A review on anaerobic digestion with focus on the role of biomass co-digestion, modelling and optimisation on biogas production and enhancement

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Abstract

The status, recent trends and future perspectives in modelling and optimisation of anaerobic co-digestion is investigated. Areas that can be focused on and those which need further research towards enhancing biogas production are pointed out. Co-digestion, modelling and optimisation of anaerobic digestion as well as techno-economic aspects are reviewed in this paper. It was noted that co-digestion requires more research into a variety of bio-resources and their specific blend proportions. Modelling and optimisation of co-digestion with substrate seasonal fluctuations has not been addressed in previous studies. Controlling key process factors including temperature, pH, and carbon to nitrogen ratio is critical in improving biogas yield. Biogas hybridisation is yet to be explored in depth. The majority of researches are focused on mono-digestion, feedstock co-digestion, modelling, and optimisation of anaerobic digestion needs significant further investigations. A multi-objective approach taking all technical and economic parameters in the modelling and optimization is essential.

Keywords: Anaerobic digestion; Co-digestion; Biogas enhancement; Modelling and optimisation; Techno-economic analysis

1. Introduction

The energy sectors world over are faced with a task to come up with alternative sources of energy to substitute fossil derived fuels. There is urgent need for boosting energy generation to fill in the shortfalls in supply to the ever increasing energy demand. Generating energy from alternative sources will help in climate change mitigation and minimisation of alarms posed to the environment (Kang et al., 2020). There has

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been a high uptake of renewable energy technologies (RETs) world over in a bid to deal with the detrimental effects paused by fossil related energy generation technologies. In a bid of increasing energy accessibility whilst simultaneously restricting worldwide temperature increament to 2°C, adoption of RETs and energy efficiency must be encouraged and raised significantly (Sawin et al., 2016). This growing impetus for renewable energy alternative avenues demands the consideration of different feedstocks, development of novel techniques, as well as improvements to existing technologies.

Bio-energy can be regarded as the most substantial renewable energy source due to its cost-effective advantages and its great potential to substitute non-renewable fuel sources. Bioenergy comes from biomass materials: any biological organic matter obtained from plants or animals. Biomass energy sources include but are not limited to terrestrial plants, aquatic plants, timber processing residues, municipal solid wastes, animal dung, sewage sludge, agricultural crop residues and forestry residues. It is one of the most versatile among the renewable energies since it can be made available in solid, liquid and/or gaseous forms. Different avenues can be explored to haverst energy from biomass materials.

Biogas originates from anaerobic digestion (AD) of biodegradable biological materials. Biogas generation via AD has advantages of better compatibility with the environment. The process makes use of continuously generated accumulating quantities of bio-wastes, value adding them into some form of energy (Adekunle and Okolie, 2015). This technology reduces the discharges of greenhouse gases leading to a sustainable form of energy and a cleaner environment (Maile et al., 2016).

Anaerobic digestion is the breaking down of biomaterials by bacteria in an environment without oxygen. It is the most favourable substitute to discarding of biodegradable organic municipal solid waste, agricultural residues and animal wastes because of its efficient energy recovery nature. The bio-conversion is catalysed by a huge consortia of microorganisms complementing each other, catalysing the diverse biochemical reactions, therefore the metabolic pathways accompanying anaerobic digestion are quite complex. In anaerobic digestion, co-digestion entails simultaneous digestion of varied wastes having harmonising features. In the AD process biomass materials are broken down by bacterial action in an oxygen free environment producing a gaseous blend comprising mainly of methane (Reyes et al., 2015). This gaseous blend/mixture is known as biogas and it consists of methane, carbon dioxide, hydrogen sulphide, ammonia, hydrogen and water vapour. A mineral rich digestate usually referred to as spent slurry or sludge is also obtained as a secondary product of the biogas generation process.

In contrast with other biofuels, biogas production is flexible to different substrates on condition that they are biodegradable. The waste streams which are the raw materials for biogas production vary significantly due to seasonal and geographical location causing a dissimilarity in biogas yields reported by various authors (Bong et al., 2018). The substrate must have the dietary rations for the microorganisms for it to be biodegraded optimally. Therefore, structure and constituent components of feed is exceedingly crucial in AD to optimally produce biogas.

Agricultural waste, *Eichhornia crassipes* (water hyacinth) and municipal solid waste are hugely available sources to be tapped into for the attainment biogas (Kunatsa et al., 2013; Kunatsa and Mufundirwa, 2013). Multi-stage anaerobic digestion accompanied with co-digestion of different raw materials and feedstocks as well as optimisation of the biogas production process can bring about enhanced yields of biogas. With respect to substrates for anaerobic digestion, use of wastes is prioritised over other options since it addresses the environmental pollution issues while simultaneously generating energy (Horváth et al., 2016).

According to Kangle et al. (2012), co-digestion increases biogas outputs, however, it has a disadvantage of largely still remaining unstudied for many varying substrates. Biogas production is enhanced by co-digestion of different substrates rather than individual substrates but there is difficulty in getting to the exact blend ratio for optimality since it depends on the type of substrates together with actual reaction conditions availed (Adekunle and Okolie, 2015). Co-digestion technology needs scrutinised supervision and controlling since no single customary set of working parameters could be practical to all organic biodegradable wastes. Given this scenario, and that the availability of raw materials is of broad nature, further research in co-digestion and optimisation of biogas generation from varied substrate types should be undertaken.

Biogas is produced using either the wet anaerobic digestion technology or the dry anaerobic digestion technology (Angelonidi and Smith, 2015). In the wet technology the substrates are mixed with water to make a bio-slurry which constitutes about 90 % water. Examples of digesters used in the wet digestion technology include fixed dome, floating drum, polyethylene tube digesters and balloon digesters. In dry digestion technology the substrates are not mixed with water but slurry with cultured microbes can be added. Dry digestion is usually done on raw materials with a lot of fibre. The digestion chambers can look more like composting facilities. AD maybe classified as "single" or "multi" stage. In multi-stage digestion there are two or more reaction chambers separating the bioprocesses whilst in single stage there is only one reaction chamber in which all the bioprocesses occur. The digester feeding mechanisms can be categorised into batch feeding and continuous feeding. In batch feeding substrates are fed once and left till they are completely digested before a new set of substrates is fed. In continuous digestion a certain constant quantity of feed is administered to the reactor at regular intervals.

The overall aim of this review study is to retrospect previous works, modern trends and approaches in process enhancement and control strategies in anaerobic biogas production technology consequently contributing vital information in the direction of biogas enhancement and optimisation. The subject matter covered includes biochemical processes in AD, co-digestion, modelling and optimisation as well as techno-economic aspects of the same. Much emphasis is given to co-digestion, modelling and optimisation in order to investigate the previous works, progression and forecasts of the biogas production process in a bid to enhance biogas yields. This study is unique in its own regard in the sense that it zeroes in on reviewing issues of incorporation of co-digestion feedstock mixing ratios, multi-stage digestion, process conditions, techno-economic aspects and biogas hybridisation among others in the modelling and optimisation of biogas production in view of enhancing the ultimate biogas yield.

This work is of great importance as it value adds to the existing knowledge in academia and provides more opportunities for new and extra investigations in the biogas arena. Small to medium enterprises as well as commercial biogas players can also benefit from the results of this work. In general, more researches are being done in the broad spectrum of biogas and this trend suggests that biogas technology acceptance and adoption is increasing and is being taken seriously as an important contributor to the current world shift towards renewable energy technologies and can feed in to a great extent to the mitigation of climate change.

