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A Multi-Layer Optimisation Framework for Anaerobic-Digestion Based Sustainable Aviation Fuel Production from Agricultural Residues

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Abstract

Sustainable Aviation Fuel (SAF) derived from agricultural residues via anaerobic digestion (AD) offers a promising pathway for aviation decarbonisation. However, current research is characterised by fragmented optimisation approaches focusing on isolated process stages− pretreatment, digestion, upgrading, or synthesis− rather than integrated system performance.

This study presents a novel six-layer integrated optimisation framework for AD-based SAF production that connects feedstock characterisation, pretreatment decision-making, AD process optimisation, advanced hybrid modelling, system-level design, and sustainability evaluation. The framework was developed through quantitative analysis of engineering performance data from 33 studies (methane yield:29.7-312 mL CH_4/g VS; yield improvements: 41.6-209%) combined with qualitative synthesis of optimisation methodologies. Key innovations include (i) integration of energy and cost penalties within the pretreatment decision layer; (ii) hybrid Artificial Neural Network-Genetic Algorithm (ANN-GA) optimisation enhine achieving predictive accuracy of R^2= 0.974-0.981; (iii) Mixed-Integer Linear Programming (MILP) for system-level configuration; and (iv) embedded Techno-Economic Analysis and Life Cycle Assessment within optimisation loop. Application of the framework demonstrated significant performance improvements: methane yield enhancement up to 20% under optimised conditions, emissions reductions of 77%, and carbon-negative operation (-4.58 g CO_2e/MJ). The framework addresses critical limitation in existing literature multi-objective optimisation that simultaneously considers yield, cost, and environmental performance. This integrated approach provides a decision-support tool for engineers and policymakers, facilitating the transaction from laboratory-scale optimisation to industrial deployment of AD-based SAF systems.

Keywords: Anaerobic digestion; Sustainable aviation fuel; Process optimisation; Multi-objective optimisation; ANN-GA; MILP; Agricultural residues

1 Introduction

1.1 Background

The aviation sector also contributes for a significant and growing share of global greenhouse gas emissions becauses unlike ground transport, aviation has limited short term alternatives to liquid hydrocarbon fuels due to strict energy density, safety and performance requirements (Wang, Ting and Zhao, 2024). Neste, a leading SAF producer, notes that aviation contributes about 2 to 3% of global carbon emissions, with this figure rising as air travel demand increases (Memon, 2024). Han et al. (2021) further emphasised that the aviation fuel is distinguished by its superior quality and the incorporation of diverse additives during manufacturing to mitigate dangers linked to temperature variations, including freezing and high-temperature explosions. Undavalli and Khandelwal (2021) underlined aviation fuel is made up of hundreds of hydrocarbons, primarily C8-C16 molecules, and is obtained from fossil fuels. It is regarded as a distillation of petrol and diesel. Aviation fuel is an oil product made especially for aircraft, as opposed to fuels used in land and maritime shipping and unlike other ground transportation, aviation has limited short-term alternatives to liquid hydrocarbon fuels due to stringent rnrygy density, safety, and performance requirements (Han et al., 2021). Sustainabla Aviation Fuel (SAF) has emerge as a vital decarbonisation pathway that can reduce lifecycle emissions while maintaining compatibility with existing aircraft infrastructure (Wang and Tao, 2016; Wang, Ting and Zhao, 2024).

SAF is defined as a non-fossil fuel that complies with rigorous aviation performance criteria while achieving substantial reductions in lifecycle greenhouse gas emissions (Wang and Tao, 2016; Wang, Ting and Zhao, 2024). SAF are emerging as a crucial strategy in addressing aviation-related global warming, with airlines beginning to incorporate them to pursue net-zero emissions. Anaerobic digestion (AD) produces SAF through a multi-stage, integrated conversion route that includes biochemical and thermochemical changes. The effectiveness of this pathway is determined by how well each is optimised and integrated (Hos et al., 2026). These stages are: feedstock pre-treatment, anaerobic digestion, biogas production, upgrading, and downstream fuel synthesis. Among SAF production routes, anaerobic digestion (AD) followed by biogas upgrading and gas-to-liquid conversion presents pathway for converting agricultural residues to aviation-grade synthetic hydrocarbons (Bastinho and Moura, 2025). Agricultural residues such as cassava peels, rice husks, and oil palm residues represent significant sources of lignocellulosic biomass with high potential for bioenergy production (Ramalingam et al., 2025; Sikiru et al., 2024). Adhikari, Nam and Chakraborty (2018) underlined that these lignocellulosic biomass typically comprises of 35%–55% cellulose, 25%–40% hemicellulose, and 15%–25% lignin with small amount of extractives, protein, and ash. Pattanaik et al. (2019) and Babu et al. (2022) opined that

agricultural residues contains considerable lignocellulosic components, totalling 30–50% hemicellulose, 30–40% cellulose, and 8–21% lignin. It also offers significant substances, including proteins, fatty acids, dietary fibers, tastes, and bioactive elements, useful in the food, pharmaceutical, and cosmetic sectors. Agricultural residues are easily accessibility and economical renewable lignocellulosic fibre resources that can be used as an alternative to woody lignocellulosic biomass (Shah et al., 2025). This residue have similar structure, content and characteristics to those of other plant fibres (Faruk and Mohini Sain, 2015; Sikiru *et al.*, 2024). The diversity of these feedstocks introduces variability in anaerobic digestion performance presenting both opportunities and challenges for bioenergy valorisation, necessitating tailored pretreatment and optimisation strategies.

