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Research paper

Multi-objective optimization of biomass to biomethane system

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Abstract

The superstructure optimization of biomass to biomethane system through digestion is conducted in this work. The system encompasses biofeedstock collection and transportation, anaerobic digestion, biogas upgrading, and digestate recycling. We propose a multicriteria mixed integer nonlinear programming (MINLP) model that seeks to minimize the energy consumption and maximize the green degree and the biomethane production constrained by technology selection, mass balance, energy balance, and environmental impact. A multi-objective MINLP model is proposed and solved with a fast nondominated sorting genetic algorithm II (NSGA-II). The resulting Pareto-optimal surface reveals the trade-off among the conflicting objectives. The optimal results indicate quantitatively that higher green degree and biomethane production objectives can be obtained at the expense of destroying the performance of the energy consumption objective.

Keywords: Multiobjective optimization; Biomass to biomethane system; Green degree; Mixed-integer nonlinear programming

1. Introduction

Recently, severe fluctuations in fossil fuel prices and global environmental problems have greatly accelerated efforts to develop renewable energy. Biomass-based methane, as a reproducible and environmentally friendly fuel that can decrease greenhouse gas emissions and reduce the non-renewable energy consumption, has gotten increasing attentions. Meanwhile, the multi-objective optimization of the complex biomass to biomethane process is of great significance, which can enhance the material and energy efficiency of the biomethane production system and assist in realizing the energy saving and emission reduction.

In the last decades, considerable efforts have been made to assess and optimize digestion and upgrading units of a biomethane production system. Huang et al. [1] proposed a novel multiobjective control strategy to simultaneously optimize the biogas flow rate and the effluent chemical oxygen demand in a complex anaerobic bioreactor. The developed hybrid approach may offer a very effective and useful tool for simulation, design, operation and optimization of anaerobic digesters. Zaher et al. [2] addressed a simulation tool for the optimization and assessment of co-digestion of different solid waste streams. The integrated model could determine the feed ratio and hydraulic retention time to obtain the maximum biogas production rate. Mahanty et al. [3] developed a methodology to evaluate and optimize the co-digestion of five different industrial sludges, which can be utilized to predict the maximum possible biomethane yield. Xu et al. [4] studied and assessed three biogas upgrading techniques considering energy and environmental performance by using the process simulation and green degree (GD) method. Wu et al. [5] established a simulation model for the assessment of energy consumption of biogas upgrading process. Additionally, many

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experimental studies have been conducted to study the performance of anaerobic digestion [6–10].

Meanwhile, there have been many studies on multiobjective optimization of biomass to biofuels systems. Gebreslassie et al. [11] addressed a bi-criteria nonlinear programming (NLP) model for the optimal operation and design of hydrocarbon biorefinery that produced diesel and gasoline from hybrid poplar feedstock through fast pyrolysis, hydrotreating and hydrocracking. Then they proposed a mixed-integer nonlinear programming (MINLP) model for the rigorous optimization and operation of an algae-based biorefinery system with sequestration of carbon dioxide from power plant flue gas. The mathematical model integrates the techno-economic analysis and environmental impact assessment through a life cycle optimization framework [12]. Zhang et al. [13] proposed a comprehensive superstructure for the sustainable process design and synthesis of hydrocarbon biorefinery that included fast pyrolysis, biocrude collection, hydroprocessing and hydrogen production under economic and environmental criteria. The Pareto-optimal solutions provided optimal operation configuration, profit, and emission data for future decision-makers. Santibanez-Aguilar et al. [14] presented a mathematical model for the optimal design of a biomass conversion system considering simultaneously the total net profit maximization and the environmental impact minimization. Mian et al. [15] presented detailed thermoeconomic and environmental models for the multiobjective optimization of microalgae to synthetic natural gas (SNG) conversion system accounting for supercritical gasification. Martin and Grossmann [16] established an MINLP model for the superstructure optimization of bioethanol process from switchgrass via gasification. In addition, they optimized a process to enhance the production of biodiesel and bioethanol from algae through glycerol fermentation [17]. Wang et al. [18] proposed a superstructure model for the optimization of hydrocarbon biorefinery via gasification considering the economic and environmental performance. Gassner and Marechal [19] addressed a superstructure MINLP model for the conceptual design of thermochemical fuel production process by optimizing the exergy depletion and investment cost objectives.

However, little work concerns the rigorous optimization strategies of the complex biomethane production system, which covers the whole subsystem including collection and transportation, anaerobic digestion, biogas upgrading, and digestate utilization. In this paper, an MINLP model for the rigorous optimization of the superstructure-based biomethane production process is established. The model simultaneously considers the minimization of the energy consumption, the minimization of the total environmental impact, and maximization of the biomethane production as three objective functions by optimizing the combinations of the feedstocks, operation variables, and alternative operation technologies. The environmental performance takes into account the overall environmental impact estimated by the GD method. Meanwhile, the GD values of biomass (chicken manure, sugar cane and corn stalk, *etc.*) and digestate are developed on the basis of the GD method. Based on a real application, the description of the superstructure system is presented. Then it is optimized by a non-dominated sorting genetic algorithm II (NSGA-II). Finally, the Pareto optimization results are obtained and some typical optimal points are selected and analyzed.

2. Process description

This section provides a description of each of the four major processing steps, including biomass collection and transportation, anaerobic process, biogas upgrading, and digestate utilization shown in Fig. 1. In each processing unit, the alternative technologies (Fig. 1) considered are based on the environmental and thermodynamic performance of the system.