2. Anaerobic co-digestion

Anaerobic digestion of biomass wastes can be done on individual materials (mono-digestion) or mixtures of numerous materials (mixed-digestion or co-digestion). Anaerobic co-digestion enhances digestion and energy generation by increasing availability of nutrients for microbes and organic load while reducing inhibitory chemical toxicity through co-substrate dilution. Mono-digestion is commonly employed for digesting animal manure in smaller biogas production facilities, but co-digestion is frequently employed in bigger facilities which process bio-wastes from various origins (farms, residential areas and industry). Co-digestion occurs when different feed materials are concurrently digested in the same reactor. Customarily, AD technology was meant for one feed material but lately, it has been recognised that anaerobic digestion turns out to be more stable when a diversity of substrates are co-digested simultaneously. Co-digesting varied substrates improved biogas production potentials in contrast to single substrates (Maragkaki et al., 2018; Lee et al., 2020; Vivekanand et al., 2018).

Generally all biomaterials and organic wastes are augmented with numerous nutrients necessary for growth of micro-organisms. The differing nutrient quantities are interconnected with age, geographical origins and species of the organic material. A great proportion of the agricultural residues and aquatic plants are enriched with high nutrients, however, their lignocellulosic recalcitrant nature renders them resistive to micro-bacterial degradation hence reduced gas outputs. Co-digesting these multifaceted biomaterials with animal manures and other biodegradable organic substances gives enough access and potential to micro-organisms to foster optimised degradation (Kunatsa et al., 2020).

In an investigation, Patil et al. (2011), found out that more biogas was produced from co-digestion of *Eichhornia crassipes*, poultry waste and cow manure. Co-digestion presents immaculate digestibility, supreme mineral manure, odour and germs management together with costs reduction in addition to being environmentally friendly among other benefits (Yasar et al., 2017). Table 1 shows a review of a few mono-digestion and co-digestion studies some improved methane yields through co-digestion.

The major advantage of co-digestion is the improvement of biogas yields as well as methane content of the same. Animal manures are being co-digested with other biodegradable materials to increase economic effectiveness while ensuring anaerobic digestion system stability at a commercial scale (Hegde and Trabold, 2019). A number of recent previous studies, mainly centred on laboratory investigations and small-scale bio-rectors have proven anaerobic co-digestion to be the way to go when it comes to biogas production and its optimisation. According to the authors'survey, the majority of commercial reactors employ mono-digestion mainly due to availability of one specific substrate in large quantities within the vicinity of the digester geographic location. Other reasons for non-implementation of anaerobic co-digestion include ignorance, unavailability of co-digestion technical expertise, reluctance to shift and adopt new technology as well as avoiding the drawbacks of co-digestion. Some of the major drawbacks of co-digestion which hamper application of the technology with large scale commercial reactors include accummulation of undigestable solids inside the digester, high nitrogen backload, and accummulation of acids from other co-substrates (Sembera et al., 2019). The synergistic effects of the co-substrate mixture which are brought about by the dynamics of the co-digestion process as well as the microbes involved will outweigh the drawbacks of the

Table 1: Effect of co-digestion on biogas yield

Feedstocks	Comparison of mono-digestion and co-digestion biogas yields	Source
Wastewater sludge and olive pomace	mono-digestion yielded 0.18 and 0.16 $L\ CH_4/gVS_{added}$ for olive pomace and wastewater sludge respectively. Co-digestion yielded 0.21 $L\ CH_4/gVS_{added}$. Co-digestion increased methane production by $17-31\%$	(Alagöz et al., 2018)
Wastewater sludge (WAS) and fish waste (FW) or garden-grass (GG)	gradual increase of fish concentration increased methane generation up to 1.9 when 75% was added. With grass methane production only improved after adding 25%, adding more than 50% grass increased the production rate and final product by 1.5 and 1.7 times, respectively.	(Cardona et al., 2019)
Sugarcane press mud (P) and vinasse (V)	The combination V_{75}/P_{25} had the best methane generation rate of $69.6N\ mL\ CH4g^{-1}\ COD_{fed}^{-1}d^{-1}$. In co-digestion, methane outputs of 365 $L\ CH_4kg^{-1}VS$ and biogas production output of 1.6 LL^{-1} were achieved, which was 64% greater than mono-digestion.	(González et al., 2017)
Microalgae and primary sludge	Co-digestion of microalgae and primary sludge (25/75% on a volatile solids basis) was compared to microalgae mono-digestion. co-digestion improve methane generation by 65%.	(Solé-Bundó et al., 2019)
Poultry droppings (PD) and lignocellulosic co-substrates (LCSs) (wheat straw (WS) and meadow grass (MG))	In co-digestion, maximum methane concentrations were found to be 330.1 and 340.1 Nl kg1 VS at a blending ratio of 70:30 (PD:WS) and 50:50 (PD:MG) respectively. This was an increase of 1.14 and 1.13 times higher than the LCSs individually.	(Rahman et al., 2017)

technology. With the advancement of technology, inclusive of process regulation and control amongst other interventions such as pretreatment, the benefits of anaerobic co-digestion can be fully realised. However, research and development into the co-substrate blending proportions needs to be further investigated for a wide variety of co-digestion substrates.

Table 1 shows that there is a vast potential of biogas generation from the co-digestion of a wide range of biomass wastes. The recalcitrant nature of most of the lignocellulosic substrates can be overcome by co-digesting them with animal manures which already has bacteria for anaerobic digestion and this in turn enhances biogas yield from them. It can also be deduced that a different combination of substrates as well as different mixing ratios consequently lead to different biogas production volumes and hence different methane concentrations. This section concludes that further research has to be conducted on a wide range of co-digestion feedstock combinations and their respective blend ratios.

3. Modelling and optimisation of anaerobic digestion

Co-digestion logically and concurrently manages biological organic matter thereby obtaining an alternative form of energy. It is more vulnerable to process instability due to substantial dissimilarity in feed stock composition. Mechanistic models emanating from the anaerobic digestion model no.1 (ADM1) framework are more well-known in anaerobic co-digestion modelling. Nevertheless, major aspects in present-day anaerobic co-digestion, particularly interactions between system performance and co-substrate ratios and properties for optimal biogas yields still remain underdeveloped.

There is a necessity of the development of models of different levels for the respective different categories of users. The small to medium enterprises (SMEs) only need a general understanding and as such require low level-less complicated models. Commercial entities and all big revenue focused companies require general to medium level models for the purposes of just informing on the expected biogas yields in relation to time, rate of return on investment, and profits. Lastly senior technical managers, engineers and researchers have the capacity and ability to understand deeper technical models with higher level of sophistication and complexity. It is necessary to take into consideration different research interests in the development of models of different levels. Table 2 shows the 2 major model categories and the respective research interests together with the aspects to be considered in model development.

Optimisation of anaerobic digestion can be improved through proper modelling (Ramachandran et al.,

Table 2: Research interests and model level categories

Model Category	Aspects to be considered
Production level	medium to high level modelling Process control and regulation *(temperature and pH monitoring)* Substrate blend ratios *(in case of co-digestion)* Reaction kinetics
Utilisation and management level	low to medium level modelling Optimising CH_4 proportion in biogas biogas production vs demand side management Impurity removal and quality improvement for advanced uses Slurry and other by-products management biogas yields in relation to time, rate of return on investment and profits

2019). Process monitoring and control have been noted as further improvements needed for the biogas production process (Wu et al., 2019). Research and investigations on modelling, together with optimisation, inclusive of control and regulation of the AD reactions are critical to the biogas fraternity. In comparison to other well established fields, the modelling and optimisation of biochemical reactions such as the ones in biogas generation are still a challenge mainly attributed to by the peculiarity and unsimilar nature of the reaction progressions (Fedailaine et al., 2015). The bacteria involved in the biogas generation process drastically respond to environmental alterations hence making it a challenge to predict and control the process (Thorin et al., 2012). Thorin et al. (2012) concluded that for anaerobic digestion processes, the available detailed models are too complex for practical use and recommended the use of a combination of empirical and physical and/or biological models as a possible approach.