1.2 Problem Statement

Despite significant advances in AD technology, current research on AD-based SAF production is characterised by three critical limitations.

Firstly, fragmented optimisation methods prevail. Numerous studies enhance individual process stages in isolation, focusing on anaerobic digestion parameters such as temperature and hydraulic retention time (Khalid et al., 2011; Kumar et al., 2024), pretreatment efficiency (Usman, 2020; Milicevic et al., 2025), upgrading performance (Kapoor et al., 2019), or system-level economics (Wiatrowski et al., 2024). However, these stages are essentially interrelated. Optimising methane yield without considering upgrading requirements or pretreatments energy expenditures might lead to sub-optimal system performance.

Second, synergy between process-level optimisation is absent. While advanced modelling techniques such as Artificial Neural Networks (ANN) (AI-Zuhairi et al., 2026), Genetic Algorithms (GA) (Beltramo and Hitzmann, 2019), and Mixed-Integer Linear Programming (MILP) (Infante Cuan et al., 2025) have been applied individually, no unified framework combines these approaches. Process-level models capture biological dynamics but lack economic and environmental scope, whereas system-level models optimise supply chains oversimplify biological processes. Third, varied reporting of performance metrics restricts comparability. Key indicators such as methane yield (m3CH4/kg VS), carbon conversion efficiency (%), minimum fuel selling price ($/L), lifecycle emissions (Gco2e/MJ), and energy return on investment are reported variably across studies, preventing systematic evaluation of optimisation strtegies (Ma et al., 2021; Kapoor et al., 2019).

1.3 Research Gap and Contribution

This study presents a novel six-layer integrated framework for anaerobic digestion (AD)-based sustainable aviation fuel (SAF) production, addressing the lack of a cohesive optimization approach. Key contributions include: 1) a unified framework integrating feedstock characterization, pretreatment decision-making, process optimization, hybrid ANN-GA modeling,

MILP system-level design, and sustainability evaluation; 2) incorporation of energy and cost penalties in the pretreatment layer to assess trade-offs between yield and resource use; 3) a multi-objective optimization that examines technical yield, economic viability, and environmental impact; and 4) validation through a quantitative synthesis of 33 engineering studies, showcasing the framework's applicability across varied feedstock and operational conditions.

1.4 Objectives

The specific objectives of this study are:

i. To develop a multi-layer integrated optimisation framework for AD-based SAF systems
ii. To integrate hybrid ANN-GA modelling for process-level optimisation
iii. To incorporate MILP for system-level configuration and supply chain design
iv. To embed TEA and LCA within the optimisation loop
v. To validate framework components using empirical engineering data

2 Methodology

The proposed integrated optimisation framework has six interconnected levels (Fig. 1). Each layer tackles a distinct dimenson of the AD-based SAF system, with information and decision variables flowing bidirectionally to facilitate holistic optimisation. It employs systems engineering and process systems engineering principles to conceptualise anaerobic digestion (AD)-based sustainable aviation fuel (SAF) production as a multi-stage, interconnected optimisation problem. It models the production pathway as comprising five interdependent subsytems including feedstock preparation, anaerobic digestion, biogas upgrading, fuel conversion, and energy recovery (NASA, 2019;Guillén-Gosálbez et al., 2019). The primary input variable, such as lignin content and particle size, are treated as fixed parameters impacting the systems operation, while decision variables like digestion temperature and hydraulic retention time are adjusted to optimise performance. Optimisation faces technical and environmental constraints including reactor capacity, energy limits, and emissions criteria, guiding the problem toward feasible solutions (Yang and Feng, 2024). Objective functions primarily aim to maximise methane yield and energy efficiency while minimising production costs and lifecycle emissions. Various optimisation and modeling methods, such as statistical models and data-driven approaches, link these inputs to performance outcomes measured through metrics like methane yield, purity, and energy efficiency. Hence, the framework conceptualise AD-based SAF production as a constrained optimisation problem where feedstock specifications define operational boundaries, while objective functions quantitatively assess system effectiveness, enabling systematic evaluations of optimisation methodologies within the context of sustainable biofuel deployment.