2.1. Collection and transportation

Distribution of biomass resources is broad and non-uniform. So collecting biomass feedstock from fields is a great challenge for biomass power plants in China. A mathematical model is addressed for the optimal design and analysis of geographic distribution of biomass power plant and satellite storages based on a square sub-collection-region [20,21]. Singh et al. [22] proposed a circular island-based mathematical model of biomass collection and transportation costs. In this article, it is assumed that all biofeedstocks collected are in centralized covered collection and all biomass transported is done by diesel trucks.

2.2. Biomass handling and anaerobic digestion

Agricultural residues should be shredded into a small particle size prior to entering into the anaerobic digestion tank, because the decomposition and methane (CH_4) potential of biomass could be considerably enhanced by pretreating for reduction of particle size [23,24]. The length of cereal residues is usually cut into the range of 2–3 cm.

The major component in this system is anaerobic digestion technique. Anaerobic digester is a sophisticated process in which insoluble organic polymers are broken down and converted into CO_2 and CH_4 by anaerobic bacteria in the absence of oxygen. Several factors within the reactor such as temperature, pH, retention time, inoculum-to-feed ratio, C/N ratio, and organic loading rate can impact the efficiency of anaerobic digester, degradation rates, biogas production, and biomethane content [25]. In this model, the influence of different temperature is taken into account in detail: mesophilic anaerobic digestion and thermophilic anaerobic digestion.

Generally, the higher operating temperature can bring higher metabolic activities. Anaerobic process can be operated at ambient temperatures exhibiting a low efficiency. So, most reactors are operated at either mesophilic conditions (30–40 °C) or thermophilic conditions (50–60 °C).

Compared to mesophilic reactor, thermophilic reactor usually possesses higher decomposition efficiency, COD

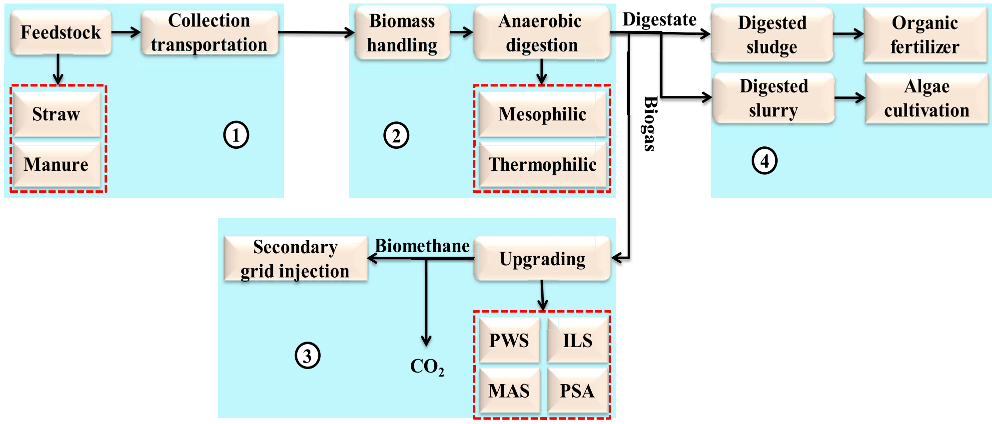

Fig. 1. Biomass to biomethane superstructure.

removal rate, and CH_4 content at smaller digester volumes or in a shorter time [26,27]. However, the higher temperature cannot always get better optimal operation, due to the larger energy input.

2.3. Biogas upgrading

Biogas primarily consists of CH_4 (40–75%) and carbon dioxide (CO_2) (15–60%). Trace impurities presented in biogas can reduce the calorific value and increase energy input for its transportation and storage [28]. After removing CO_2 and other impurities, the final production, biomethane, can be used as the secondary grid injection at 10 bar [29]. In this work, four alternative upgrading techniques are considered, including pressured water scrubbing (PWS), monoethanolamine aqueous (MEA)-based scrubbing (MAS), ionic liquid scrubbing (ILS), and pressure swing adsorption (PSA).

PWS is deemed to be the simplest and cheapest process. Physical absorption-based PWS employs water as an absorbent for removing H_2S and CO_2 in a gas-liquid countercurrent method. PWS can have high separation efficiency (more than 97% CH_4) and low CH_4 loss (less than 2%) at higher pressure [28]. However, The low diffusivity values result in a large column volume required and tardy absorption process [4]. Additionally, the drawback of clogging or foaming due to microbial growth is inevitable [28,30].

MAS is a chemical absorption process using MEA as an absorbent to remove CO_2 from methane rich biogas at ambient temperature and atmospheric pressure [31,32]. In addition, MAS needs less investment cost and operation cost compared to PWS due to the higher absorption capacity [31]. However, the process of solvent regeneration needs significant higher energy consumption [28,32].

As a promising technology, IL has been paid remarkable attention caused by its tunable physicochemical property, huge thermal stability, and high solubility capacity [33,34]. Additionally, ILS process can reduce the energy consumption and solvent loss due to the low vapor pressure of the IL solvent [35–37]. However, it should be noticed that higher viscosity might result in lower absorption rate and lower heat and mass transfer [4,35]. Moreover, the higher costs of ionic liquids confine their extension to industrial-scale application.

PSA uses a string of adsorption columns which are packed with adsorptive materials, such as zeolite, silica gel, and activated carbon, for differential adsorption of the CO_2, letting CH_4 passing through [5,38]. The process cycle consists principally of five steps: pressurization, feed, depressurization, blowdown, and purge. Increasing the column numbers enable to improve CH_4 enrichment, reduce offgas emission, and reduce energy demand [5]. However, a higher cost would be paid [38–40].

