Applied Chemical Engineering (2026) Volume 9 Issue 1 ISSN: 2578-2010 (O)
doi: 10.59429/ace.v9i1.5837

ORIGINAL RESEARCH ARTICLE

AI-Driven Optimization of Bio-Energy Systems: Models for Resource Assessment and Emission Reduction

Sajal Suhane[1], Rushali Rajaram Katkar[2], Smita Suhane[3,9], S. Sugumaran[4], Santosh Bhauso Takale[5], Surekha Dehu Khetree[6], Shyamsing Thakur[7], Shital Yashwant Waware[8,9], Anant Sidhappa Kurhade[8,9] *

1 Erik Jonsson School of Engineering and Computer Science, The University of Texas at Dallas, Richardson, Texas, USA-75080.

2 Department of Computer Engineering, Army Institute of Technology, Dighi Hills, Pune-411015, Maharashtra, India.

3 Department of First Year Engineering (Engineering Chemistry), Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune - 411018, Maharashtra, India.

4 Department of Electronics and Communication Engineering, Vishnu Institute of Technology, Bhimavaram - 534202, Andhra Pradesh, India.

5 MCA Department (Commerce and Management), Vishwakarma University, Laxminagar, Kondhwa (Bk.), Pune – 411048, Maharashtra, India.

6 Department of Mechanical Engineering, Bharati Vidyapeeth College of Engineering, Navi Mumbai – 400614, Maharashtra, India.

7 Department of Mechanical Engineering, D. Y. Patil College of Engineering, Akurdi – 411044, Pune, Maharashtra, India, Affiliated to Savitribai Phule Pune University, Maharashtra, India.

8 Department of Mechanical Engineering, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri - 411018, Pune, Maharashtra, India.

9 Dnyaan Prasad Global University (DPGU), School of Technology and Research - Dr. D. Y. Patil Unitech Society, Sant Tukaram Nagar, Pimpri - 411018, Pune, Maharashtra, India.

***Corresponding author:** Anant Sidhappa Kurhade; a.kurhade@gmail.com

ARTICLE INFO

Received: 22 November 2025
Accepted: 16 December 2025
Available online: 29 December 2025

ABSTRACT

The increasing complexity of bio-energy systems is a reason for the need of advanced analytical methods to enhance resource utilization, process stability and environmental performance. AI methods are popular in this domain, but many papers neglect concerns around data quality, interpretability, scalability and the low generalization potential of models toward plants and feedstocks different from those they were trained on. This paper intends to offer a systematic review on AI techniques available for biomass resource assessment, conversion-process optimization, and supply-chain planning and emission management. The review is structured adopting a rigorous review approach focusing on model, data set, optimization framework and hybrid method developed in the scope of bio-energy value chain. Highlights – The key findings are that AI improves the prediction of biomass availability and biogas/syngas yields, of feedstock properties and emission behavior; surrogate and hybrid models result in expedited simulation time and facilitate real-time decision making. The review also highlights an emerging trend with digital twins, remote sensing with application of machine learning, and federated learning in multi-plant optimization. These findings also have important implications for researchers, engineers and policy-makers who aim to develop robust low

emissions bio-energy systems that are economically feasible.

Keywords: Artificial intelligence in bio-energy; biomass resource assessment; machine-learning optimization; bio-energy supply chains; emission prediction and mitigation; sustainable energy systems.

1. Introduction

Bio-energy is still a significant renewable resource because it can be used to convert agricultural residues, and organic feed into useful products like biogas, bioethanol, biodiesel, and bioheat. The performance of these systems is highly sensitive to accurate resource assessment, cost-effective conversion and managed emission. A number of these tasks also include non-linear behavior, unknown characteristics of the feedstock and dynamic operating conditions which can limit conventional modelling methods.

AI approaches offer system tools to capture and learn patterns from a variety of data types as well as means to manage uncertainty and aid predictive decision making along the bio-energy chain. Up-to-date AI models are broadly applied for predicting the biomass potential, predicting biogas yield, optimizing operational parameters and evaluating environmental effects. In this paper, we introduce major AI applications in the areas and summarize the research trends. Bio-energy processes that convert biomass to various forms of energy are at the heart of global efforts to make a transition from conventional (fossil-based) to sustainable and renewable energy sources [1]. With the AI techniques, these systems could be developed to take new opportunities of reducing product costs and also supporting a greener environment [2]. And now AI tools are used across the entire bio-energy lifecycle, from prediction of biomass properties to optimization of conversion processes, supply chain management, and assessment of environmental performance [3] [4]. This paper reviews cutting-edge AI-based optimization models, which target resource assessment and emission reduction in bio-energy systems [3] [4]. It also reviews how machine learning, which is capable of capturing complex nonlinear phenomena characterizing such systems, has led to enhanced energy harvesting and addressed concerns associated with energy security and environmental sustainability [5].

AI has been widely adopted over the past 10 years, particularly for predictive and optimization applications. Researchers have emphasized energy-use analysis, process value-chain evaluation, and risk management [6]. Most AI models are black-box systems: they train on input-output relationships and predict well on observational data. This method is appropriate for nonlinear processes like anaerobic digestion [7]. The method allows building models to forecast optimal operating conditions for enhanced energy yield without a thorough mechanistic understanding [8].

Various segments of the bio-energy chain possess different data and uncertainty structures as well as mechanistic limitations, so that certain classes of models may a priori be more appropriate than others. Black-box models, such as ANN, RF and SVR seem to be more efficient in biomass resource assessment and feedstock quality prediction for they are based on large-sized and heterogeneous databases where the existence of complex nonlinear patterns and physical mechanisms is less obvious. Hybrid and physics-guided models are better suited for conversion systems in which the reaction paths and biochemical constraints affect the system response. Such models can retain predictive ability, and at the same time to be compatible with the known thermodynamic, kinetic, or other principles. Interpretable and model-agnostic methodologies are considered to be more suitable for supply-chain planning and emissions management as well, where transparency, interpretability, and traceability of the solution can be helpful in making operational decisions or supporting regulatory reporting/sensitivity analysis. Taken together, this differentiation helps to explain how each type of AI model corresponds with the technical requirements, data availability and operational objectives of distinct stages in the bio-energy value chain.

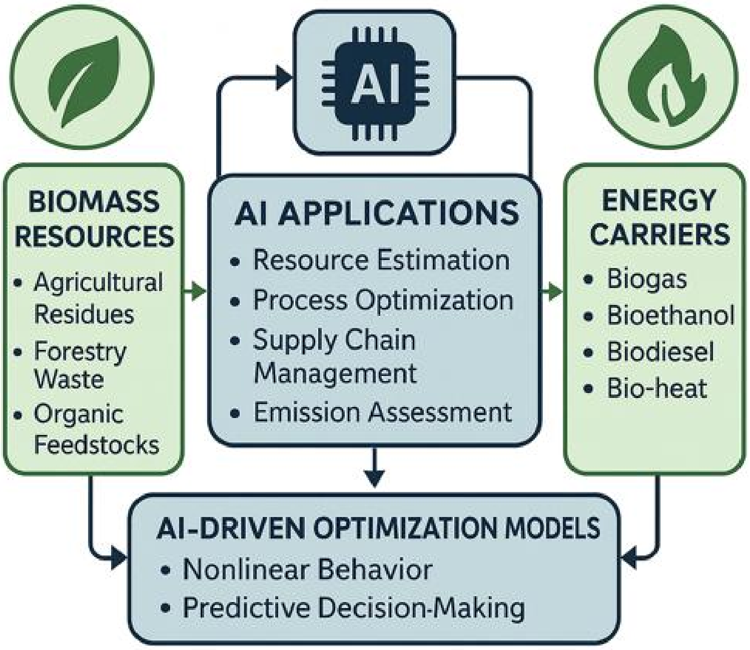

Figure 1. AI-Integrated Framework for Bio-Energy Systems

Figure 1 illustrates how AI methods interact across resource assessment, conversion, logistics, and emission management, showing the flow of information that links these stages. The figure highlights that predictive models function as decision-support tools rather than isolated components.

Neural networks, random forest and support vector machines are applied in many studies since they can use online data learning to adapt current state [8]. This functionality is critical for anaerobic digestion, which exhibits rich and sensitive dynamics impacting renewable energy production [5, 9]. Digestion behavior under different circumstances can be estimated by machine learning, and real-time control power can enhance the stability and efficiency [8]. Hybrid ML– optimization techniques, e.g., GA and PSO to improve biogas and methane yield, minimize overfitting, and optimize prediction accuracy [10]. These models are faster than the mechanistic type and more appropriate for real use [10]. They can also rapid predict the main outputs in order to support online monitoring [10, 12]. AI methods continue to require extremely large and accurate training datasets, and may be unable to generalize without additional real-world constraints [8, 10]. They are not, however, arbitrary-function approximators and do not support parallel processing but are still effective in modelling bio-energy systems [11]. Biochemically detailed mechanistic models like ADM1 are hard to calibrate for use in real time [8]. Machine learning is not burdened with solving (heavy) differential equations and has smooth connections to heuristic optimization tools [10, 7]. Interpretable tools must also be incorporated to demonstrate why ML is successful, enhance yield prediction and lead to optimal operating points [10, 13]. Explainable AI can also enhance trust in industry [8]. The absence of benchmarking datasets and in-depth validation principles hinders scale-bridging as well as feedstock translation [14]. Interpretative models are necessary to go beyond black-box predictions and provide process understanding [13]. Hybrid mechanistic–ML models merging biochemical information with data-driven power bring great potential for the enhancement of anaerobic digestion and other bio-energy systems [15, 8]. Important challenges such as preprocessing, interpretability, scalability and model selection are open and data standards and benchmarking frameworks need to be improved before it can scale and be applied in bio-energy systems [13, 15].

Table 1. AI Applications and Research Directions in Bio-Energy Systems

Aspect	Description	AI Role	Common Algorithms	Strengths of AI Models	Limitations / Gaps	Future Directions
Bio-energy Resources	Biomass from agriculture, forestry, and waste converted into biogas, bioethanol, biodiesel, and bio-heat.	Predict biomass availability and properties.	ANN, RF, SVM	Handles nonlinear and uncertain data.	Needs large datasets; limited transferability.	Build standardized datasets.
Conversion Processes	Anaerobic digestion and other processes show nonlinear behaviour.	Forecast biogas/methane yields and optimize conditions.	ANN, GA-ANN, PSO-ANN	Rapid predictions; adaptive learning.	Black-box behaviour.	Develop explainable and hybrid models.
Process Control	Real-time control improves stability in digestion and conversion units.	Predict operating conditions for stable performance.	ANN, SVM	Fast response; adaptive updates.	Accuracy depends on training quality.	Use model-agnostic interpretability tools.
Supply Chain & Logistics	Biomass transport and storage depend on variability and demand.	Support planning and supply-chain optimization.	RF, GA, PSO	Addresses uncertainty in multi-stage systems.	Lack of unified validation protocols.	Establish evaluation metrics and model guidelines.
Environmental Assessment	Emission control and lifecycle impact prediction.	Predict emissions and environmental impacts.	Ensemble models	Captures complex interactions.	Lacks embedded physical laws.	Link mechanistic and AI-based models.
Model Integration	Mechanistic models give insight but are computationally intensive.	Combine data-driven and mechanistic models.	Hybrid mechanistic–ML	Reduces overfitting; improves reliability.	Integration complexity.	Strengthen hybrid modelling frameworks.
Research & Scalability Challenges	Data pre-processing, interpretability, and scalability issues.	Improve prediction quality and stability.	Explainable AI, hybrid models	Supports transparency and wider adoption.	Incomplete datasets; inconsistent metrics.	Create stronger validation frameworks.

