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ORIGINAL RESEARCH ARTICLE

Machine Learning Strategies for Enhancing Syngas Quality, Biofuel Stability, and Air Pollution Control in Bio-Energy Plants

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ABSTRACT

Bio-energy plants play a key role in the transition toward low-carbon energy systems, yet their large-scale deployment is constrained by variability in syngas quality, biofuel instability during storage, and fluctuating air pollutant emissions. This review examines how machine learning (ML) methods support improved decision-making across bio-energy value chains by linking multi-source data with predictive and adaptive control strategies. The study synthesizes recent advances in ML-based modelling for syngas composition prediction, biofuel stability assessment, and real-time emission monitoring and mitigation. Emphasis is placed on uncertainty-aware models and hybrid approaches that combine data-driven learning with process knowledge to address feedstock heterogeneity and dynamic operating conditions. The findings show that ML enhances operational efficiency, supports cleaner production, and improves system reliability by enabling proactive control rather than reactive adjustments. From a sustainability perspective, these outcomes directly contribute to SDG 7 (Affordable and Clean Energy) through higher efficiency and reliability of bio-energy systems, SDG 9 (Industry, Innovation, and Infrastructure) by promoting intelligent and resilient industrial processes, SDG 12 (Responsible Consumption and Production) via optimized resource use and reduced waste, and SDG 13 (Climate Action) through lower emissions and improved carbon performance. Overall, the review highlights ML as a practical

decision-support tool for industry and policy stakeholders seeking resilient, data-driven pathways toward sustainable bio-energy deployment.
Keywords: Air Pollution Control, Bio-Energy Plants, Biofuel Stability, Machine Learning, Syngas Quality

1. Introduction

Bioenergy plants are vital renewable energy facilities that process biomass – agricultural residues, municipal waste and energy crops – into useful forms of energy. Main end products such as syngas (carbon monoxide, hydrogen and other gases) and biofuels are generally afflicted by variability caused by feedstock variability and process variations. In addition, PM, NOx, SOx and volatile organic compounds (VOC) emissions represent environmental problems. This challenging demand turns out to require sophisticated analytical and predictive tools that go far beyond the classical control systems [1]. Machine learning and artificial intelligence provide a potential solution for optimizing these complex bioenergy systems, through precise predictions and better optimization of the overall performance since optimal operating conditions are known [2,3]. In particular, ML algorithms might be employed to predict the composition of syngas for various types of biomass feed-stocks and operation settings in order to have a constant quality product suitable for its further use [4,5]. Similarly, ML algorithms can predict fuel stability by considering feedstock properties and processing conditions which in turn inform the necessity of proactive modifications to maintain desired biofuel properties [6]. In addition, implementation of ML in the following uses is increasing: real-time monitoring and predictive control of gas emissions to the atmosphere—also allowing adaptive strategies for compliance and environmental protection [2]. This intercourse leads not only to an increased efficiency in terms of operation but also serves a large part of society's overall objective, which means decarbonizing energy systems by better and sustainable bioenergy production [7]. The adaptability of ML to merge in new evidence renders it a good candidate for optimizing complex bioenergy systems that cannot be solved through conventional approaches [8]. ML is a promising tool for energy efficiency experts who aim to optimize bio refinery systems and the efficiency of bio-waste processing due to its capacity to manage datasets with larger dimensions and identify non-linear relationships complex in nature [8,9]. Further, ML methods can be used to optimize the entire biomass supply chain in order to make better feedstock selection and logistics decisions that can reduce costs and environmental impact [10]. ML designs can also be used to refine real-time process control, while overseeing different operating conditions such as predicting key performance indicators for the bioenergy systems [11]. Such models are especially useful for the production of data that is difficult to measure directly, improving traditional conversion models and compensating shortcomings of classical computing methods when designing and optimizing a bioenergy supply chain [12].