Notice that except for the first technology which releases the CO_2 into atmosphere, the other three processes would obtain high purity CO_2 product.

2.4. Digestate utilization

In this model, plenty of digested slurry and sludge produced during the digestion process are pumped into gas separator. Then the solid phase could be utilized as solid organic fertilizer, while part of the digested slurry could be used as algae cultivation.

3. Model formulation

A multicriteria optimization model based on an elitist evolutionary algorithm is constructed to determine the best operation of biomass to biomethane process by minimizing energy consumption and maximizing the green degree and the biomethane production. The model formulation is presented as follows.

3.1. Mass balance

The total mass flow rate of feedstock to the anaerobic digester is given by

$$m_{total} = m_{manure} + m_{straw} + m_{water} \tag{1}$$

where m_{manure}, m_{straw}, and m_{water} are the mass flow rates of manure, straw residue and water, ton d^{-1}, respectively.

The total mass balance on digestion process states that the total mass flow rate of raw material equals to the raw biogas mass flow rate plus the digestate mass flow rate.

$$m_{total} = m_{bio} + m_{dige} \tag{2}$$

The raw biogas mass flow rate is modeled with the equation below.

$$m_{bio} = m_{bio,CH_4} + m_{bio,CO_2} \tag{3}$$

where m_{bio,CH_4} and m_{bio,CO_2} are the mass flow rates of CH_4 and CO_2 in raw biogas, ton d^{-1}, respectively. In this model, minor impurities (hydrogen sulfide, siloxanes, *etc.*) are ignored, assuming that there are only CH_4 and CO_2 produced in the anaerobic digester.

The volume flow rates of CH_4 and CO_2 in biogas are given by

$$V_{bio,met} = V_{bio} \times x_{met} \tag{4}$$

$$V_{bio,cad} = V_{bio} \times x_{cad} \tag{5}$$

$$\sum_g x_g = 1,\ g \in \{met, cad\} \tag{6}$$

where x_{met} and x_{cad} are volume fractions of CH_4 and CO_2 in raw gas mixture, respectively.

In the biogas upgrading unit, the raw biogas is decanted into the high purity CH_4 product and the CO_2 rich stream as shown in the equation below:

$$m_{bio} = m_{CH_4} + m_{CO_2} \tag{7}$$

The mass balance of the digestate recycling unit states that the digestate from anaerobic digester is split into liquid digested slurry and solid digested sludge.

$$m_{dige} = m_{dig,l} + m_{dig,s} \tag{8}$$

3.2. Objective function

The objective function simultaneously considers the energy consumption minimization, the environmental impact minimization, and the biomethane production maximization.

The energy consumption objective is optimized to achieve the minimum energy consumption of the whole system described as follows:

$$EC_{BBS} = \frac{EC_{cotr} + EC_{andi} + EC_{biup} + EC_{redi}}{10^6 \times TS_T \times m_{total}} \tag{9}$$

where EC_{BBS} is the energy consumption of the whole system, MJ kg^{-1} TS feedstock. EC_{cotr}, EC_{andi}, EC_{biup}, and EC_{redi} are the energy consumption of biomass collection and transportation, anaerobic digestion, biogas upgrading, and digestate utilization, kJ d^{-1}, respectively. TS_T is the total solid (TS) content of biofeedstock.

The energy consumption of anaerobic digestion process includes biomass handling EC_{hand}, feedstock heating EC_{heat}, the heat loss EC_{loss} and the power consumption for mechanical agitation EC_{ma}.

$$EC_{andi} = EC_{hand} + EC_{heat} + EC_{loss} + EC_{ma} \tag{10}$$

The selection among the biogas upgrading techniques is modeled using binary variables that ensure only one technology selected. If the corresponding technology is selected, y

Table 1
Energy consumption models for different technologies.

Items		Mathematical models	Ref.
Collection&Transportation		$EC_{cotr} = DHV \times FC_b \times m_{straw} \times \gamma \left[\frac{2}{3} m_{straw}^{0.5} (\pi\rho)^{-0.5} + L\right]$	[22]
	Handling biomass	$EC_{hand} = 83.55 S_L^{-1.08} m_{straw}/\sigma + 38600 m_{straw} + m_{water} W_{pump}/\sigma$	[41,42]
	Heating feedstock	$EC_{heat} = C_p m_{total} (T_D - T_{amb})$	[43]
Anaerobic digestion	Heat loss	$EC_{lose} = 86.4(T_D - T_{amb}) \left[\frac{(\pi \times D \times H_D + S_{top})}{\frac{\delta_D}{\lambda_D} + \frac{\delta_{ins}}{\lambda_{ins}} + \frac{1}{\alpha}} + \frac{\pi \times D^2/4}{\frac{\delta_D}{\lambda_D} + \frac{\delta_{ins}}{\lambda_{ins}}}\right]$	[43]
	Mechanical agitation	$EC_{ma} = 24 W_{ma}/\sigma$	/
	PWS	$EC_{PWS} = 3600 \beta_{CH_4}^r V_{bio} x_{met} (1.075 x_{met}^2 - 1.70625 x_{met} + 0.008325 P + 0.82805)$	[4]
Biogas upgrading	MAS	$EC_{MAS} = 3600 \beta_{CH_4}^r V_{bio} x_{met} (-0.0445 x_{met} - 0.0195\varepsilon + 0.1524)$	[4]
		$+3600\left(V_{bio,cad} - V_{CH_4}\left(1 - \beta_{CH_4}^r\right)\right)(41.375\varepsilon^2 - 21.51\varepsilon + 3.318)$	
	ILS	$EC_{ILS} = 3600 \beta_{CH_4}^r V_{bio} x_{met} (-0.883 x_{met} + 0.012 P^2 + 1.907)$	[4]
	PSA	$EC_{PSA} = \frac{r}{r-1} R (273 + T_{amb}) \frac{V_{com}}{22.4\eta} \left[\left(\left(\frac{P_h}{P_l}\right)^{r-1/r} - 1\right)\right]$	[5,38]
Digestate utilization		$EC_{redi} = 4070.066 \left(m_{total} - \frac{V_{bio}}{22400} (16 x_{met} + 44 x_{cad})\right)$	/

Table 2
Green degree values of some substances.