The objective of this study is to conduct a systematic review on use of artificial intelligence techniques along the bio-energy value chain i.e. biomass resource assessment, process optimization, supply-chain planning, and emission management in order to provide a knowledge base for researchers in this field. The research investigates how various AI models, datasets and unified hybrid optimization approaches cope with system nonlinearity, operation uncertainties and environmental constraints of the bio-energy system. By analyzing the recent trends, and finding shortcomings of present methodologies, this review aims to elucidate research gaps and provide future directions that can facilitate developing more effective, scalable and low-emissions bio-energy systems. **Table 1** explains AI Applications and Research Directions in Bio-Energy Systems.

While there is no shortage of studies that show the promise of AI for resource mapping, process optimization and emission reduction in this field, a unified overview considering all classes of models over the full range of processes along the bio-energy chain as well as their relevance with respect to data availability, the complexity of processes and operational constraints has been lacking. The majority of these reviews concentrate on single processes such as anaerobic digestion or specific algorithms, without consideration to addressing realistic decision-making requirements at a system level. This results in a disjointedness between the performance of different AI methods, where they fail to perform, and how they can be coordinated with mechanistic knowledge and new tools such as digital twins and federated learning. Filling this gap is a crucial step toward implementing AI-based workflows that enhance the reliability, transparency and scalability of real bio-energy applications.

2. AI applications in biomass resource assessment

AI methods have broadened the scope of bio-energy research by providing means to capture relative nonlinear dynamics, to respond to varying operational and environmental contexts, and learn from different data sources. These models contribute to more accurate predictions for biomass availability, biogas yield and emission patterns that are problematic to estimate using only traditional methods. Their increasing popularity through laboratory studies, pilot plants and, industrial-scale plants demonstrate the trend towards a data-driven process monitoring approach for both tactical planning and daily operation decisions. This shift also underscores the requirement for thorough evaluation of data quality, model interpretability and scalability to enable practical and reproducible results at the scale required for a range of bio-energy systems.

2.1. Biomass quantity estimation using remote sensing and ML

Determining the biomass resource is crucial for planning of any bio-energy project. It serves to screen plant sites, forecast annual material spectrally and minimize supply risks. Remote sensing has attracted attention in recent years, since it offers regular and extensive measuring opportunities. From satellite imagery, drone surveys and airborne LiDAR, we can acquire very fine details on land cover, condition of vegetation dynamics as well as surface structure. This data is then consumed by machine learning models which predict biomass more accurately compared to traditional field surveys. Methods such as RF, SVR and CNNs examine the correlation between spectral signatures, vegetation indices (VIs), soil moisture, and land surface temperature (LST). By incorporating these inputs with field measurements from reference sites, the models generate spatial maps of agricultural residue availability, forest biomass density and municipal waste output. These maps are useful for long-term planning and offer better use of biomass estimates.

In addition, AI application in remote sensing also supports the ability to monitor biomass growth and yield over different landscapes, enabling a more responsive resource-management approach. This facilitates the dynamic realignment of feedstock supply chains, mitigating logistical inefficiency and securing a continued supply of biomass for bio-energy plants [16]. AI-based strategies are also vital to facilitate genetic selection and engineering of energy crops while enhancing biofuels production yield and total system efficacy [17] [18]. The applicability of these models is highly dependent on the availability of high-quality, application-specific data, which are often expensive and time-consuming to collect [4]. More powerful data augmentation and transfer learning strategies across different geospatial datasets should be designed to solve this shortcoming and enhance model generalizability. Despite these improvements, reliable biomass mapping in complex forest structure areas is still challenging and the selection of appropriate algorithms and approaches for resource estimation at different scales is needed [19] [20].

2.2. Predicting feedstock quality

The quality of the biomass feedstock is a key factor in the conversion of biomass (including combustion, gasification, pyrolysis and anaerobic digestion. Characteristics such as the moisture, ash, carbon/nitrogen ratio and volatile matter contents are directly related to energy production and process efficiency. Machine learning models built on the basis of proximate and ultimate analysis data could provide a more accurate prediction as opposed to general empirical correlations. Modelling methods, including gradient boosting and ANNs, are trained with vast laboratory datasets to recognize patterns and predict critical parameters such as HHV, biodegradability, and methane potential. These predictions enable operators to estimate the applicability of agricultural and forest residues, the choice of blending options and proper pre-treatment routes prior to conversion. The ability to predict saves expensive and time-consuming experiments, leading to improved process optimization and root performance in bio-energy systems.

AI will also be able to predict the impact of storage conditions and season on feedstock quality, enabling proactive actions to keep these at suitable properties for conversion processes [21]. For the case of biomass pyrolysis, machine learning is also utilized to predict bio-oil yield and quality, which have been shown to achieve higher predictive accuracy than conventional empirical models [22]. During the biofuel life cycle, machine learning has been used for applications, especially in aspects relevant to Industry 4.0 to enhance feedstock screening and supply-chain management [23]. These tasks range from logistics optimization, rheological property analysis and impact on biofuel quality, serving the purpose of a more efficient conversion [23]. The combination of machine learning with advanced analytical methods provides an excellent route for the online feedstock characterization and adaptive control of process settings and permits a basis to optimize bio-energy production [17].

Table 2. AI Applications in Biomass Resource Assessment and Feedstock Quality Prediction

Topic	Focus Area	AI / Data Sources	Key Contributions	Current Challenges
Biomass Quantity Estimation	Assessment of agricultural residues, forest biomass, and municipal waste	Remote sensing (satellite, drones, LiDAR); RF, SVR, CNNs	Spatial biomass maps; supports site selection, forecasting, and supply-risk reduction	Limited datasets; difficult mapping in complex forest regions
Remote Sensing Integration	Continuous monitoring of vegetation and land-use patterns	Spectral indices, soil moisture, LST with ML	Dynamic resource management; improves feedstock supply stability	Costly data collection; limited transfer learning ability
Energy Crop Improvement	Selection and improvement of biomass crop varieties	ML with remote sensing and genomic data	Improves crop breeding and yield prediction	Need better data augmentation and generalization strategies
Feedstock Quality Prediction	Estimation of moisture, ash, C/N ratio, volatile matter, HHV, biodegradability	Gradient boosting, ANN, large lab datasets	Predicts conversion suitability; guides blending and pre-treatment	Seasonal and storage-related variations need stronger models
Biofuel Process Support	Quality prediction in pyrolysis, gasification, and Industry 4.0 supply chains	ML with analytical and process data	Forecasts bio-oil properties; supports logistics and rheological assessment	Needs stronger real-time datasets and integration frameworks

Table 2 outlines how AI combined with remote sensing improves biomass resource assessment by generating accurate spatial maps, supporting long-term supply planning. It also highlights predictive tools used to evaluate feedstock quality, which help refine conversion processes and enhance overall bio-energy system performance. Insights from biomass availability and feedstock quality assessment. It is these materials discussed in Process understanding in bio refining application of AI to bioenergy processing" that help underpin the performance of the materials under downstream conversion pathways and hence naturally lead to consideration of AI-backed optimization within bio-energy conversion processes.

3. AI for process optimization in bio-energy conversion

The optimization of process performance is a key concern for enhanced stability, efficiency and environmental impact of bio-energy system operation because the conversion pathways are frequently characterized by complex reaction pathways and narrow operating potentials. AI approaches provide a systematic technique to examine such nonlinear behaviors by estimating the input-output relationships of processes, identifying early symptoms of instability and offer appropriate control actions. These methods supplement the traditional kinetic and mechanistic models to minimize computational expense with acceptable predictive performance. Their increasing deployment in bio-gas production, thermo-chemical conversion and integrated bio-refinery processes are indicative of the possibilities for enhancing on-line control, resource utilization and emission footprints.

3.1. Anaerobic digestion and biogas systems

The anaerobic digestion process is sensitive to temperature, pH, organic loading rate (OLR) and the composition of feedstock. AI methods are currently applied to predict biogas yield, monitor the first indications of the process instability and propose appropriate feed ratios. Models including ANNs, LSTMs and ensembles have all been used to predict methane production with high accuracy. Hybrid ML–kinetic models Hybrid ML–kinetic models add machine learning (ML) to the kinetic M−CMBD model so as to achieve better generalization scenarios. For instance, ANNs have been successfully combined with particle swarm optimization to predict and maximize biogas production from palm oil mill effluent in solar bioreactors [17]. This kind of integration allows for real-time optimization of operating parameters and better energy conversion efficiency, particularly under changing environmental conditions [22]. Reinforcement learning (RL) has begun to be used in the context of real-time control of digesters. RL agents are capable of adjusting the operating factors, OLR or mixing strength, for example, according to observed digester behavior and may be applied on-the-fly. This approach also optimizes the biogas yield and process stability, so that the accumulation of toxic matter can be avoided for a stable bio-energy production [15]. The improvement of dynamic optimization is even more pronounced by integrating it into operation with online sensor information or forecasting data in order to predict transitions between feedstock quality or environmental states [15]. Machine learning also enables more general decision-making. The inclusion of ML in the life cycle assessment and techno-economic analysis allows for a rapid identification of viable equipment configurations and cost estimates as opposed to using conventional process simulations [17]. Applications of machine learning in ad have expanded to monitoring, modelling and optimizing the bioprocesses key parameters, and have led to considerable improvement in biogas production efficiency [15].

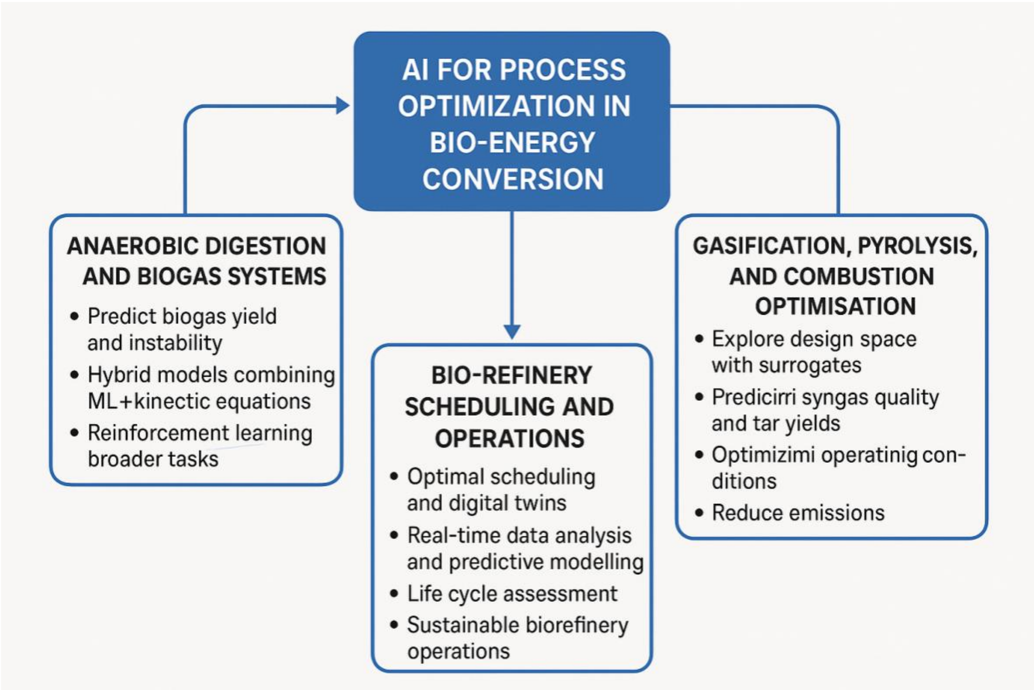

Figure 2. AI-Driven process optimization framework for bio-energy conversion systems

Figure 2 outlines how AI supports monitoring and control in major conversion pathways, showing the shift from static modelling toward adaptive, data-driven operation. The layout makes clear that process optimization relies on iterative feedback between reactor conditions and model predictions.