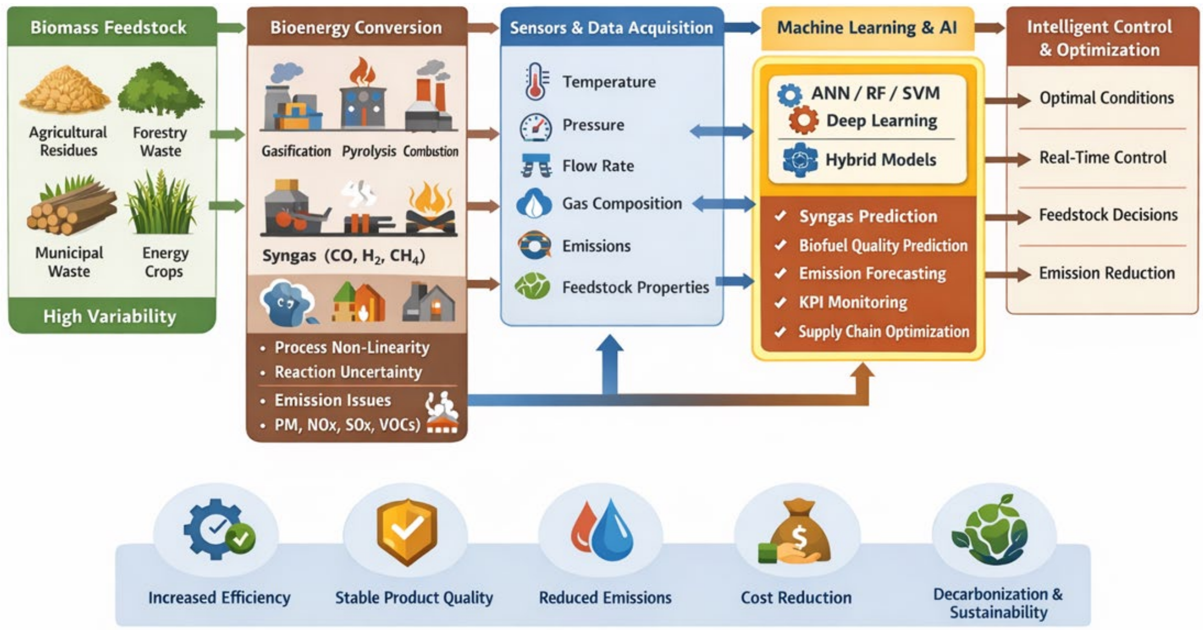

Figure 1. Machine learning–enabled optimization framework for bioenergy plants

Figure 1 illustrates how machine learning integrates biomass feedstock characteristics, real-time sensor data, and bioenergy conversion processes to predict product quality, emissions, and key performance indicators. ML models enable adaptive process control, optimal operating conditions, and improved feedstock selection despite biomass variability. This results in enhanced efficiency, reduced environmental impact, and sustainable bioenergy production. These data-centric methods particularly attractive considering the inherent complexity and high-dimensionality present in biomass engineering tasks, which traditional mechanistic models might fail to capture as complex relationships between inputs and response variables are common [13]. This is especially the case for bio refinery concepts, where ML can contribute to techno-economic assessments, life cycle assessments and reaction kinetics and consequently speed up process development and optimization [9]. On the other hand, since variation in biomass feedstock is an obstacle to bioenergy production [14], ML models predicting the properties of these materials and optimizing conversion processes represent a potential solution. Furthermore, ML and AI provide strategies to deal with differential non-linear dynamics of biomass conversion process leading to the robustness observed in the designs and optimization as well as in intensified reactor setups [2]. Machine learning enables researchers to accelerate the production of advanced biofuels made directly from non-food biomass (i.e., crop residues, leaves, forestry and agricultural waste) or algae while also improving existing bio refineries through a higher-fidelity process modelling and multi-objective optimization [6, 13]. Moreover, ML applications offer broad prospects to alleviate challenges due to non-linear effects, large errors in complex reaction dynamics which are frequently encountered when using the traditional design of experiment toolset such as ANOVA and RSM [15].