Substances	Chicken manure[a]	Dairy manure[a]	Pig manure[a]	Agricultural residues[a]	Rice straw[b]	Wheat straw[b]
GD/gd kg^{-1}	−0.1076	−0.0317	−0.0727	0	−0.428	−0.434
Substances	Sugar cane[b]	Corn stalk[b]	Pig manure[b]	Dairy manure[b]	Chicken manure[b]	Sheep manure[b]
GD/gd kg^{-1}	−0.509	−0.525	−0.883	−0.661	−0.788	−0.666
Substances	Digestate[c]	Digestate[d]	CH_4	CO_2	H_20	MEA
GD/gd kg^{-1}	−0.0179	−0.00174	−5.765	−0.2502	0	−0.001

[a] The average GD value of biomass resource discharged into environment.
[b] The average GD value of biomass combustion.
[c] The average GD of the biogas slurry and biogas residues produced in mesophilic reactor.
[d] The average GD value of the digested effluent and sludge in thermophilic reactor.

equals to 1; otherwise y equals to 0. The relationship can be determined as follows:

$$EC_{biup} = \sum_{bg} EC_{bg} \times y_{bg}, \quad bg \in \{PWS, MAS, ILS, PSA\} \tag{11}$$

$$\sum_{bg} y_{bg} = 1, \quad y_{bg} \in [0,1] \tag{12}$$

Energy consumption functions of these operation processes are summarized in Table 1.

The environmental assessment considers the global environmental impact measured with the GD method, which is applied to quantitatively assess and analyze the environmental impact of a complicated system [44,45]. The GD of biomass to biomethane system can be calculated as follows [44].

$$\Delta GD_{BBS} = \frac{\left(\sum_k GD_k^{s,emis} + \sum_k GD_k^{e,out} + \sum_k GD_k^{s,in} + \sum_k GD_k^{e,in}\right)}{(10^3 \times TS_T \times m_{total})} \tag{13}$$

where ΔGD_{BBS} is the GD value of whole system, gd kg^{-1} TS feedstock. $GD_k^{s,emis}$ and $GD_k^{e,out}$ are the output GD value of a material and energy stream from the system, gd d^{-1}, respectively. $GD_k^{s,in}$ and $GD_k^{e,in}$ are the input GD value of stream and energy source into the system, gd d^{-1}, respectively. $\Delta GD_{BBS} > 0$ means that the process is environmentally friendly. Correspondingly, $\Delta GD_{BBS} < 0$ indicates that the process discharges pollution into environment. The GD values of some substances are calculated on the basis of its element property shown in Table 2.

The biomethane production is considered as an objective function to be maximized shown in Eq. (14).

$$V_{BBC,CH_4} = \frac{V_{CH_4}}{(10^3 \times TS_T \times m_{total})} \tag{14}$$

V_{BBC,CH_4} is the biomethane production per kg TS feedstock. V_{CH_4} is the biomethane yield in m^3 d^{-1}, which associates with the digestion and upgrading technologies. The function is given by:

$$V_{CH_4} = \frac{\beta^r_{CH_4} \times V_{bio} \times x_{met}}{\beta^p_{CH_4}} \tag{15}$$

where $\beta^p_{CH_4}$ is the CH_4 purity in product gas. $\beta^r_{CH_4}$ is the CH_4 recovery ratio. V_{bio} is the volume flow rate of biogas in m^3 d^{-1}. We have fitted the experience formulas (Table 3) of biogas production rate (V_r) on the basis of the literature data [43,46].

Some assumptions about the objective functions are presented below.

1. The agricultural residues density (ρ) is a constant.
2. Specific heat of the biofeedstock (C_p) is approximately equal to that of water in low TS content.
3. The distribution of temperature and concentration is homogeneous in the anaerobic digester.
4. The biofeedstock temperature is same with the ambient temperature.

Table 3
Regression equations of V_r in the co-digestion of chicken manure (CM) with rice straw (RS), wheat straw (WS), and corn stalk (CS).

Feed ratio (dry matter)	Regression equation	R^2/%
CM/RS 1:1	$V_r = 1103.88 - 176.94T_D + 4.03T_D^2 + 11.59T_D^3 - 0.39T_D^4 + 0.0075T_D^5$	98.73
CM/RS 2:1	$V_r = -22.5 - 0.16T_D + 0.25T_D^2 - 0.016T_D^3 + 0.00046T_D^4$	98.21
CM/RS 3:1	$V_r = 110.81 - 21.364T_D + 1.63T_D^2 - 0.064T_D^3 + 0.00141T_D^4$	98.26
CM/WS 1:1	$V_r = 1356.56 - 216.47T_D + 14.11T_D^2 - 0.48T_D^3 + 0.0091T_D^4$	95.73
CM/WS 2:1	$V_r = 1082.78 - 172.65T_D + 11.25T_D^2 - 0.38T_D^3 + 0.0072T_D^4$	98.72
CM/WS 3:1	$V_r = 1153.19 - 183.89T_D + 11.98T_D^2 - 0.41T_D^3 + 0.0077T_D^4$	99.51
CM/CS 1:1	$V_r = 261.33 - 42.51T_D + 2.83T_D^2 - 0.099T_D^3 + 0.0019T_D^4$	99.15
CM/CS 2:1	$V_r = 1341.70 - 212.93T_D + 13.81T_D^2 - 0.46T_D^3 + 0.0087T_D^4$	99.11
CM/CS 3:1	$V_r = 1192.02 - 190.47T_D + 12.44T_D^2 - 0.42T_D^3 + 0.008T_D^4$	98.73