3.2. Gasification, pyrolysis, and combustion optimisation

Gasification or pyrolysis are (high temperature) processes, particle size-dependent and sensitive to temperature, residence time and equivalence ratio. Artificial neural network models enable fast screening of the design space and help in finding conditions in which syngas can be enhanced or tar formation suppressed. ML techniques have also been successfully applied to the air–fuel ratio control for combustion systems, and a feedstock blending strategy based on ML for reducing the pollutant emissions.

Sophisticated machine learning-based methods are used to forecast outputs (methane, hydrogen, carbon monoxide, carbon dioxide and higher heating value) from the downdraft biomass gasification process with R^2 values greater than 0.9, demonstrating better predictive ability compared to conventional modelling techniques [22]. Combining machine learning methods, such as artificial neural networks with genetic algorithms, has been proven to be quite effective in optimizing the biomass pyrolysis and gasification, resulting in better performance in terms of energy recovery [24]. These techniques well extend to predict the combustion efficiency and very appropriate for the determination of optimal operating conditions in regard to emission reduction with data sets covering various operational modes [17]. In addition to the prediction, ML algorithms are also used for the optimization of bio-oil products and experiment-based studies have demonstrated their high yield and good energy recovery [22]. To this aim, it is necessary to develop accurate, fast and robust models for complex thermos-chemical processes. Machine learning offers robust alternatives to time consuming conventional methods, and provides dependable performance over a range of scenarios [25]. High predictive accuracy ($R^2 > 0.90$) of syngas composition and product distribution in gasification was obtained using models like support vector machines, random forests or artificial neural networks and in certain cases, these models performed better to conventional mechanistic models [26] [24]. A combination of machine learning with computational fluid dynamics (CFD) aids in the improvement of predictive performance. These models will be more useful to predict the yield of tar and the content of hydrocarbon in gas, which provides the possibility towards pyrolysis and gasification processes optimization [27] [28]. ETR has proven to be especially effective in the prediction of syngas properties in biomass chemical looping gasification when few data samples are available [29], outperforming artificial neural networks and random forests in terms of accuracy. These AI-assisted optimizations lead to smaller emission footprints and higher sustainability in bio-energy systems by optimizing process parameters [30]. They tend to use resources more efficiently and produce cleaner energy, enabling the bio-economy to become more environmentally sustainable [31].

3.3. Bio-refinery scheduling and operations

Bio-refineries handle several products and processes depending on each other, where optimized feedstock input, reactor operation, and energy flows become a key point. Machine learning-enabled optimization integrates machine learning predictions with mathematical programming models to reduce energy and emission levels. With Twins, advanced operating results tracking in real time is made possible by the digital twins underpinned by machine learning. Such digital twins enable predictive maintenance, anomaly detection and proactive adjustments to operating conditions, with the potential that they lead to enhanced refinery efficiency and profitability [32]. Even in the smart integrated bio refinery case, machine learning is used to analyses data and make predictive models in real-time monitoring for better utilization of resources, decrease waste [32]. The use of machine learning in combination with LCA tools enables assessment of the environmental and economic impact across various pre-treatment strategies, to promote sustainability considerations in bio refinery design and operations [17]. The support by AI and ML shines a light on the commercial developments of innovative bio refineries by giving assistance and improvements to critical aspects, toward future biofuels and biochemicals. These technologies favor the integration of data) processing, and system-level decision making in catalyst design, synthesis and characterization critical to the effective conversion of ligno-cellulosic biomass [33]. This integrated analytical and predictive framework offers a better understanding and control of complex bio-refining operations, advancing ourselves toward a sustainable bio-based economy [17] [34]. Smart models can further support lignocellulosic biomass bioconversion thanks to the possibility of do a preliminary screening and identifying compatible windows on operating the needed pre-treatments as well as also for optimizations [17]. **Table 3** shows how AI techniques promote important bio-energy conversion processes for prediction, monitoring and operational control. It emphasizes the use of machine learning and hybrid models for the enhancement of anaerobic digestion, thermos-chemical reactions, and bio-refinery operations towards improved efficiency and stability.

Table 3. AI for Process Optimization in Bio-Energy Conversion

Area	Process Focus	AI Methods Used	Key Contributions	Challenges / Needs
Anaerobic Digestion & Biogas Systems	Stability control, methane prediction, feed ratio management	ANN, LSTM, ensemble models, PSO–ANN hybrids, RL	Forecasts methane yield, detects instability, supports real-time adjustments, improves system efficiency	Needs high-quality sensor data; limited generalisation across feedstocks
Hybrid ML–Kinetic Modelling	Mechanistic–data fusion for digesters	ML combined with kinetic equations	Better prediction across varied conditions; supports adaptive optimisation	Integration complexity; varied performance across reactor scales
Thermo-Chemical Conversion	Gasification, pyrolysis, combustion	ANN, GA-ANN, SVM, RF, Extra Trees	Predicts syngas composition, reduces tar, improves bio-oil yield and emission control	Requires robust datasets; complex reaction pathways still difficult to capture
ML-Enhanced CFD & Surrogate Modelling	High-temperature reactor optimisation	Hybrid ML–CFD models, surrogate models	Faster design exploration; better prediction of tar and hydrogen output	Accuracy depends on calibration; limited transferability
Bio-Refinery Scheduling & Operations	Feedstock scheduling, pretreatment, energy flow control	ML with optimisation, digital twins	Real-time monitoring, predictive maintenance, improved scheduling and resource use	Needs strong data integration and coordination of complex workflows

Based on the set of studies reviewed, several points of consensus and contestation emerge. A large number of studies consistently claim that black-box models (e.g., ANN and ensemble methods) provide good predictive accuracy for nonlinear biomass and conversion processes, in line with observations across anaerobic digestion, pyrolysis and gasification literature. There is, however some imprecision from studies which describe the model's generalization differently, with conclusions regarding strong model transferability across feedstocks as well as claims for lack of transfer since data is scarce and operating conditions vary are published. A smaller number of studies present hybrid or physics-driven models, which present better reliability and interpretability, providing insights beyond pure prediction. Such differences illustrate that, although the literature concurs generally with regards to AI benefits in bio-energy improvement operations, various modelling approaches address distinct concerns and overcome them only given an appropriate level of data quality, reactor scale and process variability. These comparisons serve to make clear why the guidance on model selection is so varied across the field. As the process-level optimization ensures more stable and efficient individual conversion units, attention is shifted to the supply-chain rationale that supports continuous operation, including the usage of AI to make transport-, storage- and planning-decisions safer.

4. AI-enhanced supply-chain optimization

AI increasingly assists in the efficiency and stability of bio-energy supply chains, which tend to be subject to seasonal, spatially dispersed, and high transport costs influencing factors. The use of data-driven models to improve the accuracy of the decision-making process by associating the physical information with real-time operational data. **Figure 3** depicts how AI algorithms coordinate routing, scheduling, and multi-objective planning across dispersed biomass networks. The structure underscores that supply-chain stability emerges from combining real-time data with optimization routines.

Figure 3. AI-Enhanced supply-chain optimization framework

4.1. Transport and logistics planning

Bio-energy supply chains represent multi-stage networks of systems, involving harvesting, collection, baling, storage and transportation. At every stage, uncertainties due to weather, biomass quality, labor availability and equipment performance are added. AI tools can help to mitigate these uncertainties through route optimization, vehicle schedules, and cost predictions. Machine learning models analyses historical and real-time data to predict travel delays, fuel consumption and loading efficiency. These methods can also help to determine suitable transportation modes and storage accordingly (including aspects as, moisture content, crop variability and degradation risk due to handling and storage). All these help logistics to be more reliable, timely and economical.

Real-time supply chain data-supported digital twin technology that allows for dynamic optimization, for example, facilitates antifragility supply-chain development through autonomous adaptation or corrective action in unplanned events [16]. Other reinforcement learning algorithms could further aid to resilience by determining reliable suppliers and forecasting how adaptable they are towards uncertainty, such as price fluctuations and delivery delays, using previous information [35]. In such a configuration, the inclusion of AI not only maximizes current operational efficiency but also renders the whole bio-energy supply chain resistant to uncertainties, aiding in efficient and reliable energy systems. [36]. Artificial intelligence in clean energy - Market potential. The worldwide AI market for clean energy is estimated to grow over USD 75.82

billion by 2030, registering a strong annual growth as the strategic role of AI in the optimization of renewable energy supply chains and power generation continues to expand [37].

4.2. Multi-objective optimization

It is a problem of the trade-off between the factors associated to economic, environmental and social. Multi-objective optimization methodologies integrate NSGA-II, particle swarm optimization and machine learning models to search for very large numbers of potential supply-chain configurations. Such hybrid methods balance considerations of transport distance, carbon footprint, energy loss and total cost. By visualizing the resulting Parsley-optimal solutions, decision-makers can select strategies that minimize emissions while enhancing resource utilization and ensuring an economical supply. This is conducive to long-term planning and enhances bio-energy systems' resilience. AI also assists in drawing up more cognitively nimble and resilient supply chains, which help support decarbonization efforts as well as wider sustainability targets [37, 38]. Furthermore, AI can help to detect potential health and safety hazards in bio-energy supply chains, for ensuring ethical behavior, fair labor standards and human rights are respected [39]. AI-based apps also help in transparency by recording the flow of biomass and ascertaining compliance with sustainability certificates or ethical sourcing norms [37]. Use of explainable AI The use of explainable AI would aid in decision-making by providing the transparency and clarity into how complicated models work, and this can help decrease mistakes, highlighting any possible flaws in strategies to optimize the supply chain [35]. These analyses also make it possible to conduct a trade-off review based on the reduction of GHG emissions, contributing to decision-making that balances economic productivity and environmental conservation [39]. Recent developments also apply to predictive analytics, with machine-learning logic predicting demand and the generation of energy. It helps in the better utilization of the grid and reduces reliance on fossil fuels [40] [41].

5. AI for emission prediction and reduction

AI techniques are increasingly integrated into bio-energy systems to measure, predict, and manage emissions with greater accuracy. These tools address both real-time operational needs and long-term planning by analyzing large datasets and identifying patterns that are difficult to capture through conventional models.

5.1. Real-time emission monitoring

AI models are being utilized to predict emissions in combustion, fermentation or gasification units through training with process conditions including temperature, pressure, feed rate and moisture content. These analytical tools predict major pollutants, such as CO_2, CH_4, NOx, SOx and particulate matters, allowing operators to correct the emissions before things get worse. Machine-learning-based an early warning system is utilized for early detection of methane slip in anaerobic digestion systems when patterns are detected in sensor data. If deviations are identified, the system can suggest changes to load rate, mixing intensity, or digester temperature to minimize losses and keep the reactor running efficiently. The Bayesian Networks and Extreme Gradient Boosting similarly improve the prediction accuracy for biogas production by properly addressing uncertainties and aggregating weak learners into strong ensembles. Such models convert qualitative and vague information into quantitative knowledge in order to assist in process decisions and optimizations [15]. Such proactive control of emissions becomes relevant, considering the stringent environmental legislations and in the direction of achieving net-zero emissions [40]. Big data analytics platforms for e.g. Hadoop, Spark, are employed to filter large datasets and discover emission patterns or trends that in turn facilitate a better understanding on how emissions react to operational changes [42]. These considerations assist in dynamic calibration of emission abatement measures and provide guidance in selecting the value range of operational parameters under which to minimize the environmental impact but still produce a relatively high level of energy [43]. AI techniques also increase biogas production monitoring accuracy, which leads to higher productivity and lower operating cost [44]. More sophisticated machine learning and deep learning models can also enhance computational efficiency and predictive accuracy in real-time modelling of carbon emissions involving various sectors [45] [46].