3.1. Modelling

3.1.1. The Buswell biogas prediction equation

(Buswell and Sollo, 1948) developed a mechanism for methane fermentation which describes biogas constituent composition after anaerobic digestion as per the chemical composition of the initial substrates entering into the digestion process. The elemental composition of the majority of substrates employed in biogas production comprises of C, H, O, N and S in a complex molecular structure. The complex structure is subjected to the biochemical reactions and biogas is obtained as the main product together with slurry as a by-product. If it is assumed that a total coversion of biomass to biogas occurs after the complex interdependant bio-chemical reactions, then the elemental composition approach developed by (Buswell and Mueller, 1952), is arrived at; that biogas is constituted mainly of CH_4, CO_2, NH_3 and H_2S and that other trace elements and gases are negligible. This is typical high level steady state modelling which takes material balances into account. Since some of the biomass is not completely converted to biogas but goes to slurry, a conversion factor of 0.8 is assumed and applied to the resultant biogas quantity to arrive at a more accurate representation of the entire process. The Buswell equation for predicting biogas output is as shown in equation (1).

$$\begin{aligned} C_aH_bO_cN_dS_e + \left(a - \frac{b}{4} - \frac{c}{2} + \frac{3d}{4} + \frac{e}{2}\right)H_2O \Rightarrow \left(\frac{a}{2} + \frac{b}{8} - \frac{c}{4} - \frac{3d}{8} - \frac{e}{4}\right)CH_4 \\ + \left(\frac{a}{2} - \frac{b}{8} + \frac{c}{4} + \frac{3d}{8} + \frac{e}{4}\right)CO_2 + dNH_3 + eH_2S\,. \end{aligned} \tag{1}$$

a, b, c, d and e are given by percentage composition by mass of each of the elements devided by the relative atomic mass (Ar) of each of the elements as depicted below:

$$a = \frac{Carbon\ ultimate\ mass}{Ar_C}, \tag{2}$$

$$b = \frac{Hydrogen\ ultimate\ mass}{Ar_H}, \tag{3}$$

$$c = \frac{Oxygen\ ultimate\ mass}{Ar_O}, \tag{4}$$

$$d = \frac{Nitrogen\ ultimate\ mass}{Ar_N}, \tag{5}$$

$$e = \frac{Sulphur\ ultimate\ mass}{Ar_S}. \tag{6}$$

Equation (1) helps to build a material balance model. Reference is made to Kunatsa et al. (2020), when there are three different substrates. In this previous work, a biogas generation model for the determination of optimal substrate blend ratios is formulated and optimised. Equation (1) can be expressed in the form of equations (7), (8) and (9) for substrates 1, 2 and 3 respectively.

$$\begin{aligned} C_{a_1}H_{b_1}O_{c_1}N_{d_1}S_{e_1} + \left(a_1 - \frac{b_1}{4} - \frac{c_1}{2} + \frac{3d_1}{4} + \frac{e_1}{2}\right)H_2O \Rightarrow \left(\frac{a_1}{2} + \frac{b_1}{8} - \frac{c_1}{4} - \frac{3d_1}{8} - \frac{e_1}{4}\right)CH_4 \\ + \left(\frac{a_1}{2} - \frac{b_1}{8} + \frac{c_1}{4} + \frac{3d_1}{8} + \frac{e_1}{4}\right)CO_2 + d_1NH_3 + e_1H_2S, \end{aligned} \tag{7}$$

$$\begin{aligned} C_{a_2}H_{b_2}O_{c_2}N_{d_2}S_{e_2} + \left(a_2 - \frac{b_2}{4} - \frac{c_2}{2} + \frac{3d_2}{4} + \frac{e_2}{2}\right)H_2O \Rightarrow \left(\frac{a_2}{2} + \frac{b_2}{8} - \frac{c_2}{4} - \frac{3d_2}{8} - \frac{e_2}{4}\right)CH_4 \\ + \left(\frac{a_2}{2} - \frac{b_2}{8} + \frac{c_2}{4} + \frac{3d_2}{8} + \frac{e_2}{4}\right)CO_2 + d_2NH_3 + e_2H_2S, \end{aligned} \tag{8}$$

$$\begin{aligned} C_{a_3}H_{b_3}O_{c_3}N_{d_3}S_{e_3} + \left(a_3 - \frac{b_3}{4} - \frac{c_3}{2} + \frac{3d_3}{4} + \frac{e_3}{2}\right)H_2O \Rightarrow \left(\frac{a_3}{2} + \frac{b_3}{8} - \frac{c_3}{4} - \frac{3d_3}{8} - \frac{e_3}{4}\right)CH_4 \\ + \left(\frac{a_3}{2} - \frac{b_3}{8} + \frac{c_3}{4} + \frac{3d_3}{8} + \frac{e_3}{4}\right)CO_2 + d_3NH_3 + e_3H_2S. \end{aligned} \tag{9}$$

The aggregate biogas yield obtainable from these 3 substrates was modeled as:

$$B_{cod} = 0.8 \times \sum_{i=1}^{3} V \tag{10}$$

where B_{cod} is the summative biogas that is realised from the co-digestion of the 3 substrates and 0.8 is the substrates' biomass to biogas conversion factor. V_1, V_2 and V_3 are the biogas volumes from substrates 1, 2 and 3 respectively and are determined as shown below:

$$V_1\ (m^3) = \frac{(22.4 \times 10^{-3}) \times (CO_{2_1} + NH_{3_1} + H_2S_{\ 1} + CH_{4_1})}{Mr_{WH}}, \tag{11}$$

$$V_2\ (m^3) = \frac{(22.4 \times 10^{-3}) \times (CO_{2_2} + NH_{3_2} + H_2S_{\ 2} + CH_{4_2})}{Mr_{MSW}}, \tag{12}$$

$$V_3\ (m^3) = \frac{(22.4 \times 10^{-3}) \times (CO_{2_3} + NH_{3_3} + H_2S_{\ 3} + CH_{4_3})}{Mr_{CD}}. \tag{13}$$

$CO_{2_{1,2,\&3}}$, $NH_{3_{1,2,\&3}}$, $H_2S_{\ 1,2,\&3}$and $CH_{4_{1,2,\&3}}$ are the number of moles of carbon dioxide, ammonia, hydrogen sulphide and methane for water hyacinth (WH), municipal solid waste (MSW) and cow dumg (CD) respectively and are determined as shown below.

$$
\begin{aligned}
CH_{4_1} &= \frac{a_1}{2} + \frac{b_1}{8} - \frac{c_1}{4} - \frac{3d_1}{8} - \frac{e_1}{4};\\
CO_{2_1} &= \frac{a_1}{2} - \frac{b_1}{8} + \frac{c_1}{4} + \frac{3d_1}{8} + \frac{e_1}{4};\\
NH_{3_1} &= d_1 \text{ and}\\
H_2S_1 &= e_1
\end{aligned}
$$

$$
\begin{aligned}
CH_{4_2} &= \frac{a_2}{2} + \frac{b_2}{8} - \frac{c_2}{4} - \frac{3d_2}{8} - \frac{e_2}{4};\\
CO_{2_2} &= \frac{a_2}{2} - \frac{b_2}{8} + \frac{c_2}{4} + \frac{3d_2}{8} + \frac{e_2}{4};\\
NH_{3_2} &= d_2 \text{ and}\\
H_2S_2 &= e_2
\end{aligned}
$$

$$
\begin{aligned}
CH_{4_3} &= \frac{a_3}{2} + \frac{b_3}{8} - \frac{c_3}{4} - \frac{3d_3}{8} - \frac{e_3}{4};\\
CO_{2_3} &= \frac{a_3}{2} - \frac{b_3}{8} + \frac{c_3}{4} + \frac{3d_3}{8} + \frac{e_3}{4};\\
NH_{3_3} &= d_3 \text{ and}\\
H_2S_3 &= e_3
\end{aligned}
$$

Mr_{WH} is the relative molecular mass of water hyacinth, Mr_{MSW} is the relative molecular mass of municipal solid waste and Mr_{CD} is the relative molecular mass of cow dung. These relative molecular masses are as denoted in equations (14), (15) and (16) respectively.

$$Mr_{WH}\ (kgmol^{-1}) = a_1 * Ar_C + b_1 * Ar_H + c_1 * Ar_O + d_1 * Ar_N + e_1 * Ar_S, \tag{14}$$

$$Mr_{MSW}\ (kgmol^{-1}) = a_2 * Ar_C + b_2 * Ar_H + c_2 * Ar_O + d_2 * Ar_N + e_2 * Ar_S, \tag{15}$$

$$Mr_{CD}\ (kgmol^{-1}) = a_3 * Ar_C + b_3 * Ar_H + c_3 * Ar_O + d_3 * Ar_N + e_3 * Ar_S. \tag{16}$$

where Ar is the relative atomic mass of each respective element in the substrate molecule.