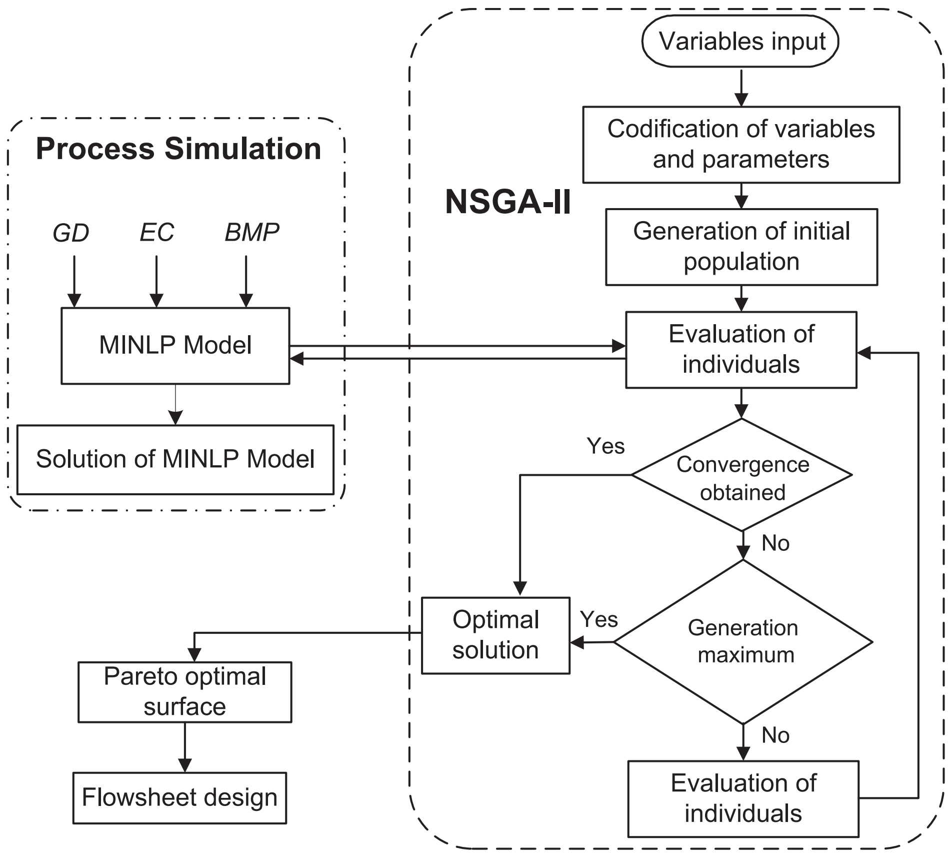

Fig. 2. Framework of the multiobjective optimization model.

5. There exist only CO_2 and CH_4 in the raw biogas product of the anaerobic digestion process.
6. The solvent losses of ILS and MAS processes are negligible.
7. The GD values of biomethane product and corresponding byproducts are assumed to be 0.
8. The GD values of agriculture residues used for anaerobic digestion are assumed to be zero because the straw returning application is benign to the environment.

4. Solution method

The multicriteria optimization model is performed by combining the energy consumption objective (EC) given by Eq. (9), the environmental performance objective given by Eq. (13), and biomethane production objective (BMP) given by Eq. (14) as shown in Eq. (16).

$$\begin{aligned}
&\min(x,y)EC\\
&\max(x,y)GD\\
&\max(x,y)BMP\\
&\text{s.t.}\\
&h(x,y)=0\\
&g(x,y)\le 0\\
&\sum_j y_{i,j}=1\\
&x\in R,\quad y\in[0,1]
\end{aligned} \tag{16}$$

where the equality constraints h (x,y) are mass and energy balances. The inequality constraints g (x,y) denote the operation indexes. x indicates continuous variables representing the operation parameters (temperatures, pressures, recovery rate and performance variables, *etc.*). y denotes the binary

Table 4
Characteristics of feedstock used in digestion [46].

Item	CM	WS	CS	RS
TS/%	28.79	81.08	81.74	77.92
VS/%	65.24	90.29	91.42	94.23
C/N	11.15	91.17	88.13	92.91

Table 5
Characteristics of the digester.

Parameter	Value	Unit
Digester volume	500	m^3
Diameter of the digester (D)	7.5	m
Height of the digester (H_D)	7.5	m
Top area of the digester (S_{top})	46.5	m^2
Thickness of the digester (δ_D)	8	mm
Thickness of the insulating layer (δ_{ins})	120	mm
Thermal conductivity of the digester (λ_D)	49.8	W m^{-1} $°C^{-1}$
Thermal conductivity of the insulating layer (λ_{ins})	0.035	W m^{-1} $°C^{-1}$
Heat transfer coefficient (α)	6.812	W m^{-1} $°C^{-1}$
Total power of agitator (W_{ma})	13	kW

Table 6
Main parameters of biomethane production system.