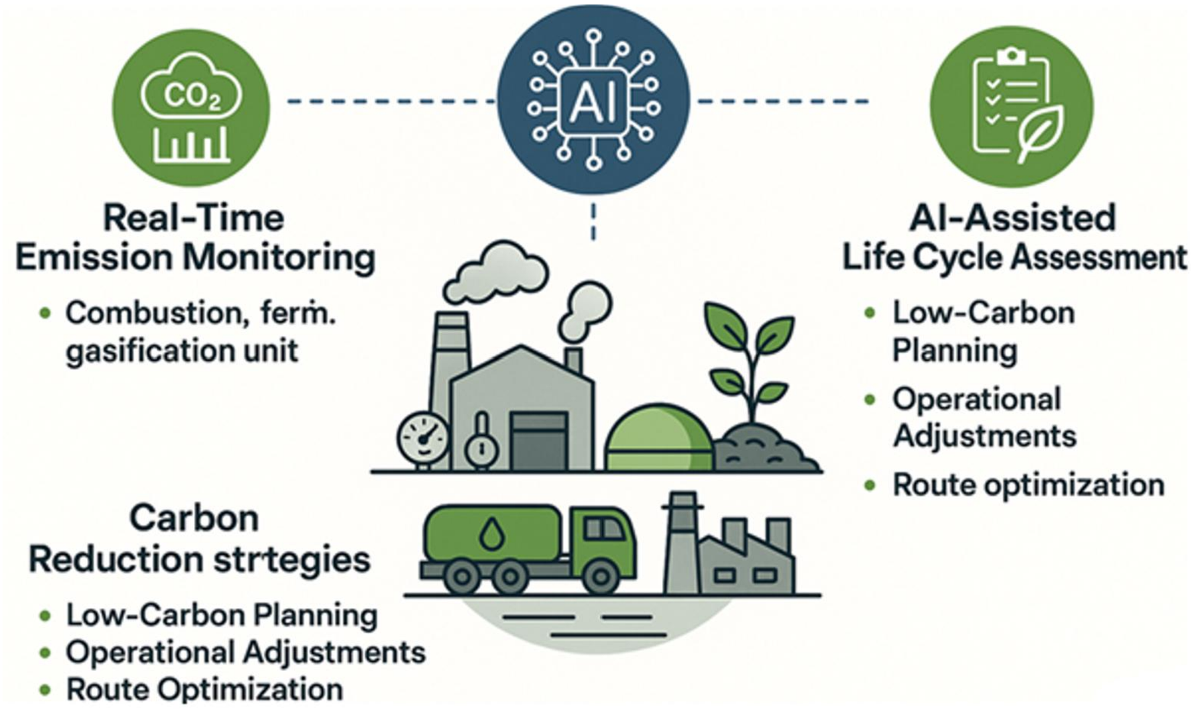

Figure 4. AI for Emission Prediction and Reduction

Figure 4 presents the role of AI in detecting emission patterns and linking them to operational parameters. It shows that real-time analytics combined with predictive models enable more proactive emission control.

5.2. AI-assisted life cycle assessment (LCA)

Life cycle assessment (LCA) demands comprehensive data on energy consumption, water use, air emissions, transportation, and land-use effects. Some of these datasets are noisy or incomplete. Serving as a complement to LCA, AI can predict missing parameters, create artificial datasets, and facilitate the quick study of scenarios. Machine-learning surrogate models can mimic the computational requirements of detailed LCA calculations, but on a much coarser timescale, which is enough to rapidly compare feedstocks and conversion technologies. This gives a more accurate picture of environmental burdens and improves decision-making along the bio-energy value chain. AI is also used to evaluate building carbon emissions through the analysis of real-time energy consumption data, providing effective plans for reaching carbon reduction targets, and helping other sustainability objectives [45]. In a similar field, infrared spectroscopy combined with machine learning helps measure carbon content in biological or fossil samples to determine the impact of solid refuse burning on emissions reduction and resource efficiency [47]. Advanced AI calculations have been growing in popularity for comparative studies such as comparing emissions from 2G ethanol production chains to fossil-based processes, used to guide the transition towards biofuel transport systems [48]. Machine learning also has helped in the LCA process, for instance, by using it to predict biogas production curves from different compositions of lignocellulosic feedstock blends and optimization of anaerobic digestion as well as predicting ethanol yield and NaOH requirement in bio-ethanol refineries [17]. These findings improve the accuracy of the estimation process using advanced techniques and big data, which leads to precise predictions with negligible errors [45]. Indeed, this integration facilitates a new perspective of how LCA can be included in design, which overcomes long-standing limitations stemming from the limited data availability and static system boundaries [49]. By using AI-powered methods to derive proxy values for missing information, they can also narrow down data gaps and enhance the completeness and accuracy of estimated environmental impacts [50].

5.3. Carbon reduction strategies

AI enables low-carbon planning that could identify feasible ways of reducing emissions at various stages within the bio-energy system. Typical approaches include using feedstock blends on a predicted emission factor basis, identifying high-emission conversion or transport process steps, suggesting process adjustments to decrease pollutant generation and assessing land-use-change impacts using spatial AI as well as geospatial data. These methods enable planners to compare the performance of alternate system designs, evaluate mitigation potential and implement measures that reduce overall carbon intensity while continuing to serve system load. AI-enabled platforms can automate data collection from a wide variety of sources, analyse emissions information and churn sustainability reports, which are in line with regulatory bodies; hence empowering more accountability in organizations [51]. AI can optimize transportation routes over traffic, road condition and even weather information to reduce travel time, save fuel and alleviate pollution [46]. This type of AI-leverage optimization of transport systems (also, incorporating the renewable energy and biomass technologies) are significant in terms of carbon reduction in the mobility sector [52]. AI is also employed to analyses the traffic data, estimate congestion and propose real-time re-routing with minimum fuel consumption and emissions [46]. The AI-aided advanced LCA models have been adopted by urban mobility for its journey toward zero emissions. This approach allows the modelling, assessment and optimization of transport systems based on data-driven policy-inducing measures [53]. AI can process intricate models of mobility and measure impact towards the environment, thus enabling valuable inputs into policies for decreasing carbon emissions and favoring sustainable urban transport [53]. This comprehensive approach enables cities to be in harmony with international environmental targets, such as the Paris Agreement, while also supporting tailored carbon-emission analyses for mobility-hub location selection and operations planning [54]. **Table 4** contributes to gaining and reducing emissions, including its ability of real-time monitoring, life cycle assessments and low-carbon strategies. It also discusses the most relevant tools employed, the primary contributions of each approach and the main challenges to be addressed for broader deployments.

Table 4. AI for Emission Prediction and Reduction

Area	AI Methods / Tools	Key Contributions	Challenges / Needs
Real-time Emission Monitoring	ANN, XGBoost, Bayesian Networks, Hadoop, Spark, Deep Learning models	Predicts CO_2, CH_4, NOx, SOx, PM; detects methane slip; enables proactive control; improves accuracy	Needs high-quality sensor data; uncertainty in real-time datasets; integration across diverse systems
AI-assisted LCA	Surrogate ML models, data imputation, infrared spectroscopy + ML	Fills missing LCA inputs, generates synthetic data, speeds scenario analysis, supports environmental comparisons	Incomplete datasets; static system boundaries; difficulty capturing spatial and temporal variations
Carbon Reduction Strategies	Spatial AI, route optimisation models, transport analytics, automated reporting systems	Identifies high-emission steps, improves feedstock selection, optimizes transport routes, supports emission-focused policies	Requires large geospatial datasets; coordination across mobility networks; regulatory compliance needs

In bio-energy, AI-supported reviews are increasingly important for policy and decision-making. Biomass availability and conversion efficiency estimates will be improved, leading to more reliable emission profiles that help the design of well-founded sustainability criteria and benchmarks for bio-energy plants. In combination with AI-supported LCA tools and real-time emission monitoring systems can form the basis for dynamically adjustable compliance thresholds instead of having only static compliance limits. Such capacities also help policymakers in better estimating the impact of land-use, carbon intensity ratings and technology-specific incentives. Through increased transparency and predictive consistency as AI technologies advance, the latter can be reinforced even more through certification schemes, subsidy allocation and in the development of risk-responsive regulatory regimes consistent with national and international climate goals.

6. Key research trends

Current research highlights several directions that are shaping the use of AI in bio-energy systems.

6.1. Hybrid models combining mechanistic principles with ML

These models combine physical laws with data-based learning, resulting in increased accuracy of prediction without compromising on process behavior. They are especially useful when sensor information is scarce or the system has a nonlinear behavior. For instance, fitting neural networks to thermodynamic equations can yield more accurate predictions of biofuel yields for a range of operating conditions [3]. This makes the prediction more robust and generalizable, especially for predictions outside of the range of observed data [2]. Insight ability - Hybrid models provide stronger interpretability, allowing to gain an insight into the mechanisms that influence how systems respond, instead of merely observing their outputs. This interpretability is crucial for the input design of process and risk assessment in bio-energy systems. Another popular theme is the construction of multi-fidelity models that incorporate information from multiple resolutions and data sources in order to achieve a more accurate overall representation of the system while minimizing computational costs.

6.2. Remote sensing with AI for regional biomass mapping

Satellite and drone information analyzed through machine learning techniques provides valuable information on biomass to then move towards crop conditions and spatial variability. This enables even better anticipation on feedstock supply and making plans for harvesting and transport. This ability is especially significant for regional evaluations, due to the inclusion of finer information relative to that obtained with traditional ground-truthed surveys, and helps in more detailed resource estimation for bioenergy production [55]. The integration of remote sensing data with AI enables the real-time monitoring of biomass growth and health, providing early signals for disruptions in supply from climate events, disease etc [3]. They also assist in developing predictive models for yield optimization and sustainable land-management practices [4] [17]. Such developments are needed if bioenergy systems are to be improved through enabling for a stable and well-managed feedstock supply that influences the economics and environmental sustainability [36]. Lastly, AI-based interpretation of remote sensing data can be applied to assist with land use planning by pinpointing appropriate locations for energy crop cultivation, dedicated areas that minimize competition with food production and promote biodiversity conservation [1].

6.3. Digital twins for real-time plant monitoring and optimization

Digital twins link data on actual operations to a virtual model of the plant, enabling detection of operational anomalies, experimentation with operational concepts, and prediction of system behavior without risk to real-time operation. This coupling facilitates predictive maintenance, enhanced operational efficiency and smarter decisions for complex bio-energy plants [36]. Digital twins also offer immediate feedback on simulations and optimization, and they can be combined with techno-economic performance analysis for directing system enhancements [56]. With AI technology embedded, these digital twins inform predictive maintenance, real-time of energy optimization and grid resourcing for better process efficiency and resilience [57]. Through coupling state-of-the-art simulation and real-time data analysis, digital-twin architectures enable multi-criteria decision-making concerning environmental, economic and social issues in bio-based sectors [58]. The advancement of automated experiments with artificial intelligence, coupled with AI research systems, advances the optimization in bio-energy processes for optimal operating conditions and materials [59].

6.4. Reinforcement learning for adaptive control of digesters and gasifiers

Reinforcement learning agents acquire control strategies through interacting with the system and getting feedback from distributed performance scores. This has to be considered in terms of stability, disturbance rejection, and permanent process efficiency. It allows optimization of the law degree, temperatures, and feeds ratios and thus leads to higher biogas yields and lower operational costs in AD (anaerobic digestion) as well as gasification plants [17]. In fact, given that RL can deal with changing environments and learn from historical data, it is well suited for the complex and nonlinear dynamics exhibited by bio-energy production systems, and can be used to support incremental improvements in both efficiency and system stability [60]. Recent trends involve using transformer-based models to predict failures in biogas generators, as well as utilizing generative adversarial networks in digital twin environments towards dynamic optimization. Those approaches replicate several operating conditions and suggest appropriate operation strategies for online process control [15].