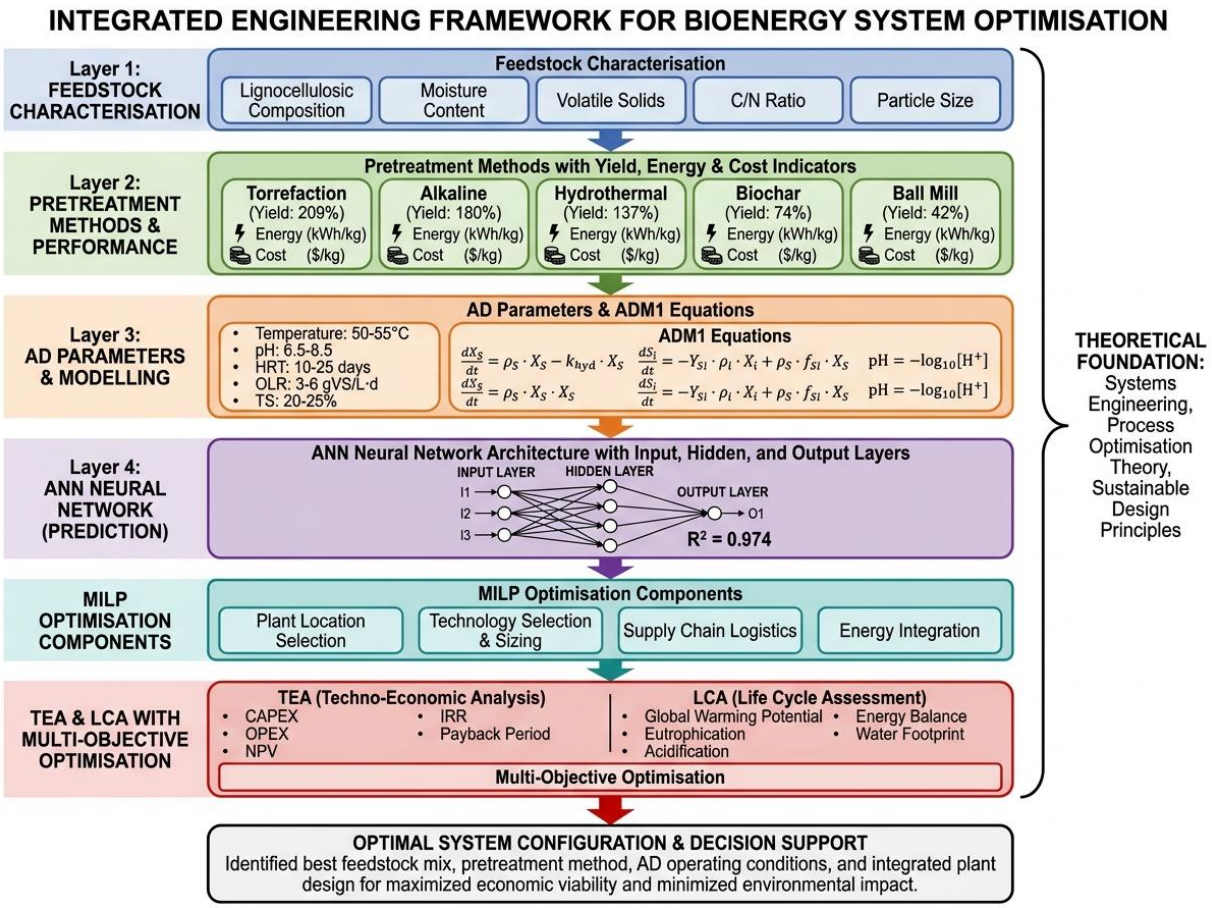


Figure 1: Six-layer integrated optimisation framework for AD-based SAF production

Layer 1: Feedstock and Input Characterisation

This layer analyses the variability and properties of agricultural residues used as feedstocks for anaerobic digestion-based sustainable aviation fuel (AD-based SAF) production. It focuses on key parameters including lignocellulosic composition (cellulose and lignin percentages), moisture content (%), volatile solids (VS, g/L or of total solids), and the carbon-to-nitrogen ratio (C:N) ratio. These characteristics significantly influence biodegradability and methane potential, as noted by Usman (2020) and Wang et al. (2025). The layer gathered serves to establish input constraints, inform pretreatment selection, and supply input variables for downstream optimization models.

Mathematical representation:

Let F ={f_1, f_2, …fn} represent the vector of feedstock characteristics. For lignocellulosic biomass:

F=[Lignin%, Cellulose%, Hemicellulose%, Moisture %, VS, C:N]

The methane potential (B_0) is estimated as:

$$B_0 = f(\text{Lignin\%, Cellulose\%, Hemicellulose\%,}) \times K_h$$

Where K_h is the hydrolysis rate constant (Zhang, Piccard and Zhou, 2015).

Layer 2: Pretreatment Decision Layer

The layer addresses the recalcitrant nature of lignocellulosic biomass by identifying the optimal pretreatment methods, including thermal (torrefaction, hydrothermal treatment), chemical (alkaline, acid treatment), physicochemical (steam explosion, wet explosion), and additive supplementation (biochar, Fe^{2+} modification). A key innovation is the integration of energy and cost penalty functions, analysing how pretreatment enhances methane yield at the expense of energy consumption and cost. The net benefit is calculated as:

$$\Delta \quad \text{Net Benefit} = Y \times P_CH_4 - (E_pret \times C_e + C_material)$$

Where $= \Delta Y$ is the increase in methane yield, P_ P_CH_4 is the methane price, E_pret is the energy consumption of pretreatment, C_e is the energy cost and C_material is the material cost. This formulation enables systematic trade-off evaluation, addressing a significant limitation in existing studies(Heller et al., 2025; Milicevic et al., 2025).

