu's [110] robust-adaptive control strategy can be combined with a state asymptotic observer or an internal observer and a parameter estimator to estimate unknown kinetics of the process online and withstand disturbances and noisy data acting on the process and more importantly uncertainties in the growth rate and influent substrate concentration [76].

Nevertheless, there still remains several technical challenges: (1) Can their proposed control method be applied on different types of anaerobic reactors, e.g., UASB, UASFF, and UASB-HCPB?; (2) Since most of the water treatment plants handle large effluent, is there proposed method scalable to different scales of water treatment plants?; (3) Can their method handle different types of effluents, e.g., POME, pulp and paper mill effluent, and olive mill effluent?

Use of meta-heuristics in anaerobic digestion suffers similar drawbacks. The published articles implemented meta-heuristics for specific problems, where the problems size, inputs, and outputs are fixed. There is no clear evidence that demonstrates how the meta-heuristics used can be scaled up well for larger settings. Nevertheless, there are other potentials in meta-heuristics that have yet been explored. For example, genetic algorithm (GA) has various variables that can influence the anaerobic digester and lead to better prediction and control. These variables include crossover probability, mutation probability, elite preservation, selection, population size, and generation size. There are also more opportunities in implementing more sophisticated meta-heuristics such as ant colony optimization (ACO), simulated annealing (SA), tabu search (TS), artificial bee colony algorithm (ABC), cuckoo search (CS), charge system search (CSS), glowworm swarm optimization (GSO), and firefly algorithm (FFA). In-depth studies have to be performed in order to determine the best controller to be applied for a particular system where further optimization can be done to achieve best performance.

The use of anaerobic digestion systems in wastewater treatment is growing immensely in Southeast Asian countries. This is due to the increasing production of palm oil especially in Malaysia and Indonesia, which are the largest crude palm oil-producing countries. Chin et al. [3] have projected that an estimated 3.2 million MWh of electricity, equivalent to the electricity consumption by 700,000 households, can be generated from the treatment of POME generated in Malaysia in 2011. The investment of palm oil mills on high-rate anaerobic digesters could potentially generate immense profits, overturning the conventional image of wastewater treatment in process plants that used to be just a part of the process to comply with government regulations. Thus, it is vital to devise and develop the right model and a robust controller that can suit anaerobic digestion of different wastewaters to ensure consistent production of biogas.

Though anaerobic digestion is an established method for wastewater treatment, the current anaerobic digestion technology is also evolving to anaerobic co-digestion (treatment of different wastes in a single reactor) [35, 125] and temperature-phased anaerobic digestion system [38, 126] to boost reactor performance and biogas production. These technologies offer more opportunities to improve the performance of anaerobic digester in reducing pollution level of the treated wastewater and increasing the biogas production rate. Nevertheless, the advancement of anaerobic digestion technology also implies that the control of the anaerobic digester system will become more complicated as the number of manipulated variables increases.

Conclusion

Anaerobic digester is commonly used to treat wastewater with high organic carbon content, as an alternative to aerobic digestion. However, the sensitivity of anaerobic digester has proven to be a challenge in controlling its desired output(s): treated wastewater with lower organic carbon content and/or high biogas production rate. Till to date, this challenge still persists together with scalability of the anaerobic digester and variation in the feed characteristics throughout the year. With the advancement of nonlinear approaches, meta-heuristics, and their combinations, there are plenty of rooms for further improvements for both anaerobic digester models and controllers. More importantly, increasing production of palm oil and economic benefits can drive greater adoption of anaerobic digester in palm oil mills, especially in Southeast Asian countries. With this comprehensive review, it is clear that adaptive controllers provide a wider option in terms of controlled and manipulated variable for wastewater treatment plants. However, because of the varied nature of parameters that affect the various operating conditions in wastewater treatment plants, it is necessary for an in-depth study to understand the particular system before determining a suitable adaptive controller.

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