Parameter	Value	Unit
Diesel consumption of loaded units (FC_b)	0.06	L km^{-1} ton^{-1}
Low heat value of diesel fuel (DHV)	35827.68	kJ L^{-1}
Tortuosity factor (γ)	1.5	/
Transport distance from the collection area to the biogas plant (L)	20	km
Biomass spatial density (ρ)	705.71	ton km^{-2}
Transformation efficiency of heat to electricity (σ)	0.38	/
Length of cereal residues (S_L)	25	mm
Power consumption of pump (W_{pump})	0.1375	kWh ton^{-1}
Specific heat of the feedstock (C_p)	4174	J kg^{-1} °C^{-1}
Ambient temperature (T_{amb}),	25	°C
Volume fraction of CH_4 in raw biogas (x_{met})	0.6	/
CH_4 purity in product gas ($\beta^p_{CH_4}$)	0.94	/
Mechanical efficiency (η)	0.8	/
Universal gas constant (R)	8.314	J mol^{-1} k^{-1}
$r = C_p/C_r$	1.5	/

variables, which represents selection of the technology j in biomethane processing section i.

The mathematical model is a mixed-integer nonlinear problem, which is solved with a fast and elitist genetic algorithm: NSGA-II [47] to obtain a set of Pareto optimal solutions. There is no single "optimal" solution to the multiobjective optimization problem since the objectives compete against one another. The multi-objective optimization framework is presented in Fig. 2.

Table 7
Variables of the multiobjective optimization problem and relevant bounds.

Parameter	Ranges	Units
Digester temperature (T_D)	[25, 60]	°C
Absorption (adsorption) pressure (P)	[8, 10]	bar
CH_4 recovery ratio ($\beta^r_{CH_4}$)	[0.9, 1]	/
Lean liquid loading (ε)	[0.13, 0.28]	/
Integer variables (y)	[0, 1]	/

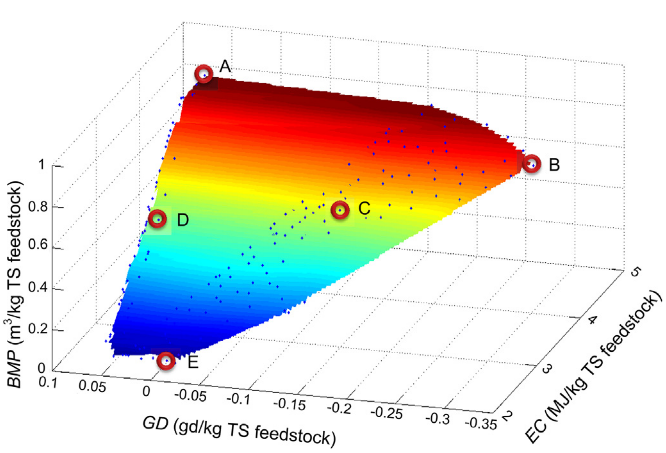

Fig. 3. Pareto optimal solution surface.