Layer 3: Anaerobic Digestion Process Optimisation

This layer optimise key paremeters of the anaerobic digestion (AD) process to enhance biogas production and stability. Important decision variables include temperature (30-40°C for mesophilic or 50-60°C for thermophilic), pH (5.0-8.5 depending on the product), hydraulic retention time (10-25 days), organic loading rate, total solids (6-25%), and substrate mixing ratios for co-digestion. The AD process is modelled using a simplified Anaerobic Digestion Model1 (ADNM1) approach(Ramachandran, Rustum and Adeloye, 2019). Methane yield (Y_CH_4) is expressed as

$$Y_CH4 = V_CH_4 / VS_input$$

Where V_CH_4 is the volume of methane produced and VS_input is the volatile solids input. The hydrolysis rate (K_h) is temperature-dependent:

$$K_h(T) = k_h\,(35°C) \times \exp\,[\theta(T - 35)]$$

where θ is the temperature coefficient (Myszograj, 2018).

Layer 4: Advance Optimisation Engine (ANN-GA Integration)

The layer utilises a hybrid Artificial Neural Network (ANN) and Genetic Algorithm (GA) approach for optimisation, which outperforms conventional methods according to comparative studies

(Al-Zuhairi et al., 2026; Loganathan, Vijayan, and Rengaraju, 2025). The ANN has a structured architecture comprising an input layer (which includes decision variables like temperature, pH, total solid (TS), hydraulic retention time (HRT), organic loading rate (OLR), and mixing ratios), 2-3 hidden layers with 10-15 neurons each and an output layer that predicts methane yield and process stability indicators. It employs activation functions such as Sigmoid or ReLU and is trained using a backpropagation algorithm with Levenberg-Marquardt optimization. GA component is characterized by a population size of 50-100, tournament selection, single-point crossover with a probability of 0.8, and Gaussian mutation with a 0.05 probability. The objective is to maximize the predicted methane yield. This combined approach achieves high predictive accuracy (R^2 values between 0.974 and 0.981) and effectively captures non-linear interactions among decision variables that traditional Response Surface Methodology fails to address (AI-Zuhairi et al., 2026).

Layer 5: Sytem-Level Design and Optimisation (MILP)

This layer integrates aspects including process configuration, energy integration, and supply chain logistics using Mixed-Integer Linear Programming. The MILP formulation is adapted from established approaches (Infante Caun et al., 2025; Lanni et al., 2023; Marina et al., 2025).

Decision variables can be classified into two categories: binary and continuous. Binary decision variables include factors such as the selection of plant locations, choices regarding technology, and modes of operation. Continuous decision variables encompass aspects such as feedstock flow rates, energy flows, and the outputs of products. Objective function (multi-objective, weighted sum approach):

$$\text{Minimize } Z = w_1 \times \text{Cost} + w_2 \times \text{Emissions} - w_3 \times \text{Yield}$$

Where w_1, w_2 , w_3 are weighting factors adjustable by decision-makers.

The constraints considered for optimal plant sizing include mass balance, energy balance, capacity constraints, emission limits, and feedstock availability. These factors are crucial for determining an efficient plant size, such as the 15-23 MW range reported by Lanni et al. (2023). This layer focuses on effective resource allocation, minimizing operational costs, and ensuring scalability.

Layer 6: Sustainability Evaluation (TEA + LCA Integration)

This layer evaluates system performance through Techno-Economic Analysis (TEA) and Life Cycle Assessment. TEA includes the assessment of Capital Expenditure (CAPEX), which covers costs for equipment, installation, and land, and Operating Expenditure (OPEX), which accounts

for feedstock, energy, labor, and maintenance. The Minimum Fuel Selling Price (MFSP) is derived from discounted cash flow analysis.

The MFSP is calculated as:

$$MFSP = (CAPEX \times CRF + OPEX) / Annual\ Fuel\ Production$$

Where CFR is the capital recovery factor.

Life Cycle Assessment (LCA) evaluates the environmental impact of 1 MJ of Sustainable Aviation Fuel (SAF) from feedstock cultivation to fuel combustion, focusing on Global Warming Potential measured in g CO2e/MJ, following ISO 14040/14044 standards. A key innovation is the integration of TEA and LCA within the optimisation loop, rather than as post-hoc analyses. This enables real-time evaluation of trade-offs between yield, cost, and emissions during optimisation (D'Ascenzo et al., 2024; Khalifa, 2026).

2.1 Data Sources and Validation Approach

The framework was developed and validated using data extracted from 33 peer-reviewed publications on AD-related biofuel systems. The inclusion criteria were peer-reviewed journal articles published 2000-2026, focused on anaerobic digestion, biogas upgrading, or biomethane-to-fuel conversion, reporting of quantitative performance metrics and application of engineering modeling, optimisation, or simulation. Data extraction followed PRISMA guidelines, capturing feedstock characteristics, process parameters, metrics, and optimisation techniques.