The aim of Kunatsa et al. (2020) was to find feedstock mixing ratios which maximise biogas output in the co-digestion combination. In a case study analysis, optimum co-digestion resulted in mixing ratios of 53.27 : 24.64 : 22.09 for WH, MSW, and CD, respectively. Biogas produced from 1 kg of substrate mixture amounted to $124.56m^3$. Biogas production was enhanced by co-digestion and optimising the substrate blend proportions. An increase by 157.11% in biogas output was noted.

3.1.2. First order dynamic model

The first order dynamic model is a high level-production level, dynamic modelling approach that looks at the overall production response. Membere et al. (2013) described and evaluated a dynamic model to generate biogas from co-substrates, it was concluded that applying the modified first order dynamic model produced higher biogas yield when compared to experiments in which it was not applied. Raw material digestability was analysed through computational formulation of first order nature for batch systems as was highlighted by Yusuf et al. (2011) as shown in equation (17):

$$\frac{y_m}{y_m - y_t} = \frac{C_o}{C_t}, \tag{17}$$

$$\text{and} \qquad \ln \frac{C_o}{C_t} = kt \tag{18}$$

where: "C_o is the initial volatile solid, C_t is the volatile solid concentration at any given time (t), y_t is the volume of biogas produced per unit mass of VS fed at any time (t) and y_m is the volume of biogas per unit of mass of VS converted at maximum time" (Yusuf et al., 2011).

$$\text{Therefore} \qquad \frac{y_m}{y_m - y_t} = e^{kt}, \tag{19}$$

$$y_t = y_m(1 - e^{-kt}). \tag{20}$$

To ascertain the change in the amount of biogas with time, the first order derivative of equation (20) is determined

$$y_t' = ky_m e^{-kt} \tag{21}$$

Equation (20) can now be written as:

$$y_t = y_m - \frac{y_t'}{k} \tag{22}$$

$$y_t' = ky_m - ky_t \tag{23}$$

Equation (23) gives the dynamic version of equation(20) that is potentially useful in future biogas production modelling using the first order dynamic model. The dynamic model offers easy foretelling of the response of the system and its output to mass and energy variations over time, easy parameter identification, easy control and optimisation variable introduction as well as easy evaluation and comparison of process control strategies (da Silva, 2015). Biogas generation kinetics are key in aiding the assessment of organic matter digestibility characteristics (Karki et al., 2021).

3.1.3. The modified Gompertz model

Unlike the first order dynamic model which gives supplementary data on hydrolysis rate, the modified Gompertz model gives time delay to biogas generation together with the highest methane generation rate (Pramanik et al., 2019). The modified Gompertz was verified to be an outstanding emperical non-linear regression model informing of gas generation time delay in addition to describing bacterial growth as exponential (Zahan et al., 2018; Pramanik et al., 2019). Many researchers reported that biogas formation rate is assumed to relate proportionally to the increase of methanogens in the bio-digester and as such biogas prediction follows the modified Gompertz equation as in equation (24) (Etuwe et al., 2016; Opurum et al., 2017).

$$P = A.exp\Big(-exp\Big[\frac{Ue}{A}(\lambda - t) + 1\Big]\Big) \tag{24}$$

in which P is the cummulative biogas production at a given time t, ml/gVS; A is biogas production potential, ml; U is highest biogas generation rate (ml/gVS.day); e is a mathematical constant, 2.718; λ is the biogas formation delay time *(minimum time to produce biogas)*, day; and t is the aggregate time for biogas formation, day. A, λ, and U are ascertained by non-linear regression. The higher U exhibits, the higher the biogas production rate. Biogas generation increases with increased values of U.

3.1.4. Artificial Neural Networks (ANNs)

Neural networks comprise of nodes (similar to human brain neurons) classified in sequences of layers interlinked in different ways and they can regulate a reaction progression through immitating the functioning human of brain (Nguyen et al., 2015). Fig. 1 shows a schematic of ANNs. Artificial Neural Networks (ANNs) can be used to forecast output data for complex systems having numerous operational input variables (Esfe et al., 2015). ANNs work using initial data provided, trains on it and simulates the reaction

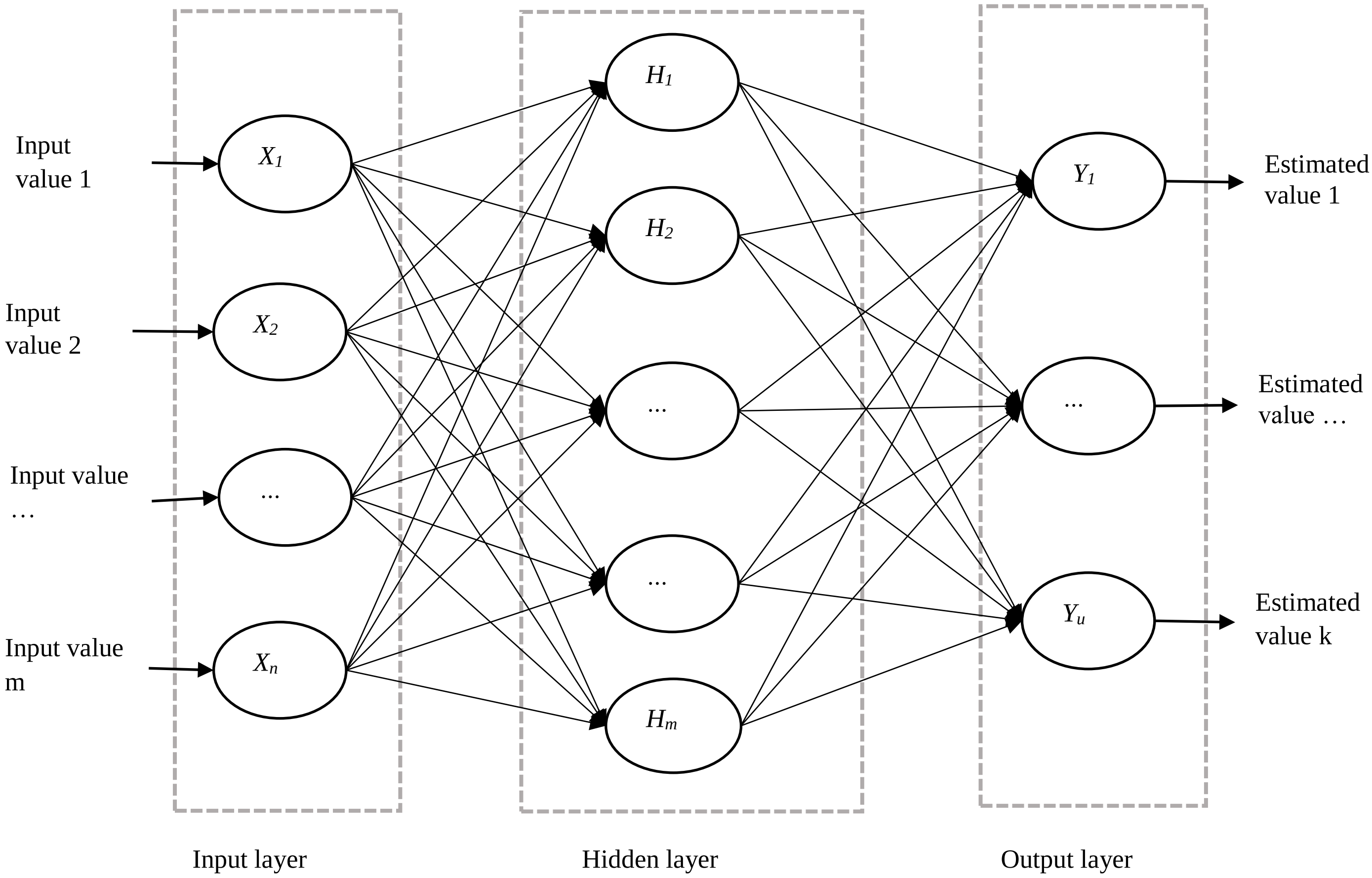

Figure 1: Artificial Neural Network schematic (Cheng et al., 2015)