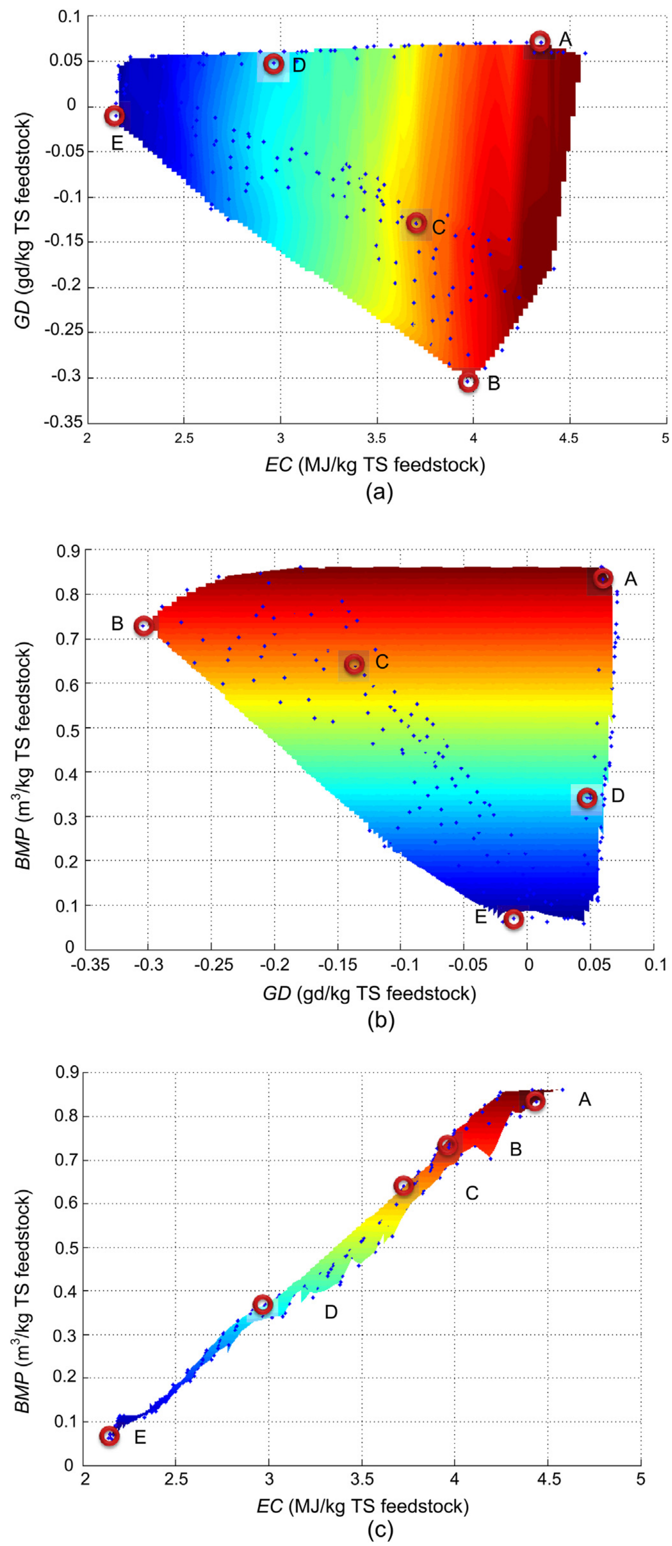

Fig. 4. (a) Projection onto the x-y plane. (b) Projection onto the x-z plane. (c) Projection onto the y-z plane.

5. Results and discussion

The benchmark data of this work is based on the biogas project in Nanjing University of Technology. The feedstock characteristics, digester and main process parameters are listed

Table 8
Decision variables and objective function values of the five Pareto-optimal points.

Pareto optimal points	T_D/°C	$\beta^r_{CH_4}$	Feed ratio (dry matter)	Upgrading	*EC*/MI kg^{-1} TS feedstock	*GD*/gd kg^{-1} TS feedstock	*BMP*/m^3 kg^{-1} TS feedstock
A	51	0.96	CM/RS 2:1	ILS	4.437	0.06	0.833
B	47	0.95	CM/RS 2:1	PWS	3.966	−0.304	0.729
C	44	0.98	CM/RS 3:1	PWS	3.719	−0.161	0.633
D	34	0.97	CM/CS 2:1	ILS	2.964	0.0477	0.344
E	25	0.90	CM/WS 1:1	PWS	2.139	−0.0188	0.0618

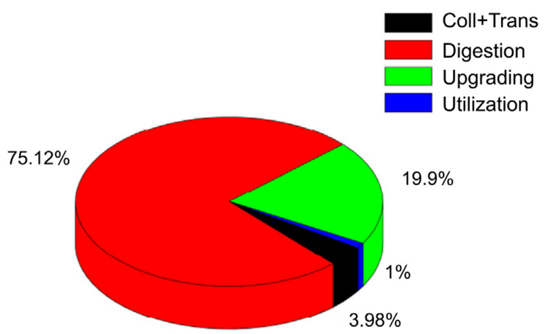

Fig. 5. Energy consumption distribution for point A.

in Tables 4–6, respectively. The manure/straw is co-digested in dry matter ratios of 1:1, 2:1, and 3:1, with the same TS concentration of 8%. The multiobjective optimization model accounts for decision variables, listed in Table 7.

The MINLP problem is solved using coded NSGA-II in MATLAB 8.0 to achieve a set of Pareto-optimal solutions. The Pareto optimal surface is shown in Fig. 3 using linear interpolation of the Pareto non-inferior solutions. The three axes represent the three objective functions. Fig. 4 is the projections of Pareto-optimal surface onto the coordinate planes. The resulting Pareto optimal surface demonstrates the tradeoff among the objectives. Five Pareto optimal solutions are selected for further analysis. Table 8 shows the decision variable and objective function values of the selected Pareto optimal solutions.

As can be seen from Figs. 3 and 4, and Table 8, the energy consumption, GD value, and the biomethane production are increasing in the direction from E to D to A. Those results are attributed to two factors: Firstly, the COD removal efficiency and decomposition efficiency increase with the enhancement of temperature. Subsequently the biogas production rate continually improves, accompanying with a decreasing of the digested slurry discharged into the environment. For example, the digesting temperature and the biogas production of point A have increased by 26 °C and 11.64 times compared with point E, respectively. Meanwhile, the digested slurry and sludge production have reduced by 14.01%. Thus its effect on the environment is suppressed. Secondly, the selected upgrading technique is ILS process. The energy consumption of the ILS process is low, when compared with that of MAS and PSA techniques [4]. Meanwhile, the CO_2 purity in byproduct can be higher than 90%, thus offgas vented to the atmosphere can be negligible. However, the performance improvement of environmental impact and biomethane production can be obtained at the cost of increasing energy consumption. The distribution of energy consumption contribution among the processing subsection for point A is given in Fig. 5, the largest energy consuming contribution from anaerobic digestion that accounts 75.15% of the total energy consumption, followed by 19.90% of energy consumption of biogas upgrading section. Within the anaerobic digestion section, 30.58% of energy consumption is attributed to the feedstock heating. Thus, the energy input of heating feedstock and raw biogas processing increases with the

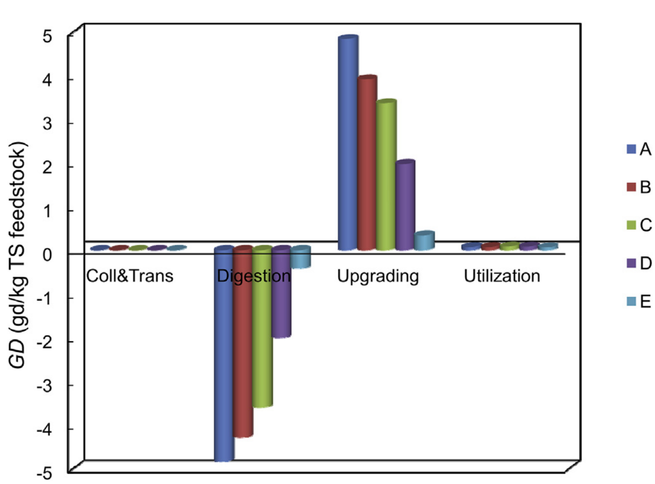

Fig. 6. Distribution of GD contributions among the processing sections for the selected Pareto optimal points.