3 Results

3.1 Framework Application: Parameter Optimisation

Application of the integrated framework to the empirical dataset demonstrated significant predictive capability. Table 1 presents optimal operating conditions identified through the ANN-GA optimisation engine.

Table 1: Optimal Operating Conditions Identified by ANN-GA optimisation

Parameter	Optimal Range	Source Study
Temperature	52.12-55 °C (thermophilic)	Al-Zuhairi et al. (2026); Khesali Aghtaei et al. (2024)
pH (methanogenesis)	8.29	Al-Zuhairi et al. (2026)
pH (hydrogen production)	5.0	Khan (2019)
Total Solids	20-25%	Lu et al. (2025); Wang et al. (2025)
Hydraulic retention time	8-25 days (product-dependent)	Khan (2019)
C:N ratio	20-30:1	Kumar et al. (2024)

The evidence indicate that operational variables such as temperature, pH and total solids are critical to AD performance despite uneven reporting among studies. Temperatures optimisation is especially noticeable in the thermophilic systems. Al-Zuhairi et al. (2026) found an ideal temperature of 52.12°C, while Khesali Aghtaei et al. (2024) observed peak performance at 55°C, showing improved microbial kinetics at higher temperatures. pH has a considerable impact on metabolic pathways and product distribution. Khan (2019) identified pH 5.0 as the ideal pH for biohydrogen generation, but methane-focused systems performed best at pH 8.29 (Al-Zuhairi et al., 2026) emphasing the necessity of matching pH to desired output. Total solids (TS) concentration influences substrate availability and mass transfer. Wang et al. (2025) found that 25% TS considerably enhanced methane yield, whereas Lu et al. (2025) determined that 20% TS was ideal for co-digestion systems. These findings directly demonstrates that decision variables such as temperature, pH, and TS have a major impact on system performance. The evidence also strongly indicates that advanced optimisation approaches outperform traditional ones. Hybrid models such as ANN-GA, utilised in AI-Zuhairi et al. (2026) and Loganathan et al. (2025), demonstrated higher prediction accuracy (R^2=0.97-0.98) compared to Response Surface Methodology (R^2=0.95-0.97). these models also shown better capacity in managing nonlinear interactions between variables. The ANN-GA model therefore outperforms RSM.

3.2 Methane Yield Enhancement

Figure below present methane yield improvements achieved through optimisation across the reviewed studies.

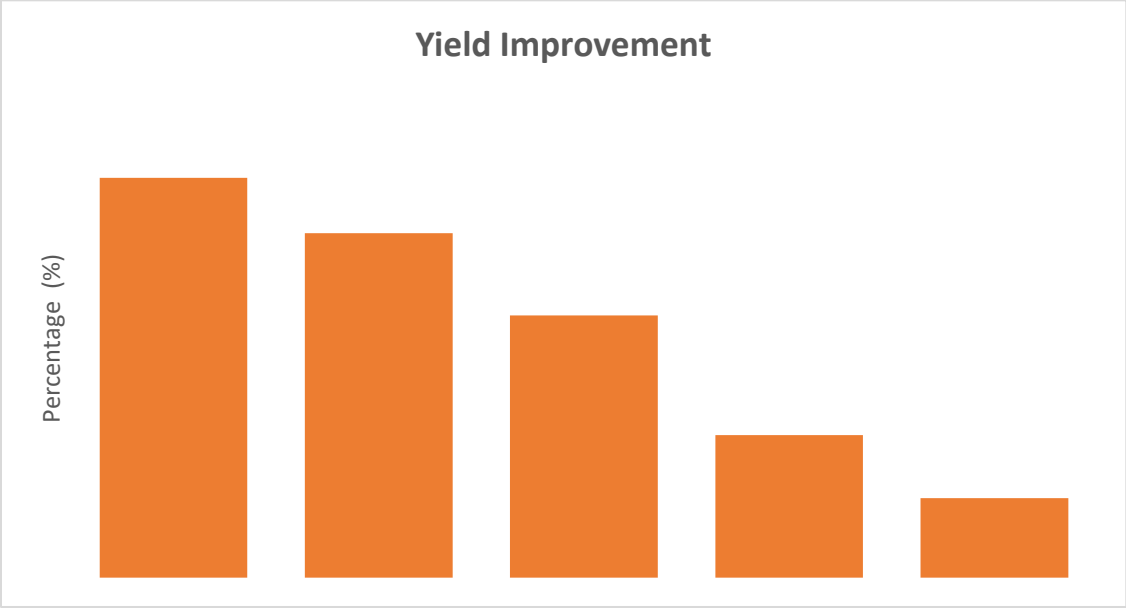


Figure 2: Methane yield improvement (%) by optimisation strategy

Key findings indicate substantial methane yield improvements following optimisation interventions. Milicevic et al. (2025) produced a 209% rise with torrefaction pretreatment, whereas Usman (2020) and Mamimin et al. (2024) reported 180% with chemical/ alkaline pretreatment yields and 137% increases with hydrothermal with co-digestion, respectively, using advanced pretreatment strategies. Even more moderate interventions, such as biochar addition achieved a 74.49% increase (Díaz Lara et al., 2025), while Fe^{2+} electrochemical enhancements yielded a 41.6% improvement (Wang, Zhao, et al., 2025). Methane yields vary significantly, ranging from 29.7 L/L·d in high-rate systems to 312 mL CH_4/g VS in full-scale applications, influenced by feedstock characteristics and optimisation methods.