progression by resembling the actual process. Many researchers used ANNs to predict, model and optimise biogas production from different substrates (Ghatak and Ghatak, 2018; Almomani, 2020; Neto et al., 2021). ANNs employ data-driven high level modelling, however, without physics, it is less useful in terms of optimising physical parameters. Another disadvantage of ANNs is that by its nature of being data driven, it disregards process kinetics.

3.1.5. The anaerobic digestion model no.1 (ADM1)

ADM1 simulates the biological transformation of intricate biodegradable matter to CH_4, CO_2 and other inert by-products (Batstone et al., 2002). The structured model has several phases that describe biological and physicochemical process reactions. The ADM1 is a complex model well suited for simulation but has significant limitations when it comes to optimisation and process control applications. The ADM1 model simulates constant volume, completely mixed systems which is not the case in many anaerobic digestion reactors especially when it comes to bigger systems.

ADM1 has physico-chemical steps integrated together with biological steps. 19 process reactions, 33 state variables in addition to 105 stoichiometry based relations and kinetic parameters (Batstone et al., 2002). According to Yu et al. (2014), the complexity of the ADM1 model necessitates requirement of several parameters, eventually leading to complicated reaction progression equations. Identification of parameters and handling of these several equations can be very difficult. (Kleerebezem and Van Loosdrecht, 2006) highlighted issues to do with stoichiometric impreciseness, glitches in solids retention time, and absence of restraints on thermodynamic bounds. However, due to the variations in the substrates under digestion only a few parameters will considerably affect the output of the model. ADM1 modelling is complex and as such an improved practicality is required when it comes to co-digesting substrates anaerobically (Xie et al., 2016).

Modelling the biogas generation process will lead to improvement of the biogas yield by manoeuvring into enhanced options for controlling the digestion process. Table 3 gives the key existing anaerobic digestion models. It can be deduced from Table 3 that the dynamic model and the steady state model dominate in the existing anaerobic digestion models. The hydrolysis kinetics are mainly of first order. The Monod and the modified Monod are the prevailing growth kinetics. Another deduction that can be made from Table 3 is that a lot of modelling has been done on sludge but only a few articles present research on organic wastes, manures and aquatic biomass. Many diverse attributes and factors are able to inhibit biogas generation as shown in the table. Inhibition is primarily influenced by nature of substrate and reaction conditions and/or parameters to which the process is subjected to.

Table 3: Summary of key existing anaerobic digestion models

Model type	Substrate	Hydrolysis kinetics	Type of inhibition	Source
stoichiometric	-	-	- [1]	(Buswell and Sollo, 1948)
dynamic; steady state	sludge	-	VFA[1], pH	(Andrews, 1969)
dynamic; steady state	organic waste	-	VFA, pH and NH_3	Hill and Barth (1977)
dynamic	complex organic material	first order	H_2, pH, NH, H_2S, Propionate	(Vavilin et al., 1994)
dynamic; steady state	organic waste	first order	LCFA, acetic acid, NH_3	(Angelidaki et al., 1999)

Model type	Substrate	Hydrolysis kinetics	Type of inhibition	Source
dynamic	swine manure	first order	-	(Massé and Droste, 2000)
dynamic; steady state	sludge	first order	H_2, pH, NH_3, acetic acid	(Siegrist et al., 2002)
dynamic; steady state	wide variety of substrates	first order	H_2, pH, NH_3, butyric acid	(Batstone et al., 2002)
dynamic	cattle manure	first order	pH, VFA and NH_3	(Keshtkar et al., 2003)
dynamic	wastewater	-	-	(Sarti et al., 2004)
dynamic	sludge	Contois	H_2	(Sötemann et al., 2005a)

Model type	Substrate	Hydrolysis kinetics	Type of inhibition	Source
steady state	sludge	first order, Monod, saturation	-	(Sötemann et al., 2005b)
dynamic; steady state	sludge	first order	H_2, pH, NH_3, butyric acid	(Blumensaat and Keller, 2005)
dynamic; steady state	agro-waste	first order	H_2, pH, iN[2] NH_3, H_2S	(Galí et al., 2009)
steady state	horse manure and cow dung	first order	-	(Yusuf et al., 2011)
Computational	organic fraction of municipal solid waste (OFMSW)	first order	-	(Membere et al., 2013)

[1]Volatile Fatty Acids [2]inorganic Nitrogen

3.2. Optimisation

According to the dictionary Rock.Holdings (2019), to optimise is "to determine the maximum or minimum values of (a specified function that is subject to certain constraints)". Hagos et al. (2017) highlighted that process optimisation and improvement of biogas production still needs more investigations to be done and that the use of simulation ways and means can lead to realisation of substantial enhancement of biogas yields. Diverse optimisation approaches are established in literature in a bid to obtain the best reaction conditions, best reaction parameters and best substrate ratios for different feed stocks so as to enhance and optimise the biogas production process.

The conventional method of optimisation of anaerobic digestion comprise of laboratory batch experiments with different ratios of co-digestion feedstocks to assess the extent of digestion of the substrates. Co-digestion of varied substrates has shown that an improved biogas production potential is achieved in comparison to mono-digestion of single substrates (Volpi et al., 2021; Muenmee and Prasertboonyai, 2021; Petrovič et al., 2021). ANNs, GAs, ant colony optimisation (ACO) and particle swarm optimisation (PSO) are possible tools for simulating and optimising the anaerobic biogas generation process. ANNs and GAs are some of the modern optimisation approaches applied to deal with complex biogas maximisation problems. Palma-Heredia et al. (2021) employed the ACO optimisation approach to anaerobic co-digestion. According to their results, employment of the ACO algorithm proved to be a beneficial way for optimising anaerobic digestion blends, leading to the effective simulation of various co-digestion optimisation scenarios. (Kegl and Kralj, 2020) investigated the appropriateness and effectiveness of a gradient-based optimiser for multi-objective anaerobic digestion process optimisation. Various optimisation problems were designed and solved using this model to gain insights into the effectiveness of this strategy. The proposed optimisation method was found to be extremely effective.

Genetic algorithms employ a random search algorithm that is created in an attempt to mimic the principles of natural selection and genetics (Roetzel et al., 2019). They work with string structures, similar to biological structures, that evolve over time and use a randomized but systematic exchanging of information to follow the theory of survival of the fittest. As a result, a fresh batch of strings is generated in every generation, using portions of the old batch's fittest members. GAs are able to cope with parallelism and complicated scenarios. They can be employed with an objective function that is static or dynamic, linear or nonlinear, continuous or discontinuous, or with random noise (Yang, 2020). Since multiple offspring in a population function as autonomous agents, the population will concurrently navigate the search space in various multiple directions, and consequently, an optimal solution is arrived at. This function makes parallelising algorithms for implementation much easier.

Linear programming approaches, response surface methodologies as well as simplex-centroid mixture design and central composite design are also among the optimisation approaches which have been applied in anaerobic digestion (Gil et al., 2019; Lu et al., 2017). Prospects of enhancing biogas generation from varied substrates such as water hyacinth, cow dung and municipal solid waste via the avenues of co-digestion and use of optimisation tools and techniques are investigated herein. Table 4 shows a summary of some of the key biogas optimisations which were done.