6.5. Automated feature extraction through deep learning for feedstock classification

Deep learning models process images, spectra and sensor signals to determine the type of biomass, its quality and contamination. This results in less hand on testing time and enables better process planning for the pre-processing and combustion facilities. Automation is crucial to maintain consistent feedstock quality, which in turn significantly impacts the efficiency and stability of the bioenergy conversion process [17]. These methods also permit fast, non-destructive feedstock characterization so that reactor operating conditions can be optimized and process upsets avoided [15]. In this context, machine learning (and in particular artificial neural networks) is applied to optimize the operations of bio refineries and to enhance the bioethanol extraction process by determining suitable operating conditions [17] [25]. Artificial neural networks have also been used in highly efficient biomass gasification combined power generation systems to predict key process variables, and provide according good prediction of parameters such as gasification temperature and air-to-fuel ratios [61-75].

6.6. AI-LCA integration for rapid sustainability assessments

AI methods allow life cycle assessments to be performed faster through interpolation of missing data, creating alternative scenarios, and tracking uncertainty. This permits quick comparison of technologies and feedstock pathways. The application of AI in LCA systems can shorten the time to assess environmental impacts and resource consumption, and provide a more adaptable and comprehensive assessment on sustainability issues related to bioenergy systems. Such a quicker review is crucial for decision-making and investment because it allows for the quick selection of environmentally and economically viable bioenergy routes. It also allows for flexible analysis of a broad array of potential bioenergy technologies, from a sighting perspective to full implementation, while including all appropriate environmental footprints [76-86]. The capacity to compare different designs and anticipate environmental results enables stakeholders to make choices that foster sustainable bioenergy development while minimizing negative impacts.

6.7. Federated learning for multi-plant model training without sharing raw data

Federated learning, where trained parameters but not sensitive operation data are exchanged to build joint models, allows for cooperation among facilities without releasing plant-level details. This was made possible by the decentralized approach, hence going on to encourage the development of anti-fragile and more generalizable AI models for bio-energy optimization that can leverage different data sources without violating privacy or security information issues [87-98]. Federated learning promotes collective intelligence in the bioenergy sector by accelerating the convergence of predictive models and optimizers. Experience from a diversified operational environment can be integrated, and thus more resilient and effective bioenergy systems will be established. Federated learning also enables continuous learning, such that models can cope with new data flows as well as operational changes across a distributed network of bioenergy plants and remain relevant over-time [99-105]. This strategy can alleviate the drawbacks of single-plant databases, which might lack sufficient samples for achieving highly accurate and generalizable AI models [106-115]. Such a decentralized learning scheme is of great advantage for future bioenergy technologies, where the lack in data from single sites may compress model building and application [116-122]

Overall, these developments are indicative of a move towards higher levels of automation, real-time decision-making support, and enhanced model transparency throughout the bio-energy sector.

6.8. Key Limitations of Current AI Approaches in Bio-Energy Systems

Though the AI technologies are advancing bio-energy research, there are some common challenges that have been limiting the accuracy and applicability. The reliance on large, high-quality datasets is also a key issue as these are often unstable across feedstocks, climates and plant designs. Small data sets for training models are suboptimal, leading to reduced generalization and possible overfitting. Furthermore, a major issue is the low interpretability of most black-box models, whose obstacle course decision space makes it difficult to deploy in practice and discourages their use within regulated industrial sectors. Combining AI and mechanistic knowledge is challenging, particularly at the level of biochemical/thermo-chemical reactions that are poorly understood. The scale-up up is also a limitation because, generally, processes worked out in lab and pilot plants are not directly operable at an industrial scale. Inconsistent performance in studies is also aggravated by variation in the quality of sensors, data pre-processing and evaluation metrics. Moreover, AI implementation relies on steady data pipelines and computational resources that are hard to maintain in distributed bio-energy plants. Taken together, these constraints highlight the necessity for standardized datasets, transparent model architecture and closer integration of data-driven and physics-based frameworks to promote more accurate and affordable bio-energy optimization.

7. Future Directions

Future research in AI-driven optimization of bio-energy systems is moving toward more integrated, reliable, and scalable solutions.

7.1. Building large, standardised, and open datasets for biomass and process variables

creating shared datasets that cover diverse feedstocks, climates, and operational conditions will improve model robustness and enable fair benchmarking across studies. Standardization of data formats and metadata will also support reproducible research.

7.2. Designing physics-guided ML models for more reliable performance

Embedding physical constraints and mechanistic principles into ML architectures can reduce prediction errors, improve extrapolation, and strengthen trust in model outputs. Such approaches are especially important for safety-critical and regulatory applications.

7.3. Developing plant-wide digital twins that link sensors, ML, and control loops

Digital twins spanning pre-processing, conversion, and emission-control units can serve as real-time decision-support tools. These virtual systems can test operational changes, forecast failures, and help maintain optimal performance without interrupting plant operations.

7.4. Integrating AI into LCA tools to support policy and planning

AI-enabled LCA frameworks will allow rapid evaluation of emerging technologies, supply-chain designs, and regional scenarios. This integration can assist policymakers in comparing pathways and selecting options with lower environmental burdens.

7.5. Using reinforcement learning for multi-objective optimization under uncertainty

Reinforcement learning can help manage trade-offs among efficiency, cost, and emissions when system conditions fluctuate. It offers adaptive strategies that update continuously as new data becomes available.

7.6. Adopting edge-AI hardware for faster on-site computation

Deploying lightweight AI models on edge devices reduces dependence on cloud platforms and supports real-time monitoring in remote or distributed facilities. This leads to quicker responses to faults, process variations, and emission spikes.

Together, these directions will contribute to stable plant operations, lower emissions, and improved sustainability across the bio-energy sector.

8. Conclusion

The data-driven method of AI from an ADDC has changed its role from an additional support tool for analysis to the cornerstone tool for optimization in bio-energy systems. Throughout the value chain — from resource assessment and conversion to supply-chain planning and emission management — AI approaches offer speedier predictions, better pattern recognition, and more stable operations. It is demonstrated that machine learning, hybrid physics-guided methods, deep learning and reinforcement learning consistently improve the prediction accuracy of biomass availability, biogas yield as well as emission behavior, such models and decrease computational time for intensive simulations. These improvements help in designing, operating and predicting more secure and efficient operation of both biological as well thermo-chemical routes. The manuscript also addresses ongoing issues in relation to the quality of data, scalability or interpretability and generalization capabilities of models. Advancing in these areas will be facilitated by standardized datasets, tighter integration of mechanistic knowledge and accelerated adoption of digital-twin platforms. Novel tools like federated learning, edge-AI deployment, and AI-embedded LCA are promising in revolutionizing real-time decision-making and sustainability assessment for future bio-energy systems. Further, an effective partnership between data scientists and researchers in energy processes will be indispensable to transition these innovations into scalable, low-emission, industry-ready solutions. In this work, such a unifying contribution is provided by converging model-level with process-level and system-level analysis of the entire bio-energy chain into one integrated analytical framework. It not only compares capabilities and weaknesses of black-box, hybrid, physics-guided and explainable models but also relates these differences with the operational requirements for resource assessment, conversion processes, supply-chain planning and emission management. An integrated perspective as such is not often covered in prior reviews, which usually discuss individual stages or zoom in on particular algorithms. By specifying model appropriateness, highlighting cross-cutting challenges and profiling emerging trends such as digital twins, federated learning and AI-assisted LCA the manuscript offers a structured basis for researchers and practitioners seeking to enable verifiably scalable low-emission bio-energy systems.

Glossary of Abbreviations

AD – Anaerobic Digestion
AI – Artificial Intelligence
ANN – Artificial Neural Network
CFD – Computational Fluid Dynamics
CNN – Convolutional Neural Network
C/N Ratio – Carbon-to-Nitrogen Ratio
DT – Digital Twin
ETR – Extra Trees Regression
GA – Genetic Algorithm
GA-ANN – Genetic Algorithm–Optimized Artificial Neural Network
HHV – Higher Heating Value
LCA – Life Cycle Assessment
LST – Land Surface Temperature
LSTM – Long Short-Term Memory Network
ML – Machine Learning
NSGA-II – Non-dominated Sorting Genetic Algorithm II
OLR – Organic Loading Rate
PM – Particulate Matter
PSO – Particle Swarm Optimization
PSO-ANN – Particle Swarm Optimization–Optimized Artificial Neural Network
RF – Random Forest
RL – Reinforcement Learning
SVM – Support Vector Machine
SVR – Support Vector Regression
VI – Vegetation Index

Author Contributions

Sajal Suhane and **Anant Sidhappa Kurhade** conceptualized the study and defined its scope. **Smita Suhane**, **Rushali Rajaram Katkar**, and **S. Sugumaran** contributed to the literature survey, data collection, and synthesis of review content. **S. Sugumaran**, **Santosh Bhauso Takale** and **Surekha Dehu Khetree** supported the methodological framework and thematic organization of the manuscript. **Shyamsing Thakur** and **Shital Yashwant Waware** assisted in the critical analysis and interpretation of results. **Anant Sidhappa Kurhade** supervised the overall work and provided technical guidance. All authors contributed to writing the original draft, reviewing, editing, and approving the final manuscript.

Acknowledgments

The authors would like to express their sincere gratitude to Dr. D. Y. Patil Institute of Technology and DPGU, School of Technology and Research - Dr. D. Y. Patil Unitech Society, Pimpri, Pune, for providing the necessary support and research infrastructure.