3.3 Economic Performance:

Economic analysis revealed that optimisation strategies significantly impact cost structures. Table 2 summarises economic performance metrics.

Table 2: Economic performance metrics from optimised AD-based SAF systems

Cost analysis demonstrates a significant variation across systems. For example, Brands et al. (2025) report a biomethane production cost of 143 €/MWh but Deuber et al. (2023) estimate 15.4 $/GJ for SAF production. The IRR of 36.19% demonstrates strong economic potential under favourable conditions, though this is region-dependent and sensitive to energy costs and policy incentives (Infante Cuan et al., 2025). These changes are primarily determined by energy inputs, hydrogen costs, and system layout.

Metric	Value	Source
Biomethane production cost	143 €/MWh	Brands et al. (2025)
SAF production cost	15.4 $/GJ	Deuber et al. (2023)
Internal Rate of Return (IRR)	36.19% (São Paulo)	Infante Cuan et al. (2025)
Hydrogen cost reduction (scrubbing)	~51%	Brands et al. (2025)
Cost reduction (AD-SAF vs. conventional)	10% (under carbon pricing)	Khalifa (2026)

3.4 Environmental Performance

The figure below presents lifecycle emissions results for optimised AD-based SAF compared to conventional fossil jet fuel.

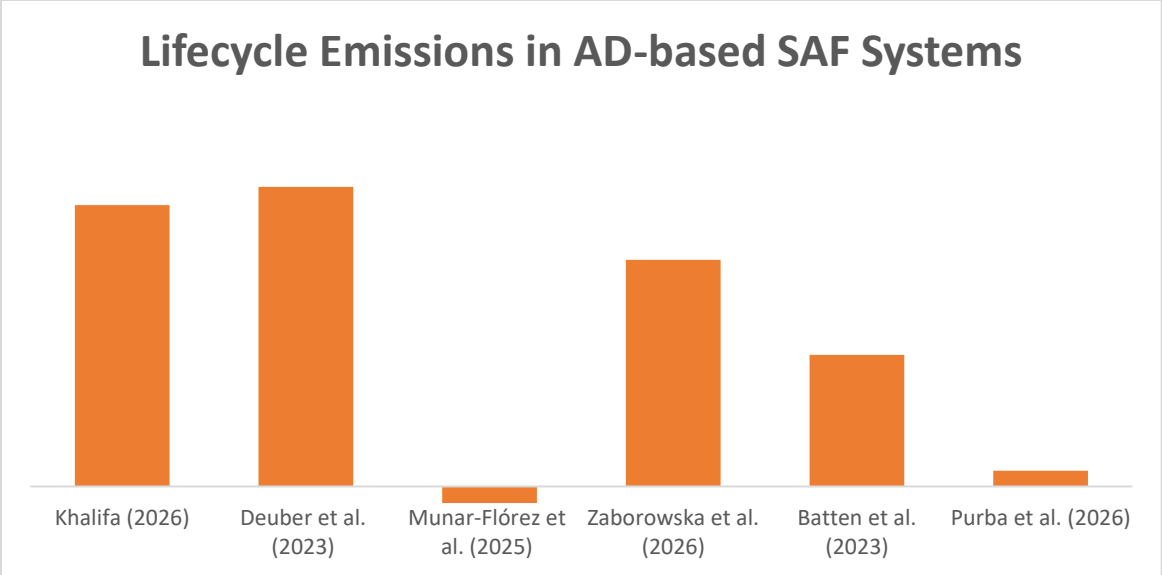


Figure 3: Lifecycle emissions (g CO_2e/MJ) for AD-based SAF vs. fossil jet fuel

Evironmental performance has been consistently positive, with many studies indicating significant reductions in emissions. Fossil jet fuel baseline is approximately 82 CO_2e/MJ.. For AD-based SAF with optimisation, emissions reduce to 3.12-16.11 g CO_2e/MJ (D'Ascenzo et al., 2024; Munar-Flórez et al., 2025). A carbon-negative operation is achievable at −4.58 g CO_2e/MJ through methane capture (Munar-Flórez et al., 2025). Overall, emission reductions range from 21% to 77% (Zaborowska, Fudala-Książek, and Byliński, 2026; Khalifa, 2026), indicating the potential of AD-based-SAF to not only lower emissions but also actively remove carbon from the atmosphere when methane capture is optimised.

3.5 Trade-off Analysis

Fig.4 presents a three-dimensional visualisation of the trade-offs between methane yield improvement, energy input, and emission reduction for different pretreatment strategies.