Table 4: Summary of key biogas optimisations

Substrates	Model used	Optimisation approach	Highlights	Source
Cassava (manioc, tapioca) processing wastewater	-	experimental	effect of pH and temperature variations with biogas production were analysed, the control strategy was based mainly on pH control	(Boncz et al., 2008)
Cob Corn Mix (CCM), Rye and pig manure	ADM1	GA and PSO	quantity and composition of substrates were varied, authors noted huge improvement capability by optimising substrate feed. It was noted that PSO was about 14 % quicker than GA in this instance	(Wolf et al., 2009)
variety of lignocellusosic biomass	ADM1, Lignogas & Lignogas-SIM	experimental, nonlinear least squares, & simplex in AQUASIM	the Lignogas model gave a closer match of modelling and measurement results	(Martin, 1979)

Substrates	Model used	Optimisation approach	Highlights	Source
grass, wheat straw, silage wastewater	-	experimental	anaerobic digestion was devided into a two-phase process and higher methane yields were realised	Wilkie et al. (1983)
organic fraction of MSW	first order kinetic	experimental	variations of organic loading rates were done, repercussions of varying total solids and retention time were analysed. A high CH_4 proportion was realised	(Rao and Singh, 2004)
Miscanthus Fuscus mixed with cow dung	-	RSM and Box-Behnken (BBD) design	Investigation was done to evaluate the effect of varying parameter settingson co-digestion was done. A pH of 6, a temperature of 30°C, HRT of 20 days and F/I ratio of 75% were idientified as the optimal process parameters. F/I ratio was observed to have a major impact on biogas production.	(Tetteh et al., 2018)

Substrates	Model used	Optimisation approach	Highlights	Source
glycerine, gelatine and pig manure	ADM1	adaptive linear programming, experimental	a linear programming to maximise chemical oxygen demand (COD) transformation which maintains reactor media as well as biogas quality was developed.	(García-Gen et al., 2014)
cow-manure and grass-silage	ADM1, ANNs	ant colony optimisation (ACO)	ADM1 model was used for simulations, ANNs to forecast biogas flow rate and ACO was used to depict important process parameters	(Beltramo et al., 2016)
maize silage, manure and the solid fraction of manure	ADM1	nonlinear model predictive control (NMPC)	an online NMPC algorithm was analysed. Authors highlighted that biogas production can be controlled and optimised	(Gaida et al., 2012)
maize silage and liquid cow manure	ADM1	nonlinear model predictive control (NMPC)	a closed-loop substrate feed control was suggested. A multi-objective NMPC was used for feed constituents regulation	(Gaida et al., 2014)

Substrates	Model used	Optimisation approach	Highlights	Source
rural household domestic waste	-	RSM	RSM was employed using central composite rotatable design. Biogas production was optimised through variation of PH, detention time and ratio of substrate to water. Highest biogas yield was obtained from a combination of detention time of 30 days, substrate to water ratio of 1:1 and pH of 7	(Jiya et al., 2019)
Carica papaya peels, poultry droppings	-	RSM and ANN	C. papaya was shown to be an excellent substrate for biogas production when co-digested with poultry droppings. Both RSM and ANN models proved to be effective in predicting methane generation from C. papaya peels and poultry dropping, according to the results of the modeling and optimisation	(Dahunsi et al., 2016)

Substrates	Model used	Optimisation approach	Highlights	Source
organic fraction of municipal solid wastes, cow manure, and municipal sewage sludge	GA	simplex-centroid mixture design (SCMD) and ANN	combination of the SCMD and ANN model and optimising with GA helped to predict biomethane generation	(Saghouri et al., 2020)
palm oil mill effluent (POME) and cattle manure (CM)	ANN	combined ANN-PSO framework	biogas production from POME was predicted and optimised using ANN and PSO in a co-digestion setup in a solar bioreactor. According to the results reported, the suggested method was successful and flexible in estimating biogas output from the co-digestion of POME and CM	(Zaied et al., 2020)
cow dung and flower waste	ANN, RSM	statistical optimization	The ANN model predicted biogas output more precisely and effectively than the RSM model. Statistical optimisation and pretreatment approaches dramatically boosted biogas generation	(Gopal et al., 2021)

Substrates	Model used	Optimisation approach	Highlights	Source
goose manure and wheat straw	experimental	statistical (regression)	methane was increased by upto 94.10 % due to C/N ratio optimisation	(Hassan et al., 2017)
Siam weed (*Chromolaena odorata*) and poultry manure	experimental	RSM	increased quanties of of biogas were attained due to co-digestion. The biogas quality was also improved. RSM proved to predict biogas well	(Dahunsi et al., 2017)
algal-bacteria biomass and cellulose	kinetic model	-	Biogas production time delay was decreased by 50 % and methane generation was improved by 35 %	(Bohutskyi et al., 2018)
cow manure and oat straw	modified Gompertz and non-linear regression	Box-Behnken test design	addition of cow manure at levels below 2/3 boosted methane yields and decreased biogas production startup time, however the methane generation rate was not affected	(Zhao et al., 2018)

Substrates	Model used	Optimisation approach	Highlights	Source
carrot, cabbage, tomato, bread (French baguette), beef meat at 5 % fat and manure (a mix of cow dung and straw)	experimental, kinetic	-	the predicted results using the model with constant endogenous generation and kinetics determined at 80 % of total batch time matched the observed methane yields well under rising organic loading rates. Data obtained from batch reactors predicted semi-continuous biogas production in an effective manner	(Kouas et al., 2018)
hemicelluloses hydrolysate, vinasse, yeast extract and sugarcane bagasse fly ashes	experimental, modified Gompertz model and the two-phase exponential model	experimental	biochemical methane potential tests were used to optimize anaerobic co-digestion of sugarcane biorefinery by-products. The sugarcane biorefinery wastes blend enhanced anaerobic co-digestion and boosted methane generation	(Adarme et al., 2019)

Substrates	Model used	Optimisation approach	Highlights	Source
pig manure and corn straw	experimental	-	the beffect of organic loading rate, total solids and crbon to nitrogen ratio was investigated in co-digestion of pig manure and corn straw. Maximum biogas output was discovered to be attained at a C/N ratio of 25, whilst the optimum biogas slurry performance was found to be at a C/N ratio of 35. Increased organic loading rates and total solids also led to significant biogas generation and biogas slurry performance.	(Ning et al., 2019)
acorn slag waste, dairy manure and bio-based carbon	experimental	-	the use of bio-based carbon in the co-digestion of acorn slag and dairy manure was researched. The carbon-based accelerant was reported to have improved the biogas yield in co-digestions	(Wang et al., 2019)

Substrates	Model used	Optimisation approach	Highlights	Source
food waste and chicken manure	experimental, computational fluid dynamics (CFD)	-	Experimental and numerical studies of the impact of mixing time on anaerobic digestion performance were conducted. Extending the mixing time did not enhance biogas output, but did increased overall input.	(Mao et al., 2019)
Laminaria digitata and animal dung	dynamic bioconversion model (BioModel) and a hybrid MATLAB-Microsoft Excel software	-	biogas yield was boosted by co-digesting Laminaria digitata and animal dung. Laminaria digitata increased biogas output, whereas cattle manure assisted in buffering. BioModel simulation validated the results from the batch and continuous reactors.	(Sun et al., 2019)

Substrates	Model used	Optimisation approach	Highlights	Source
food waste and cow manure	experimental, modified Gompertz and first-order kinetic	-	start-up conditions were optimised. Optimal substrate mixing ratio, substrate to inoculum ratio, and initial pH were verified by experimentation. A steady anaerobic digestion was started with FW/CM = 2.5, S/I less than 0.07, and an initial uncontrolled pH. These conditions were verified in a dynamic membrane bioreactor	(Xing et al., 2020)
spent coffee grounds, spent tea waste, glycerin, and macroalgae	experimental, modified Gompertz, linear regression	-	Different wastes were co-digested with oil-extracted spent coffee grounds. With the oil extraction procedure, specific methane output rose by 10 %. The results of the modified Gompertz model were generally consistent with those of the experiments.	(Atelge et al., 2021)