Conflict of interest

The authors declare no conflict of interest

References

1. Wang Z, Peng X, Xia A, Shah AA, Huang Y, Zhu X, Zhu X, Liao Q. The role of machine learning to boost the bioenergy and biofuels conversion. *Bioresource Technology*. Elsevier BV; 2021 Oct 8;343:126099. https://doi.org/10.1016/j.biortech.2021.126099
2. Anbarasu K, Sundaram T, Sathishkumar K, Alam MM, Al-Sehemi AG, Devarajan Y. Harnessing artificial intelligence for sustainable bioenergy: optimization, waste reduction, and environmental sustainability. *Bioresource Technology*. Elsevier BV; 2024 Nov 1;131893. https://doi.org/10.1016/j.biortech.2024.131893
3. Liao M, Yao Y. Applications of artificial intelligence-based modeling for bioenergy systems: A review. *GCB Bioenergy*. Wiley; 2021 Feb 18;13(5):774. https://doi.org/10.1111/gcbb.12816
4. Meena MK, Shubham S, Paritosh K, Pareek N, Vivekanand V. Production of biofuels from biomass: predicting the energy employing artificial intelligence modelling. *Bioresource Technology*. Elsevier BV; 2021 Jul 23;340:125642. https://doi.org/10.1016/j.biortech.2021.125642
5. Deshpande SV, Pawar RS, Keche AJ, Kurhade A. Real-time surface finish measurement of stepped holding shaft by automatic system. J Adv Manuf Syst. 2025 Feb 25:1-26.
6. Ramani P, Reji V, Sathish Kumar V, Murali G, Kurhade AS. Deep learning-based detection and classification of moss and crack damage in rock structures for geo-mechanical preservation. J Mines Met Fuels. 2025 Mar 1;73(3). https://doi.org/10.18311/jmmf/2025/47760
7. Kurhade AS, Siraskar GD, Deshmukh MT, Patil PA, Chaudhari SS, Kadam AA, Dolas AS, Mahajan RG, Waware SY, Yadav RS. Impact of PCM on heat dissipation from IC chips. J Mines Met Fuels. 2025 Mar 1;73(3). https://doi.org/10.18311/jmmf/2025/47522
8. Kurhade AS, Kharat PV, Chougule SM, Darade MM, Karad MM, Murali G, Charwad GA, Waware SY, Yadav RS. Harnessing the power of plastic waste: a sustainable approach to fuel production. J Mines Met Fuels. 2025 Feb 1;73(2). https://doi.org/10.18311/jmmf/2025/47354
9. Sarode GC, Gholap P, Pathak KR, Vali PSNM, Saharkar U, Murali G, Kurhade AS. Edge AI and explainable models for real-time decision-making in ocean renewable energy systems. Sustain Mar Struct. 2025 Jun 24;7(3):17-42. https://doi.org/10.36956/sms.v7i3.2239
10. Chougule SM, Murali G, Kurhade AS. Dynamic simulation and performance evaluation of vibratory bowl feeders integrated with paddle shaft mechanisms. Adv Sci Technol Res J. 2025;19(7). https://doi.org/10.12913/22998624/203873
11. Chougule SM, Murali G, Kurhade AS. Design and analysis of industrial material handling systems using FEA and dynamic simulation techniques. J Sci Ind Res. 2025 Jun 18;84(6):645-53. https://doi.org/10.56042/jsir.v84i6.17512
12. Kurhade AS, Siraskar GD, Raut PN, Dolas AS, Murali G, Dalvi SA, Waware SY, Yadav RS. Investigating the impact of oxygenated additives on exhaust emissions from unleaded gasoline vehicles. J Mines Met Fuels. 2025 Feb 1;73(2). https://doi.org/10.18311/jmmf/2025/47410
13. Siraskar GD, Kurhade AS, Murali G, Prakash MA, Bharathiraja N, Dharmadhikari DD, Waware SY. Turbulence model comparison and optimal geometry identification in trapped vortex combustors: a RANS-based study. Int J Mod Phys C. 2025 Sep 24:2650020. https://doi.org/10.1142/S0129183126500208
14. Keloth Kaithari D, Kaulage A, Ayyappadas MT, Gholap P, Puri A, Bhandari MA, et al. A review of smart AI systems for real-time monitoring and optimization of ocean-based carbon capture, utilization, and storage networks. Appl Chem Eng. 2025 Sep 17;8(3):ACE-5747. https://doi.org/10.59429/ace.v8i3.5747
15. Dhamdhere P, Dixit SM, Tatiya M, Shinde BA, Deone J, Kaulage A, et al. AI-based monitoring and management in smart aquaculture for ocean fish farming systems. Appl Chem Eng. 2025 Sep 17;8(3):ACE-5746. https://doi.org/10.59429/ace.v8i3.5746
16. Keloth Kaithari D, Ayyappadas MT, Goel S, Shahin A, Patil SK, Chaudhari SS, et al. A review on GA-NN based control strategies for floating solar-ocean hybrid energy platforms. Appl Chem Eng. 2025 Sep 15;8(3):ACE-5745. https://doi.org/10.59429/ace.v8i3.5745
17. Khan M, Chuenchart W, Surendra KC, Khanal SK. Applications of artificial intelligence in anaerobic co-digestion: recent advances and prospects. *Bioresource Technology*. Elsevier BV; 2022 Dec 17;370:128501. https://doi.org/10.1016/j.biortech.2022.128501
18. Kabir M, Ekici S. Energy-agriculture nexus: exploring the future of artificial intelligence applications. *Energy Nexus*. 2023 Dec 24;13:100263. https://doi.org/10.1016/j.nexus.2023.100263
19. Olatunji KO, Oladipo S, Madyira DM, Sun Y. Performance evaluation of clustering techniques and parameters of hybrid PSO- and GA-ANFIS for biomethane yield of alkali-pretreated groundnut shells. *Waste and Biomass Valorization*. 2024 Aug 5. https://doi.org/10.1007/s12649-024-02674-2
20. Zheng Y, Larsen OC, Muhayodin F, Hu J, Xue B, Rotter VS. Review of anaerobic digestion models for organic solid waste treatment with focus on C, N, and P cycles. *Energy Ecology and Environment*. 2024 Nov 28. https://doi.org/10.1007/s40974-024-00343-7
21. Chen L, He P, Zhang H, Peng W, Qiu J, Lü F. Applications of machine learning tools for biological treatment of organic wastes: perspectives and challenges. *Circular Economy*. 2024 May 31;3(2):100088. https://doi.org/10.1016/j.cec.2024.100088
22. Gupta R, Zhang L, Hou J, Zhang Z, Liu H, You S, Ok YS, Li W. Review of explainable machine learning for anaerobic digestion. *Bioresource Technology*. Elsevier BV; 2022 Dec 9;369:128468. https://doi.org/10.1016/j.biortech.2022.128468
23. Metwally A, Abo-bakr RM, Ahmed DS. Sustainable methane energy from bagasse treated via bokashi technology: neural network vs mathematical modeling. *Clean Technologies and Environmental Policy*. 2023 Oct 10;26(3):661. https://doi.org/10.1007/s10098-023-02601-4
24. Rutland H, You J, Liu H, Bowman K. Machine learning for FOS/TAC soft sensing in bio-electrochemical anaerobic digestion. *Molecules*. 2025 Feb 27;30(5):1092. https://doi.org/10.3390/molecules30051092
25. Zhang P, Zhang T, Zhang J, Liu H, Chicaiza-Ortiz C, Lee JTE, He Y, Dai Y, Tong YW. Machine-learning-assisted prediction of potential biochar for anaerobic digestion. *Carbon Neutrality*. 2024 Jan 8;3(1). https://doi.org/10.1007/s43979-023-00078-0

26. Osman AI, Nasr M, Farghali M, Rashwan AK, Abdelkader A, Al-Muhtaseb AH, Ihara I, Rooney DW. Optimizing biodiesel production from waste using computational chemistry and machine learning. *Environmental Chemistry Letters*. 2024 Feb 13;22(3):1005. https://doi.org/10.1007/s10311-024-01700-y
27. Achinas S, Quintero M de JD, Euverink GJW. Machine learning in the biogas power industry. *Frontiers in Energy Research*. 2025 Oct 1;13. https://doi.org/10.3389/fenrg.2025.1589782
28. Andiappan V, How BS, Ngan SL. Post-pandemic biomass supply chains: opportunities and challenges. *Process Integration and Optimization for Sustainability*. 2021 Jul 15;5(4):1003. https://doi.org/10.1007/s41660-021-00176-5
29. Nair LG, Verma P. Carbon potential of lignocellulosic biomass and the role of machine learning in biorefineries. *Bioresources and Bioprocessing*. 2025 Sep 13;12(1). https://doi.org/10.1186/s40643-025-00935-z
30. Blay-Roger R, Saif M, Bobadilla LF, Reina TR, Nawaz MA, Odriozola JA. Bioenergy innovations for a sustainable energy future. *Frontiers in Chemistry*. 2024 Jul 30;12. https://doi.org/10.3389/fchem.2024.1416102
31. Ghani WAWAK et al. Sustainable bio-economy achievements in Malaysia. *Food and Bioproducts Processing*. 2019 Sep 17;118:167. https://doi.org/10.1016/j.fbp.2019.09.002
32. Pirotti F, González-Olabarria JR, Kutchartt E. Updating aboveground biomass using satellite data and AI. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*. 2023 Dec 14;1763. https://doi.org/10.5194/isprs-archives-xlviii-1-w2-2023-1763-2023
33. Aal MAMA. Matheuristic approach and a mixed-integer linear programming model for biomass supply chain optimization with demand selection. *International Journal of Industrial Engineering Computations*. 2023 Dec 22;15(1):235. https://doi.org/10.5267/j.ijiec.2023.10.001
34. Li F, Li Y, Novoselov KS, Liang F, Meng J, Ho S, Zhao T, Zhou H, Ahmad A, Zhu Y, Hu L, Ji D, Jia L, Liu R, Ramakrishna S, Zhang X. Bioresource upgrade for sustainable energy, environment, and biomedicine. *Nano-Micro Letters*. Springer; 2023 Jan 11;15(1). https://doi.org/10.1007/s40820-022-00993-4
35. Ahmad I, Sana A, Kano M, Cheema II, Menezes BC, Shahzad J, Ullah Z, Khan M, Habib A. Machine learning applications in biofuels' life cycle: soil, feedstock, production, consumption, and emissions. *Energies*. 2021 Aug 18;14(16):5072. https://doi.org/10.3390/en14165072
36. Ascher S, Watson I, You S. Machine learning methods for modelling gasification and pyrolysis of biomass and waste. *Renewable and Sustainable Energy Reviews*. 2021 Nov 20;155:111902. https://doi.org/10.1016/j.rser.2021.111902
37. Jeon PR, Moon JH, Ogunsola NO, Lee SH, Ling JLJ, You S, Park YK. Recent advances and future prospects of thermochemical biofuel conversion processes with machine learning. *Chemical Engineering Journal*. 2023 Jul 1;471:144503. https://doi.org/10.1016/j.cej.2023.144503
38. Li J, Li L, Tong YW, Wang X. Understanding and optimizing gasification of biomass waste with machine learning. *Green Chemical Engineering*. 2022 May 27;4(1):123. https://doi.org/10.1016/j.gce.2022.05.006
39. Wang C. A novel biomass fluidized bed gasification model coupled with machine learning and CFD simulation. *arXiv*. 2025 Sep 7. http://arxiv.org/abs/2509.06056
40. Kurhade AS, Gadekar T, Siraskar GD, Jawalkar SS, Biradar R, Kadam AA, Yadav RS, Dalvi SA, Waware SY, Mali CN. Thermal performance analysis of electronic components on different substrate materials. J Mines Met Fuels. 2024 Oct 1;72(10). https://doi.org/10.18311/jmmf/2024/45569
41. Kurhade AS, Siraskar GD, Jawalkar SS, Gadekar T, Bhambare PS, Biradar R, Yadav RS, Waware SY, Mali CN. The impact of circular holes in twisted tape inserts on forced convection heat transfer. J Mines Met Fuels. 2024 Oct 16;72(9):1005-12. https://doi.org/10.18311/jmmf/2024/45505
42. Kurhade AS, Bhambare PS, Desai VP, Murali G, Yadav RS, Patil P, Gadekar T, Biradar R, Kirpekar S, Charwad GA, Waware SY. Investigating the effect of heat transfer influenced by wavy corrugated twisted tape inserts in double pipe heat exchangers. J Adv Res Fluid Mech Therm Sci. 2024;122:146-55. https://doi.org/10.37934/arfmts.122.2.146155
43. Kurhade AS, Murali G, Jadhav PA, Bhambare PS, Waware SY, Gadekar T, Yadav RS, Biradar R, Patil P. Performance analysis of corrugated twisted tape inserts for heat transfer augmentation. J Adv Res Fluid Mech Therm Sci. 2024;121(2):192-200. https://doi.org/10.37934/arfmts.121.2.192200
44. Yadav RS, Nimbalkar A, Gadekar T, Patil P, Patil VN, Gholap AB, Kurhade AS, Dhumal JR, Waware SY. Comparison of experimental and numerical investigation of mono-composite and metal leaf spring. J Mines Met Fuels. 2024 Aug 1;72(8). https://doi.org/10.18311/jmmf/2024/45325
45. Kurhade AS, Warke P, Maniyar K, Bhambare PS, Waware SY, Deshpande S, Harsur S, Ingle M, Kolhe P, Patil PA, Jadhav P. Wind rose analysis of temperature variation with sensor implantation technique for wind turbine. J Adv Res Fluid Mech Therm Sci. 2024;122(1):1-8. https://doi.org/10.37934/arfmts.122.1.118
46. Kurhade AS, Siraskar GD, Bhambare PS, Kaithari DK, Dixit SM, Waware SY. Enhancing smartphone circuit cooling: a computational study of PCM integration. J Adv Res Numer Heat Trans. 2024 Nov 30;27(1):132-45. https://doi.org/10.37934/arnht.27.1.132145
47. Kurhade AS, Darade MM, Siraskar GD, Biradar R, Mahajan RG, Kardile CS, Waware SY, Yadav RS. State-of-the-art cooling solutions for electronic devices operating in harsh conditions. J Mines Met Fuels. 2024 Aug 1;72(8). https://doi.org/10.18311/jmmf/2024/45374
48. Yadav RS, Gadekar T, Gundage V, Patil P, Patil A, Patil P, Patil A, Sutar R, Kurhade AS. Numerical and experimental investigation of the effect of overlapping angle on strength and deformation of curved plate joined using arc welding process. J Mines Met Fuels. 2024 Oct 1;72(10). https://doi.org/10.18311/jmmf/2024/45697
49. Kurhade AS, Bhambare PS, Siraskar GD, Dixit SM, Purandare PS, Waware SY. Computational study on thermal management of IC chips with phase change materials. J Adv Res Numer Heat Trans. 2024;26(1):34-43. https://doi.org/10.37934/arnht.26.1.3443
50. Yadav RS, Gandhi P, Veeranjaneyulu K, Gaji R, Kirpekar S, Pawar D, Khairnar YS, Patil S, Kurhade AS, Patil SP. Influence of plate thickness on the mechanical behaviour of mild steel curved plates: an experimental study. J Mines Met Fuels. 2024 Dec 1;72(12). https://doi.org/10.18311/jmmf/2024/46253