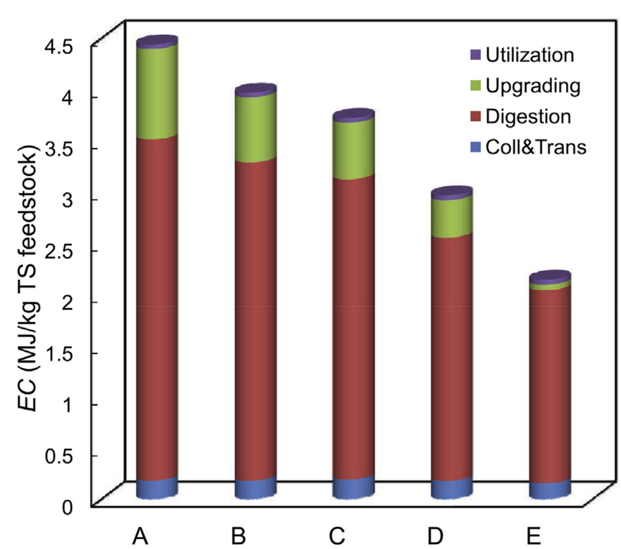

Fig. 7. Energy consumption distribution among the processing sections of the selected Pareto optimal points.

increment of operation temperature. Meanwhile, the energy consumption of the whole system continually increases. For example, the energy consumption of the anaerobic digestion and the biogas upgrading of point A have increased by 40% and 1.42 times compared to point D, respectively. Finally, the energy consumption of the whole system increases by 49.6%. Similarly, the biomethane production and energy consumption are increasing, and GD value is decreasing in the direction from point E to C to B. The major reason is that the PWS process is the selected upgrading technique, in which the CO_2 removed from biogas is discharged to the environment. So, both the biomethane production and energy consumption increase with an increasing of digesting temperature. Meanwhile, the influence on environment continues to strengthen. Therefore, there is no objective improved without hurting another objective.

Fig. 6 presents the distribution to the GD among the processing subsections of the selected Pareto-optimal points. The GD of digestion section (−4.844 gd kg^{-1} TS feedstock for point A) indicates the worst environmental performance. The gases CH_4 and CO_2 produced in the codigestion are the main greenhouse gases, and the high operating temperature (51 °C) needs large energy input. These two factors lead to a serious influence on environment. The GD value of biogas upgrading using ILS at point A is the highest and equal to 4.835 gd kg^{-1} TS feedstock, which indicates that ILS process is friendly to environment. The high GD value arises because of the high purity byproduct (CO_2, >90%), negligible solvent loss and low-energy consumption [4]. Utilization of digested slurry and sludge section is also benign to environment because of the resource utilization of digested slurry and sludge. The contribution from collection transportation and digestate utilization sections becomes negligible because there is only physical effect and no flue gas is vented [48].

Fig. 7 shows the energy consumption distribution among the processing steps of the selected Pareto-optimal points. The energy consumption differs from section to section and from Pareto point to point. For point A, the main energy consuming section is anaerobic digestion (3.333 MJ kg^{-1} TS feedstock) followed by the biogas upgrading (0.883 MJ kg^{-1} TS feedstock), collection and transportation (0.177 MJ kg^{-1} TS feedstock), and digestate utilization (0.044 MJ kg^{-1} TS feedstock). The main energy consuming section is anaerobic digestion (3.333 MJ kg^{-1} TS feedstock for point A) followed by the biogas upgrading (0.883 MJ kg^{-1} TS feedstock for point A). The major reasons for high-energy consumption of digestion are the feedstock heating and thermal loss. If 60% digestate waste heat (point A) is utilized, it can lead to 13.3% decrease in total energy consumption and 5% increase in GD value of the system. So, heat regeneration of digestate should be considered. The biogas upgrading which uses ionic liquid or pressurized water as an absorbent to obtain high purity CH_4 production will produce high power consumption. Even if the power consumption of ILS is higher than that of PWS, the ILS is preferred to PWS from the perspective of environmental impact. This is very in line with previous literature resources [4,48].

6. Conclusions

We developed a multiobjective MINLP model for the optimization of a biomass to biomethane conversion system consisting of collection and transportation, anaerobic digestion, biogas upgrading, and digestate utilization. The model simultaneously takes minimizing energy consumption and maximizing the green degree and the biomethane production as three optimization objectives subject to mass balance constraints, energy balance constraints, environmental impact constraints, and technology selection constraints.

The multicriteria problem is solved with NSGA-II method, and the resulting Pareto-optimal surface reveals the tradeoff among the considered objectives. The optimization results reveal that for ILS technique selected, the GD and biomethane production objectives can be optimized, which leads to higher energy consumption. For PWS technology selected, the biomethane production increases at the expense of deteriorating the energy consumption and environmental impact performance. So, producing biomethane product from PWS process will lead to larger environmental impact than that from ILS process. In addition, The proposed approach may provide a very worthy and useful tool that helps decision makers to select optimum operating condition for improving the performance of biomethane production process.

A possible extension direction of future research is extending the superstructure to the application of biomethane production. Another promising future research is taking the economic performance into consideration in the optimization model.

Conflict of interest

There are no conflicts of interest.

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