As noted earlier on, mathematical and analytical optimisation techniques that can be applied to biogas production include the linear programming approach, non-linear programming approaches, such as non-linear model predictive control (NMPC), artificial intelligence theory approaches, such as ANNs, fuzzy logic, GAs, PSO, ACO, simulated annealing and immunity algorithm. Gaida et al. (2014) applied the ADM1 model biogas production. NMPC was used as the optimisation approach to control the constituency and quantity of the feed. Huang et al. (2016), carried out an investigation to concurrently maximise chemical oxygen demand (COD_{eff}) and biogas flow rate (Q_{gas}). The authors reported that by using GA-ANN model, an increased biogas was attained when compared to ANNs alone. García-Gen et al. (2014), used linear programming optimisation approach to maximise methane production by way of determining the feedings into the processes. The ADM1 model was used and the method was validated experimentally. Implimentation was done in MATLAB, *'linprog'* was used to determine substrate blends and *'fminbnd'* was used to ascertain HRT that optimises methane production. The objective function was expressed as in equation (25)

$$max f_{objective} = \frac{\sum_{i=1}^{N} pMet_i \times CODt_i \times x_i}{HRT} \tag{25}$$

According to the authors, the objective function was subjected to the following linear restrictions: "(i) organic loading rate (OLR); (ii) total Kjeldahl nitrogen (TKN); (iii) moisture or liquid fraction; (iv) lipid content; (v) total alkalinity; salinity as (vi) Na^+ concentration and (vii) K^+ concentration; (viii) H_2S content in biogas; and (ix) effluent COD content".

Beltramo et al. (2016), optimised biogas flow rate using the ACO approach, the ADM1 model was used to generate data and the ANNs model was used for simulations. The ACO algorithm was used for variable selection. The selection probability of a variable prob(n) was described as in equation (26)

$$prob(n) = \frac{p(n)}{\sum_{i=1}^{N} p(n)} \tag{26}$$

Most of the biogas production models presented and discussed in subsection 3.1 were barely used in biogas optimisations. This can also be noted from Table 4. Of the models that were applied, the ADM1 was applied more often followed by ANNs and then the first order kinetic model. The majority of the reported researches on biogas optimisation were by way of laboratory experimental approaches. These laboratory experiments would be under specific conditions which might not be universal to all subatrates and geographic locations. This eventually results in gaps and lack of confidence and reliability in their data being used to commercialise biogas technologies. The authors of this current review work would like to stress out and comment that there is a disjoint or rather a discontinuity between the biogas production models developed to date and their respective application to optimise and control the the overall biogas generation process progression with a prior objective to maximise the ultimate biogas yield.

4. Techno-economic analysis of anaerobic biogas production

A techno-economic assessment enables the creation of an investment and operational cost framework for the estimation of biogas generation's possible present and future economic sustainability. Informed financial and technical decisions such as biogas plant size or scale of operation as well as commercialisation prospects amongst other key considerations can be made based on techno-economic analysis.

Al-Wahaibi et al. (2020) produced biogas from a variety of food wastes and conducted a techno-economic analysis to determine the financial feasibility of establishing a small-scale biogas plant. Economic examination gave a break even at $\$0.2944/m^3$, with all pricing beyond that yielding a positive net present value. The researchers noted that incorporation of waste management charge savings could have increased the total savings.

A techno-economic investigation by Oreggioni et al. (2017), on bio-methane generation from agricultural and food wastes indicated that pressure swing adsorption cycles gave 37% lower capital costs and a 10% lower average life-time cost when compared to solvent-based technologies. This indicates that biomass processing, pretreatment and feeding techniques have a great impact on the overall techno-economic results.

Glivin et al. (2018) carried out techno-economic studies on the installation of a biogas plant at an institution. Biogas production proved to be viable, with payback periods ranging from 1.65 to 0.61 years for cow dung based biogas plants and 1.47 to 0.38 years for kitchen waste based biogas plants. It can be deduced that the type of feedstock has a huge influence on the total biogas yield which will in turn implicate on the economic parameters such as payback period, net present value, internal rate of return, among others.

Several other researchers investigated techno-economic aspects of anaerobic biogas production (Tan et al., 2021; Imeni et al., 2020; Mahmod et al., 2021). However, the majority of the works were focussed towards ascertaining if the process was feasible or not. The previous works lack the merging of the technical and the economic aspects to come up with analytical models for the optimisation of the entire process. It is vital to examine the tradeoffs arising from the relationships between technical developments and financial aspects in order to come up with an effective biogas production system. Optimising feedstock availability, controlling and regulating process conditions, maximising biogas output through co-digestion, feeding in of optimal substrate blend proportions and process stabilisation are among the technological aspects which are lacking in previous research works and still need to be investigated in greater detail. Objectives of reducing investment and operational costs as much as possible while increasing economic benefits are among the economic considerations which need to be explored in depth.

Process designs should incorporate anticipated operational and maintenance cost evaluations as well as the investment requirements for the entire biogas production facility. This will provide a concrete foundation for techo-economic analysis. Dynamic linkages will be formed with regards to the variation of the different techno-economic aspects with time leading to the development of informed anaerobic digestion modelling and optimisation frameworks for biogas enhancement. Consequently, the techno-economic implications will not only aid technology investors and financiers in decision making but will also guide research and development in the anaerobic biogas production niche. As such, generation of multi-objective techno-economic functions are imperative to the modelling and optimisation of anaerobic digestion.

This section concludes by by discussing the whole process of conducting techno-economic assessments of typical anaerobic digestion projects as well as highlighting on how the analysis of costs and benefits is done. Investment appraisal computations are carried out based on the technical parameters of the project in order to ascertain the overal techno-economic viability of the project. The following procedure is suggested by the authors:

1. The initial investment costs (I_0) are determined basing mainly on the capital requirements of the specific project. Capital requirements include the digester construction costs, biomass harvesting equipment for use in cases where agricultural residues and aquatic bio-materials such as water hyacinth are among the substrates. Pretreatment equipment such as dryers and choppers can be included to the capital requirements. Construction and erection costs of biogas plant infrastructure and other ancillary facilities such as substrate storage compartments are included to the capital requirements and are integral components of the initial investment costs.
2. Transport costs for ferrying feedstocks/substrates to the digesters are calculated and teken into consid-

eration. The siting of most anaerobic digestion plants is usually done within the vicinity of feedstocks and water. However, transport costs have to be factored in for cases whereby the resources have to be ferried from some other locations to the biogas generation plant.

3. The operation and maintenance (O&M) costs are ascertained. The O&M costs of anaerobic digestion are a bit difficult to arrive at as these fluctuate with time and availability of replacement and/or refurbishment parts and accessories. As a rule of thumb a certain percentage of the initial investment costs for instance 2% is taken to be the value of O&M costs.
4. The price of biogas is prescribed. The price of fuel on the market has a huge bearing on the determination of the price of biogas. In many countries, the energy sectors have a regulatory board which stipulates and governs fuel prices. However, it is worthwhile to set the selling price of biogas below that of conventional fuels such as Natural Gas and Liquid Petroleum Gas (LPG) for the reason that the conventional fuels are more efficient and as such for biogas to be competitive on the market its price has to be relatively lower. Biogas generation costs generally range from USD 0.22 to USD 0.39 per cubic meter of methane for animal dung-based biogas, and from USD 0.11 to USD 0.50 per cubic meter of methane for industrial waste-based biogas (International Renewable Energy Agency (IRENA), 2017).
5. Carbon dioxide emissions are dtermined and carbon credits are calculated. The Paris climate agreement intends to keep global warming below 2 degrees Celsius and promote initiatives to keep it below 1.5 degrees Celsius (Intergovernmental Panel on Climate Change (IPCC), 2019). There are specific limits which companies cannot exceed when it comes to greenhouse gas emissions. Carbon taxes are in operation world-over whereby entities pay for the amount of carbon dioxide they produce and emission trading schemes are operational creating a carbon market where businesses buy and sell carbon credits. Entities that avoid carbon dioxide emissions sell their rights to those having higher emission reduction costs (Hartmann, 2017). Proceeds from carbon credits are taken as benefits and they positively influence the revenue of a company.
6. The amount of bio-slurry/bio-fertilizer is determined. It is not all the biomass material fed into the biogas reactor that is digested completely. The residue sludge normally referred to as sludge or bio-slurry can be used as a bio-fertiliser as it is rich in nutrients. This bi-product of anaerobic digestion can be sold to farmers and other interested stakeholders after drying it or in its wet form. Revenue is

realised from selling this bio-fertiliser.