51. Chippalkatti S, Chekuri RB, Ohol SS, Shinde NM, Barmavatu P, Shelkande VD, Murali G, Kurhade AS. Enhancing heat transfer in micro-channel heat sinks through geometrical optimization. J Mines Met Fuels. 2025 Mar 1;73(3). https://doi.org/10.18311/jmmf/2025/47773
52. Raut PN, Dolas AS, Chougule SM, Darade MM, Murali G, Waware SY, Kurhade AS. Green adsorbents for heavy metal removal: a study on zinc ion uptake by *Tinospora cordifolia* biocarbon. J Mines Met Fuels. 2025 Jan 1;73(1). https://doi.org/10.18311/jmmf/2025/47121
53. Kurhade AS, Siraskar GD, Bhambare PS, Murali G, Deshpande SV, Warke PS, Waware SY. Simulation and analysis of heat transfer in counter-flow helical double-pipe heat exchangers using CFD. Int J Mod Phys C. 2025 Mar 15. https://doi.org/10.1142/S0129183125500433
54. Patil Y, Tatiya M, Dharmadhikari DD, Shahakar M, Patil SK, Mahajan RG, Kurhade AS. The role of AI in reducing environmental impact in the mining sector. J Mines Met Fuels. 2025 May 1;73(5).
55. Waware SY, Ahire PP, Napate K, Biradar R, Patil SP, Kore SS, Kurhade AS. Advancements in heat transfer enhancement using perforated twisted tapes: a comprehensive review. J Mines Met Fuels. 2025 May 1;73(5). https://doi.org/10.18311/jmmf/2025/48438
56. Chougule SM, Murali G, Kurhade AS. Finite element analysis and design optimization of a paddle mixer shaft. J Mines Met Fuels. 2025 May 1;73(5). https://doi.org/10.18311/jmmf/2025/48664
57. Chougule SM, Murali G, Kurhade AS. Failure investigation of the driving shaft in an industrial paddle mixer. J Mines Met Fuels. 2025 May 1;73(5). https://doi.org/10.18311/jmmf/2025/48627
58. Kurhade AS, Sugumaran S, Kolhalkar NR, Karad MM, Mahajan RG, Shinde NM, Dalvi SA, Waware SY. Thermal management of mobile devices via PCM. J Mines Met Fuels. 2025 May 1;73(5):1313-20. https://doi.org/10.18311/jmmf/2025/48437
59. Kurhade AS, Bhavani P, Patil SA, Kolhalkar NR, Chalapathi KS, Patil PA, Waware SY. Mitigating environmental impact: a study on the performance and emissions of a diesel engine fueled with biodiesel blend. J Mines Met Fuels. 2025 Apr 1;73(4):981-9. https://doi.org/10.18311/jmmf/2025/47669
60. Kurhade AS, Siraskar GD, Chekuri RB, Murali G, Pawar P, Patil AR, Waware SY, Yadav RS. Biodiesel blends: a sustainable solution for diesel engine performance improvement. J Mines Met Fuels. 2025 Mar 1;73(3). https://doi.org/10.18311/jmmf/2025/47628
61. Kurhade AS, Siraskar GD, Darade MM, Murali G, Katkar TR, Patil SP, Charwad GA, Waware SY, Yadav RS. Enhancement in heat transfer with nanofluids in double-pipe heat exchangers. J Mines Met Fuels. 2025 Jan 7;73(1):165-72. https://doi.org/10.18311/jmmf/2025/47225
62. Napte K, Kondhalkar GE, Patil SV, Kharat PV, Banarase SM, Kurhade AS, Waware SY. Recent advances in sustainable concrete and steel alternatives for marine infrastructure. Sustain Mar Struct. 2025 Jun 4:107-31. https://doi.org/10.36956/sms.v7i2.2072
63. Kurhade AS, Chougule SM, Kharat PV, Kondhalkar GE, Murali G, Raut PN, Charwad GA, Waware SY, Yadav RS. Integrated approach to enhance vehicle safety: a novel bumper design with energy-absorbing mechanisms. J Mines Met Fuels. 2025 Jan 1;73(1). https://doi.org/10.18311/jmmf/2025/47168
64. Yadav R, Nimbalkar A, Kirpekar S, Patil PJ, Dalvi SA, Jadhav PA, Kurhade AS, Wakchaure GN. Effect of transformed-induced plasticity steel plate thickness on ultimate tensile strength of butt welded joint using Nd:YAG laser. Int J Veh Struct Syst. 2024;16(6):857-62. https://doi.org/10.4273/ijvss.16.6.08
65. Jalalifar S, Masoudi M, Abbassi R, Garaniya V, Ghiji M, Salehi F. A hybrid SVR-PSO model to predict a CFD-based optimised bubbling fluidised bed pyrolysis reactor. *Energy*. 2019 Nov 7;191:116414. https://doi.org/10.1016/j.energy.2019.116414
66. Wang Z, Mu L, Miao H, Shang Y, Yin H, Dong M. Machine learning prediction of syngas properties in biomass chemical looping gasification using extra trees regression. *Energy*. 2023 Apr 5;275:127438. https://doi.org/10.1016/j.energy.2023.127438
67. Khandelwal K, Dalai AK. Machine-learning-based prediction of gas yields in supercritical water gasification of lignocellulosic biomass. *Molecules*. 2024 May 16;29(10):2337. https://doi.org/10.3390/molecules29102337
68. Kargbo HO, Zhang J, Phan AN. Optimisation of two-stage biomass gasification for hydrogen production via artificial neural network. *Applied Energy*. 2021 Aug 20;302:117567. https://doi.org/10.1016/j.apenergy.2021.117567
69. Marzban N, Psarianos M, Herrmann C, Schulz-Nielsen L, Olszewska-Widdrat A, Arefi A, Pecenka R, Grundmann P, Schlüter O, Hoffmann T, Rotter VS, Nikoloski Z, Sturm B. Smart integrated biorefineries for zero-waste and self-sufficient energy systems. *Biofuel Research Journal*. 2025 Mar 1;12(1):2319. https://doi.org/10.18331/brj2025.12.1.4
70. Parveen F, Slater AG. Digitalisation of catalytic processes for sustainable biobased chemical production. *Catalysis Science & Technology*. 2025 Jan 1. https://doi.org/10.1039/d4cy01525h
71. Cao L, Su J, Saddler J, Cao Y, Wang Y, Lee G, Siang LC, Pinchuk R, Li J, Gopaluni RB. Real-time tracking of renewable carbon content with AI-aided methods for biofeedstock co-processing. *Applied Energy*. 2024 Feb 10;360:122815. https://doi.org/10.1016/j.apenergy.2024.122815
72. Habibi F, Chakrabortty RK, Abbasi A. Addressing uncertainties in biofuel supply chains: a systematic review. *Environmental Science and Pollution Research*. 2023 Sep 2;30(45):100360. https://doi.org/10.1007/s11356-023-29331-w
73. Nneoma UC, Chukwudi OF, Nnenna UJ, Ugwu OPC. Hybrid biofactories integrating microalgae and engineered microbiomes for improved biofuel production. *Frontiers in Energy Research*. 2025 Sep 23;13. https://doi.org/10.3389/fenrg.2025.1654079
74. Sahebi IG, Edalatipour A, Dabaghiroodsari M, Hasheminasab SMH, Masoomi B, Kamali SE. AI-driven transformation of renewable energy supply chains: a strategic roadmap. *Energy for Sustainable Development*. 2025 Feb 8;85:101663. https://doi.org/10.1016/j.esd.2025.101663
75. Srivastava S, Shardeo V, Dwivedi A, Paul SK. Enablers of artificial intelligence for decarbonization in circular supply chains. *Annals of Operations Research*. 2025 Oct 14. https://doi.org/10.1007/s10479-025-06843-x
76. Hao X, Demir E. Artificial intelligence in supply chain decision-making: ESG-related drivers and technological barriers. *Journal of Modelling in Management*. 2023 Jul 13;19(2):605. https://doi.org/10.1108/jm2-01-2023-0009