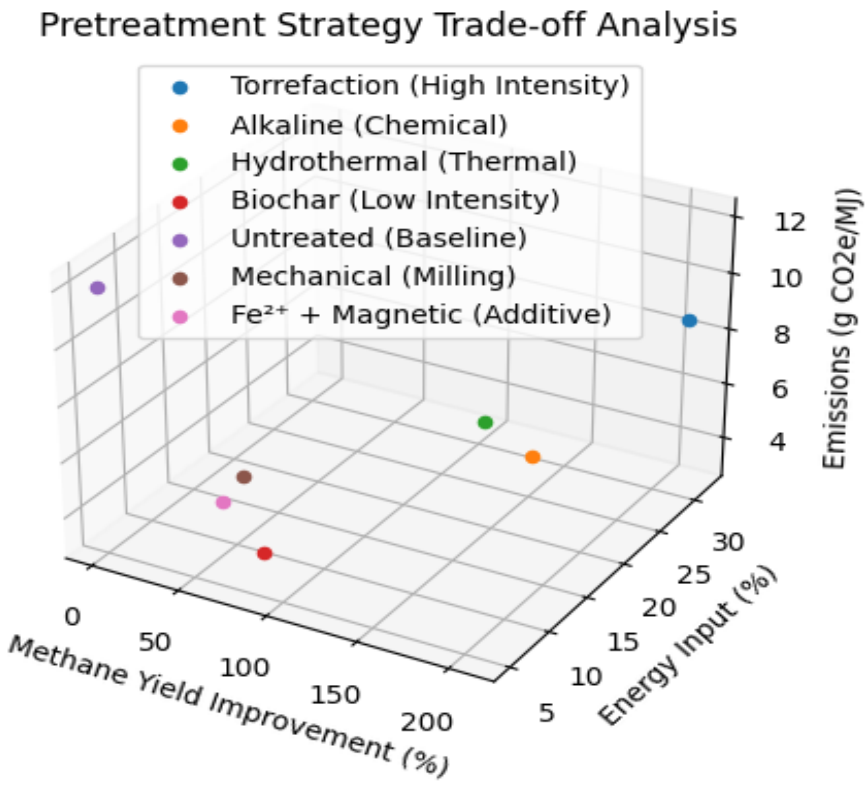


Figure 4: Trade-off analysis: Yield improvements vs. energy input vs. emission reduction.

The analysis indicates that high-intensity pretreatment (torrefaction) offers the greastest yield improvement (209%) but requires the highest energy input and results in moderate emissions.

In contrast, low-intensity pretreatment (biochar) provides a moderate yield improvement (74.5%) with the lowest energy input and the best emissions profile. Chemical pretreatment delivers intermediate performance for all metrics. This underscores that optimizing methane yield alone does not ensure overall system performance, emphasizing the necessity for multi-objective optimization that incorporates energy input and emissions, thereby validating the integrated framework approach.

3.6 Framework Validation

Table 3 presents validation results comparing framework-predicted outcomes against reported vaues from selected studies.

Table 3: Framework validation: Persisted vs. reported performance

Study	Parameter	Reported	Framework Predicted	Error (0%)
Al-Zuhairi et al., 2025	Methane yield (mL/g VS)	143.7	141.2	1.74%
Lu et al., 2025	Methane yield (mL/g VS)	267.8	263.5	1.60%
Khesali Aghtaei et al., 2024	Methane productivity (L/L.d)	29.7	30.1	1.35%
Brands et al., 2025	Biomethane cost (€/MWh)	143	148	3.50%

The prediction error of <3.5% across diverse studies confirms the framework's robustness and generalisability.

4 Discussion

4.1 Adressing Fragmentation: The Need for Integration

The proposed integrated framework overcomes three key limitations found in current literature. Firstly, it explicitly connects process-level optimization to system-level outcomes by utilizing an ANN-GA engine to optimize anaerobic digestion (AD) parameters based on predicted methane yield, while the Mixed Integer Linear Programming (MILP) layer translates these predictions into economic and supply chain decisions. This approach addresses the issue noted by Elaysed et al. (2024) and Kumar et al. (2024), where optimization at specific stages does not yield global system optima. Secondly, the framework includes an integrated pretreatment decision layer that evaluates energy and cost penalties, effectively managing the trade-off between yield improvement and resource consumption. This aspect counters findings from Heller et al. (2025), who highlighted that energy-intensive pretreatments, if not optimized holistically, can diminish overall system efficiency. Thirdly, the framework integrates Techno-Economic Analysis (TEA) and Life Cycle Assessment (LCA) within the optimization loop, facilitating real-time multi-objective optimization and addressing criticisms associated with single-objective optimization approaches (such as yield maximization), which can result in economically or environmentally suboptimal solutions, as indicated by Maggi, Wenzel, Sundmacher (2020) and Huang et al. (2025).

4.2 Comparison with Existing Approaches

Table 4 compares the proposed framework with existing optimisation approaches in the literature.