7. The Net Present Value (NPV), Internal Rate of Return (IRR) and Payback Period (t_{PB}) among other project appraisal criterion parameters are employed to ascertain the financial viability of the project under study. The following formulae can be used in calculating the parameters highlighted:

   - Net Present Value (NPV)

$$\begin{aligned} NPV &= -I_0 + \sum_{1}^{n} \frac{B - C}{(1 + r)^n} \\ &= -I_0 + [PWAF \times (B - C)] \end{aligned} \tag{27}$$

     where I_0 is the initial investment, B represents the benefits (revenue), n is the project life time, r is the interest rate or discount rate, C represents the project costs, B-C is equivalent to the Net Profit, PWAF is the Present Worth Annuity Factor which is given by:

$$PWAF = \frac{1 - (1 + r)^{-n}}{r} \tag{28}$$

   - Payback Period (t_{PB})

$$t_{PB} = \frac{-\ln(1 - \frac{I_0 r}{CF})}{\ln(1 + r)} \tag{29}$$

     where CF = Annual cash flow = $B - C$

   - Internal Rate of Return (IRR)

$$IRR = r_1 + \frac{(r_2 - r_1 \times NPV_1)}{NPV_2 + NPV_1} \tag{30}$$

     where r_1 is the initial discount rate, r_2 is a new assumed discount rate which brings the NPV closer to zero, NPV_1 is the initial Net Present Value and NPV_2 is the new Net Present Value arrived at using r_2.

5. Research gaps and future perspectives

Co-digesting different substrates is reported to increase biogas output volumes owing to the optimistic interactions created in the digestion medium, microbial variations in diverse substrates as well as provision of missing nutrients by the co-substrates. Anaerobic co-digestion still remains largely unstudied for many varying substrates. Application of the co-digestion technology therefore needs close management since no one customary laid out operating parameters and settings are practical for all organic biodegradable wastes. Considering the availability of many different organic materials which can be feedstocks for co-digestion, further research in enhancement and controlling of biogas production from varied substrate types should be undertaken.

There is need of modelling and optimisation using specific substrates such as water hyacinth, cow dung and municipal solid waste so as to sustainably deal with the issues of environmental sustainability as well as energy demand and supply. This study notes that many previous works (Ferreira et al., 2021; Oladejo et al., 2020; Mukumba et al., 2019; Mahato, 2020), used arbitrary suppositions from a selection of uninformed different mixing ratios in co-digestion. Optimisation of the anaerobic biogas production process needs to be done so as to arrive at informed optimal substrate blend ratios and reaction parameters through co-digestion. Mathematical modelling can help researchers and the entire biogas fratenity to optimise operations more effectively and forecast biogas production in a variety of scenarios, conditions and/or constraints. The use of modelling and simulation in conjunction with analytical tools such as those in MATLAB will go a long way in planning, controlling, and predicting anaerobic co-digestions. The modelling and simulations can be coupled to optimisation of different specific target objectives such as maximising biogas output, minimising energy cost, minimising environmental detriments, amongst many others. The majority of the models in literature lack this coupling and this needs to be deeply looked into.

A lot of research and development is yet to be done with respect to mathematical modelling and application of optimisation tools in biogas production. As such it will be of interest to further develop, evaluate and compare the empirical, biological and mathematical models with regards to biogas prediction and optimisation. In line with the development of models and optimisation of the biogas production process, a wide spectrum of control options needs to be incorporated in the models in a bid to regulate the entire process for better optimal gas yields. Some control systems and/or strategies are lacking in the overall anaerobic biogas production optimisations. Incorporation of some simple controllers such as the on-off switching devices to advanced ones like the proportional integral derivative (PID) devices and fuzzy logic among others can lead to entire bio-process automation and enhancement.

The resultant AD process biogas outputs are dependant upon the amount, nature and standard of the biomass fed into the system. Thus the overall optimal yields are affected by the time of the year and the environment from which the substrates are derived from since these dictate the amount and quality of the same. Biogas production and optimisation models developed to date do not account for the geographical *(environmental)* and seasonal *(time)* variation of substrates. This offers an opportunuty for research in this direction.

This current study also highlights, from reviewing of previous works the necessity of accelerating integration of RETs into the existing energy supply mix. It is hereby reported that lots of research have been done on hybridisation of solar, wind, diesel, grid and in other instances coupled with storage such as batteries. However, the hybridisation of biogas with these and other conventional fuel supply alternatives like liquid petroleum gas (LPG) and other distributed renewable energy supply sources to meet energy and/or fuel demand is still at infancy in terms of research and development and as such is presented as an avenue for possible further research work.

Most of the previous works majored on experimental investigations and prospects of optimising single phase mono-digestion processes inclusive of the factors that affect the same. This agrees with Ilo et al. (2021) who also gave demerits to the laboratory experimental approaches owing to inconsistency in specific conditions under which the experiments are carried out. It is however realised in this study that research gaps do exist in regard to optimisation of co-digestion processes using biogas production models incorporating the concept of a multi-stage AD reaction mechanism inclusive of the factors that affect the same, mainly the pH and temperature parameters. This is as well being presented herein as a future research work direction.

There is need of taking a multi-objective approach when it comes to the techno-economic analysis of the anaerobic biogas production process. The modelling and optimisation will be more effective if all technical and economic parameters and conditions are employed. Given the current bid to combat climate change world-over, environmental aspects such as CO_2 equivalent emissions avoided can also be incorporated into the overall techno-economic analysis and this will contribute immensely towards the research and development of anaerobic biogas production technology.

The application of anaerobic digestion does not only tackle waste management issues, but also comes with a new paradigm to energy generation. Anaerobic digestion, co-digestion in particular, has sparked a lot of interest among scientists because of its good potential health implications, environmental merits, economic advantages, and most importantly its enhanced waste-to-energy biogas generation yields (Van et al., 2020). However, its adoption world over at large scale is still at infancy especially when it comes to the management of solid wastes by municipalities among other commercial biogas production entities. Widespread awareness of this technology needs to be extensively accelerated for commercial adoption worldwide given its renewable nature and many other benefits.

6. Conclusions

The status, current trends and future perspectives in the field of biogas production with regards to co-digestion, modelling, and optimisation were reviewed in this study. Co-digestion needs a great deal of further research on varied feedstocks and optimal mix ratios. Modelling and optimisation incorporating co-digestion feedstock seasonal variations is yet to be studied. Control of process conditions is key to achieving optimal biogas. Hybridisation of biogas with conventional and non-conventional energy sources needs to be explored in depth. The majority of research investigations are centred on mono-digestion. Coupling of co-digestion, modelling, and optimisation needs significant further research and investigations.

CRediT authorship contribution statement

Tawanda Kunatsa: Conceptualisation, Methodology, Original draft preparation, Writing, Reviewing and Editing. **Xiahoua Xia:** Supervision, Reviewing and Editing. **Lijun Zhang:** Supervision, Reviewing and Editing

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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