77. Devarakota P, Tsesmetzis N, Alpak FO, Gala A, Hohl D. AI and the net-zero journey: energy demand, emissions, and transition pathways. *arXiv*. 2025 Jul 14. http://arxiv.org/abs/2507.10750
78. Джусупова Р, Bosch J, Olsson HH. Strategic pathways for AI integration in engineering companies. *Journal of Systems and Software*. 2023 Dec 24;210:111945. https://doi.org/10.1016/j.jss.2023.111945
79. Onunka O, Orikpete OF, Daraojimba C, Fawole AA, Egbokhaebho BA, Gidiagba JO. The role of ICT in climate change mitigation and adaptation. *Ecofeminism and Climate Change*. 2023 Jun 20;4(2):102. https://doi.org/10.26480/efcc.02.2023.102.111
80. Rinchi O, Alsharoa A, Shatnawi I, Arora A. Intelligent transportation systems and AI for energy efficiency and emission reduction. *arXiv*. 2024 Jan 25. http://arxiv.org/abs/2401.14560
81. Oliveira P, Marcondes FS, Duarte MS, Durães D, Gonçalves C, Martins G, Nováis P. Incdualpathnet: a hybrid architecture for predicting energy production in wastewater treatment plants. *Neural Computing and Applications*. 2025 Aug 15. https://doi.org/10.1007/s00521-025-11545-3
82. Hua J, Wang R, Hu YC, Chen Z, Chen L, Osman AI, Farghali M, Huang L, Feng J, Wang H, Zhang X, Zhou X, Yap P. Artificial intelligence for calculating and predicting building carbon emissions: a review. *Environmental Chemistry Letters*. 2025 Mar 21. https://doi.org/10.1007/s10311-024-01799-z
83. Chen L, Chen Z, Zhang Y, Liu Y, Osman AI, Farghali M, Hua J, Al-Fatesh AS, Ihara I, Rooney DW, Yap P. Artificial intelligence-based solutions for climate change. *Environmental Chemistry Letters*. 2023 Jun 13;21(5):2525. https://doi.org/10.1007/s10311-023-01617-y
84. Fang B, Yu J, Chen Z, Osman AI, Farghali M, Ihara I, Hamza E, Rooney DW, Yap P. Artificial intelligence for waste management in smart cities: a review. *Environmental Chemistry Letters*. 2023 May 9;21(4):1959. https://doi.org/10.1007/s10311-023-01604-3
85. Mohanty R, Balachandra P, Dasappa S. Circular economy framework for agro-waste to ethanol-based supply chains in Karnataka, India. *Frontiers in Sustainability*. 2024 Jun 26;5. https://doi.org/10.3389/frsus.2024.1232611
86. Wang H. Integrating machine learning into life cycle assessment: review and future outlook. *PLOS Climate*. 2025 Oct 16;4(10). https://doi.org/10.1371/journal.pclm.0000732
87. Pérez-Almada D, Galán-Martín Á, Contreras M del M, Castro E. Techno-economic and environmental assessment of biorefineries: review and future directions. *Sustainable Energy & Fuels*. 2023 Jan 1;7(17):4031. https://doi.org/10.1039/d3se00405h
88. Hasan MR. AI-enhanced decision-making for sustainable supply chains in the USA. *arXiv*. 2024 Dec 8. http://arxiv.org/abs/2501.10364
89. Wang X, Dong X, Zhang Z, Wang Y. Transportation carbon reduction technologies: fundamentals, applications, and performance. *Journal of Traffic and Transportation Engineering*. Elsevier BV; 2024 Dec 1. https://doi.org/10.1016/j.jtte.2024.11.001
90. Wang Q. Towards zero-emission urban mobility using AI and LCA for targeted interventions. *Building Simulation*. 2024 Oct 1;17(10):1653. https://doi.org/10.1007/s12273-024-1193-7
91. Bencekri M, Kim S, Fan YV, Lee S. Identifying carbon-neutral mobility hubs using artificial intelligence. *Scientific Reports*. 2024 May 29;14(1). https://doi.org/10.1038/s41598-024-62701-z
92. Luo S, Hu W, Huang Q, Chen Z. Prospects of artificial intelligence in low-carbon energy transitions. *Science China Technological Sciences*. 2023 Jun 26;66(7):2158. https://doi.org/10.1007/s11431-022-2329-3
93. Yu S, You L, Zhou S. Optimization modeling and solution methods in renewable energy systems: a review. *Frontiers of Engineering Management*. 2023 Nov 22;10(4):640. https://doi.org/10.1007/s42524-023-0271-3
94. Ayadi R, Forouheshfar Y, Moghadas O. Enhancing system resilience to climate change using artificial intelligence: a systematic review. *Frontiers in Climate*. 2025 Aug 18;7. https://doi.org/10.3389/fclim.2025.1585331
95. Shah M, Wever M, Espig M. Framework for assessing AI potential in the circular bioeconomy. *Sustainability*. 2025 Apr 15;17(8):3535. https://doi.org/10.3390/su17083535
96. Lange L, Skiadas IV, Gavala HN, Jensen AD, Sárossy Z, Thomsen TP, Dam-Johansen K, Meyer AS, Angelidaki İ. Sustainable bioenergy and biofuels innovation challenge. *Research Portal Denmark*. 2018 Jan 1;63. https://local.forskningsportal.dk/local/dki-cgi/ws/cris-link?src=dtu&id=dtu-b1645ffa-393f-4c34-a8fc-2bdbea3c9970
97. Goldenits G, Mallinger K, Raubitzek S, Neubauer T. Reinforcement learning-based digital twins in agriculture: current applications and future directions. *Smart Agricultural Technology*. 2024 Aug 1;8:100512. https://doi.org/10.1016/j.atech.2024.100512
98. Rehan M, Nizami A, Tabatabaei M, Amjad M, Qyyum MA, Javed MH, Al-Muhtaseb AH, Ali AM, Ahmad A, Μουστάκας K, Lam SS, Ali I, Farooq M. Integrated waste biorefineries and sustainable development goals: editorial. *Frontiers in Energy Research*. 2023 Dec 13;11. https://doi.org/10.3389/fenrg.2023.1339666
99. Taware RD, Deshmukh A, Singh C, Rathod N. Magnitude of data science & big data in fitness care. InAIP Conference Proceedings 2025 Feb 14 (Vol. 3162, No. 1, p. 020020). AIP Publishing LLC.
100. Singh C, Khilari S, Taware R. Active Machine-to-Machine (M2M) and IoT Communication Architecture for Mobile Devices and Sensor Nodes. InInternational Conference on Internet of Things and Connected Technologies 2023 Oct 12 (pp. 25-38). Singapore: Springer Nature Singapore.
101. Taware R, Godase M, Singh C. IoT-Enabled Wearable Sensors for Real-Time Stress Monitoring Using Machine Learning Classifiers. InInternational Conference on Internet of Things and Connected Technologies 2024 Sep 27 (pp. 109-122). Singapore: Springer Nature Singapore.
102. Bhambare PS, Kaulage A, Darade MM, Murali G, Dixit SM, Vali PSNM, et al. Artificial intelligence for sustainable environmental management in the mining sector: a review. Appl Chem Eng. 2025 Sep 18;8(3):ACE-5756. https://doi.org/10.59429/ace.v8i3.5756
103. Dharmadhikari DD, Ray A, Shinde BA, Raut SV, Taware RD, Desai S, et al. Machine learning applications in ore grade estimation and blending optimization for modern mining. Appl Chem Eng. 2025 Nov 6;8(4):ACE-5790. https://doi.org/10.59429/ace.v8i4.5790

104. Tatiya M, Darade MM, Shinde BA, Kumbhare MP, Taware RD, Chougule SM, et al. AI applications in tailings and waste management: improving safety, recycling, and water utilization. Appl Chem Eng. 2025 Nov 5;8(4):ACE-5789. https://doi.org/10.59429/ace.v8i4.5789
105. Upadhe SN, Mhamane SC, Kurhade AS, Bapat PV, Dhavale DB, Kore LJ. Water saving and hygienic faucet for public places in developing countries. In: Techno-Societal 2018: Proceedings of the 2nd International Conference on Advanced Technologies for Societal Applications. Vol 1. Cham: Springer; 2019. p. 617-24. https://doi.org/10.1007/978-3-030-16848-3_56
106. Kurhade AS, Siraskar GD, Darade MM, Dhumal JR, Kardile CS, Biradar R, Patil SP, Waware SY. Predicting heat transfer enhancement with twisted tape inserts using fuzzy logic techniques in heat exchangers. J Mines Met Fuels. 2024;72(7):743-50. https://doi.org/10.18311/jmmf/2024/45348
107. Kurhade AS, Siraskar GD, Kondhalkar GE, Darade MM, Yadav RS, Biradar R, Waware SY, Charwad GA. Optimizing aerofoil design: a comprehensive analysis of aerodynamic efficiency through CFD simulations and wind tunnel experiments. J Mines Met Fuels. 2024;72(7):713-24. https://doi.org/10.18311/jmmf/2024/45361
108. Kurhade AS, Kadam AA, Biradar R, Bhambare PS, Gadekar T, Patil P, Yadav RS, Waware SY. Experimental investigation of heat transfer from symmetric and asymmetric IC chips mounted on the SMPS board with and without PCM. J Adv Res Fluid Mech Therm Sci. 2024;121(1):137-47. https://doi.org/10.37934/arfmts.121.1.137147
109. Kurhade AS, Siraskar GD, Bhambare PS, Dixit SM, Waware SY. Numerical investigation on the influence of substrate board thermal conductivity on electronic component temperature regulation. J Adv Res Numer Heat Trans. 2024;23(1):28-37. https://doi.org/10.37934/arnht.23.1.2837
110. Kurhade AS, Waware SY, Munde KH, Biradar R, Yadav RS, Patil P, Patil VN, Dalvi SA. Performance of solar collector using recycled aluminum cans for drying. J Mines Met Fuels. 2024 May 1;72(5). https://doi.org/10.18311/jmmf/2024/44643
111. Kurhade AS, Kardekar NB, Bhambare PS, Waware SY, Yadav RS, Pawar P, Kirpekar S. A comprehensive review of electronic cooling technologies in harsh field environments: obstacles, progress, and prospects. J Mines Met Fuels. 2024;72(6):557-79. https://doi.org/10.18311/jmmf/2024/45212
112. Kurhade AS, Waware SY, Bhambare PS, Biradar R, Yadav RS, Patil VN. A comprehensive study on *Calophyllum inophyllum* biodiesel and dimethyl carbonate blends: performance optimization and emission control in diesel engines. J Mines Met Fuels. 2024;72(5):499-507. https://doi.org/10.18311/jmmf/2024/45188
113. Kurhade AS, Biradar R, Yadav RS, Patil P, Kardekar NB, Waware SY, Munde KH, Nimbalkar AG, Murali G. Predictive placement of IC chips using ANN-GA approach for efficient thermal cooling. J Adv Res Fluid Mech Therm Sci. 2024;118(2):137-47. https://doi.org/10.37934/arfmts.118.2.137147
114. Waware SY, Chougule SM, Yadav RS, Biradar R, Patil P, Munde KH, Kardekar NB, Nimbalkar AG, Kurhade AS, Murali G, Kore SS. A comprehensive evaluation of recent studies investigating nanofluids utilization in heat exchangers. J Adv Res Fluid Mech Therm Sci. 2024;119(2):160-72. https://doi.org/10.37934/arfmts.119.2.160172
115. Kurhade AS, Murali G, Rao TV. CFD approach for thermal management to enhance the reliability of IC chips. Int J Eng Trends Technol. 2022;71(3):65-72. https://doi.org/10.14445/22315381/IJETT-V71I3P208
116. Kurhade AS, Rao TV, Mathew VK, Patil NG. Effect of thermal conductivity of substrate board for temperature control of electronic components: a numerical study. Int J Mod Phys C. 2021 Oct 26;32(10):2150132. https://doi.org/10.1142/S0129183121501321
117. Waware SY, Kore SS, Kurhade AS, Patil SP. Innovative heat transfer enhancement in tubular heat exchanger: an experimental investigation with minijet impingement. J Adv Res Fluid Mech Therm Sci. 2024;116(2):51-8. https://doi.org/10.37934/arfmts.116.2.5158
118. Kurhade AS, Murali G. Thermal control of IC chips using phase change material: a CFD investigation. Int J Mod Phys C. 2022 Dec 28;33(12):2250159. https://doi.org/10.1142/S0129183122501595
119. Rami Reddy S, Murali G, Dhana Raju V. Assessment of diethyl ether as a fuel additive on diesel engine characteristics powered with waste mango seed biodiesel blend. Int J Ambient Energy. 2022 Dec 31;43(1):3365-76. https://doi.org/10.1080/01430750.2020.1824944
120. Emeema J, Murali G, Reddi BV, Mangesh VL. Investigations on paraffin wax/CQD composite phase change material: improved latent heat and thermal stability. J Energy Storage. 2024 Apr 30;85:111056. https://doi.org/10.1016/j.est.2024.111056
121. Rami Reddy S, Murali G, Dhana Raju V. Influence of decanol as fuel additive on characteristics of diesel engine powered with mango seed biodiesel blend. Int J Ambient Energy. 2022 Dec 31;43(1):2875-88. https://doi.org/10.1080/01430750.2020.1783356
122. Tamiloli N, Venkatesan J, Murali G, Kodali SP, Sampath Kumar T, Arunkumar MP. Optimization of end milling on Al-SiC-fly ash metal matrix composite using TOPSIS and fuzzy logic. SN Appl Sci. 2019;1(10):1204. https://doi.org/10.1007/s42452-019-1191-z