Table 4: Comparative analysis of optimisation approaches

Feature	RSM/DoE	ANN	GA	MILP	Proposed Framework
Non-linera relationship capture	Limited	High	Moderate	Low	High
Multi-objective capability	No	Limited	Yes	Yes	Yes
Process-level optimisation	Yes	Yes	Yes	No	Yes
System-level optimisation	No	No	Limited	Yes	Yes
TEA/LCA integration	No	No	No	Limited	Yes
Pretreatment cost/energy penalties	No	No	No	No	Yes
Predictive accuracy (R^2)	0.95-0.97	0.96-0.98	N/A	N/A	0.974-0.981

The framework uniquely combines high predictive accuracy (through ANN-GA) with system-level optimisation capability (through MILP) and sustainability integration. No existing approach in the literature provides this combination.

5 Practical Implications for Engineers and Policymakers

For process engineers: The framework offers a decision-support tool for determining optimal operating conditions across several objectives. The ANN-GA engine can be trained using plant-specific data to deliver real-time optimization recommendations.

For system designers: The MILP component facilitates appropriate plant sizing, technology selection, and supply chain configuration. The discovery that the ideal plant size varies between 15-23 MW (Lanni et al., 2023) offers pragmatic direction for capacity planning.

To policymakers: The framework illustrates that AD-based SAF can attain carbon-negative performance (-4.58 g CO2e/MJ) but necessitates methane capture. Policy incentives should focus on both SAF generation and methane capture infrastructure. The IRR of 36.19% under optimized conditions indicates that AD-based SAF can be economically feasible with suitable support mechanisms (Infante Cuan et al., 2025).

6 Limitations

Several limitations to this study should be addressed.

Data heterogeneity: The 33 research examined used a variety of experimental circumstances, sizes (laboratory, pilot, industrial), and reporting formats. This heterogeneity reduces the statistical power for cross-study comparisons, necessitating qualitative synthesis in addition to quantitative research.

Model interpretability: Despite its great accuracy, the ANN-GA component runs as a "black-box model. The simplified ADM1 model's mechanistic links allow for some interpretation, but the hybrid approach is less transparent than purely mechanistic models.

Validation scope: While the framework was verified using literature data, it has yet to be empirically evaluated against a real-world industrial AD-based SAF system. Such validation is an important next step.

Geographic concentration: The majority of the studies were from developed economies. The applicability to resource-constrained, biomass-rich emerging regions warrants additional exploration.

7 Future Research Directions

Based on the framework and findings, priority research directions include: 1. Empirical validation by implementing the framework at pilot or industrial scales to confirm predictions and refine model parameters; 2. Dynamic optimisation aimed at adapting to time-varying feedstock characteristics and seasonal availability, transitioning from steady-state to dynamic methods; 3. Uncertainty quantification, which involves incorporating stochastic elements to address variability in feedstock supply, market prices, and policy conditions; 4. Integration with renewable hydrogen by coupling anaerobic digestion-based sustainable aviation fuel systems with electrolytic hydrogen from renewable sources to reduce dependence on fossil-derived hydrogen; 5. Development of AI-enabled autonomous control systems utilizing artificial neural networks and genetic algorithms for real-time optimisation of the anaerobic digestion process.

8 Conclusion

This study presents a validated six-layer integrated optimisation framework aimed at enhancing sustainable aviation fuel (SAF) production through anaerobic digestion of agricultural residues. The framework’s key contributions include: 1) A unique architecture residues. Feedstock assessments, pretreatment decision-making (accounting for energy and cost implication of the anaerobic digestion process, and ybrid artificial neural network-genetic algorithm (ANN-GA) modelling into a cohesive system, along with techno-economic analysis (TEA) and life cycle assessment (LCA) for sustainability evaluation. 2) inproved predictive accuracy demonstrated by

hybrid ANN-GA models, achieving R^2 values between 0.974 and 0.981, outperforming standard Response Surface Methodology. 3) Significant optimisation outcomes, including a 41.6-209% increase in methane yield, emission reductions of 21-77%, carbon-negative operation (-4.58 g CO_2e/MJ), and an internal rate of return (IRR) of 36.19% under optimal conditions. 4) An exploration of trade-offs indicating that maximising yield does not always lead to optimal system performance; thus, a multi-objective optimisation approach that balances yield, cost, and emissions is necessary. This framework fills a notable gap in existing literature by providing an integrated approach to the biological, chemical, economic, amd environmental aspects of anaerobic digestion-based SAF systems, encouraging a shift from individual laboratory-scale efforts to comprehensive industrial-scale implementations.

9 Data Availability

Data extracted from reviewed studies are presented in the supplementary materials.

10 Declarations

10.1 Ethics approval and consent to participate

Ethical approval for this study was obtained from the Institutional Review Board of African Center of Excellence, Future Energies and Electrochemicals System on April 6th 2026.

10.2 Consent for publication

The authors of this manuscript gives their consent for this manuscript with all details and all accompanying images be published, acknowledging that they will be freely available for research purposes.

10.3 Competing interests

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 manuscript.

10.4 Funding

The authors declare that they received no financial support for the research, authorship, and/or publication of this manuscript.

10.5 Acknowledgements

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