Machine Learning (ML) appears to be a promising approach that can address these challenges by analysing massive collections of data from sensors and process control systems to optimize operations in near-real-time, forecast product quality output, and anticipate emissions control measures. This integration enables an adaptive and predictive control approach from being reactive modifications to active optimizations throughout the whole bio-energy production chain [9,16]. Predicting product yield and composition, kinetic parameters and calorific values represent typical ML applications that can remarkably improve thermochemical biofuel conversion processes by modelling complex relations and identifying best conditions [17]. Such a predictive ability is of great importance especially in the presence of biomass heterogeneity, which can have detrimental effects on process performance and product quality [13]. E.g., ML models can deduce optimal process conditions which, for example, ensure a stable and efficient biofuel production even under different biomass feed inputs [17].

Table 1. Applications of Machine Learning in Bioenergy Plants

Aspect	Description	Key Outcomes / Benefits
Biomass Feedstock Variability	Heterogeneous agricultural residues, municipal waste, and energy crops	Improved handling of variability compared to classical models
Syngas Composition Prediction	Prediction of CO, H_2, and gas composition under different conditions	Consistent syngas quality
Biofuel Quality & Stability	Prediction based on feedstock and processing parameters	Proactive quality control
Emissions Monitoring & Control	Real-time prediction of PM, NOx, SOx, VOC emissions	Regulatory compliance and reduced impact
Process Optimization	Adaptive ML-driven control using sensor data	Higher efficiency and optimal operation
KPI Prediction	Estimation of yield, efficiency, calorific value	Improved decision-making
Supply Chain Optimization	Feedstock selection and logistics optimization	Cost reduction and lower environmental footprint
Bio-refinery Design	Techno-economic and life cycle analysis	Faster development and optimization
Non-linear Dynamics Handling	Modelling complex biomass conversion relationships	Greater robustness than ANOVA/RSM
Advanced Biofuel Production	Conversion of non-food biomass and algae	Sustainable fuel pathways
Data-Driven Modelling	High-dimensional sensor and process data utilization	Improved prediction accuracy
Decarbonization Support	System-wide optimization of bioenergy production	Reduced carbon footprint

Table 1. (*Continued*)

Table 1 summarizes the key applications of machine learning in bioenergy plants, highlighting how ML addresses biomass variability, process complexity, and emissions control. It shows ML's role in predicting syngas and biofuel quality, optimizing process operations, and improving supply chain decisions. Overall, the table demonstrates how ML enhances efficiency, sustainability, and decarbonization of bioenergy systems.

The bio-energy plants suffer for their part of the benefit from problems due to feed-stock variation, fluctuating syngas quality, degradation of biofuel and variations in pollutant emissions that hinder an overall effective performance on a large scale. The nonlinear dynamics of these processes are not well captured by traditional control methods. There is a need for an integrated, data-driven viewpoint on how the various challenges described above can be tackled using machine learning. This paper provides a comprehensive systematic review and synthesis of the use of machine learning models to improve syngas quality, increases biofuel stability, and methods for air pollution control by critically examining modeling techniques compared with their appliance in facilitating real-time decision support. It also points out critical research gaps and future trends towards robust, uncertainty-aware and operationally reliable bio-energy systems.

2. Syngas quality improvement using machine learning

The production of synthesis gas (syngas), a mixture of hydrogen (H_2), carbon monoxide (CO), carbon dioxide (CO_2), methane (CH_4), and trace gases, is central to energy and chemical processes. The quality of syngas, defined by its composition, calorific value, and impurities, directly affects downstream efficiency in applications such as power generation, fuel synthesis, and chemical manufacturing. Machine learning (ML) offers advanced methods to predict, monitor, and optimize syngas production in real-time, addressing variability caused by feedstock and operational factors. **Figure 2** illustrates how machine learning models integrate feedstock properties and gasifier operating parameters to predict syngas composition, calorific value, and impurity levels. Advanced ML techniques enable real-time optimization of gasification conditions to stabilize H_2/CO ratios and reduce tar formation despite feedstock variability. The resulting improvement in syngas quality enhances downstream energy, fuel synthesis, and chemical production efficiency.

2.1. Challenges in Syngas Production

Syngas characteristics are governed by feedstock properties and gasifier operating conditions. Variations in biomass type, moisture content, and elemental composition influence gasification behaviour and calorific value. Operating parameters such as temperature, pressure, residence time, and gasifying agent affect key reactions, including the water–gas shift and methanation, thereby controlling H_2 and CO concentrations [18,19]. Design aspects such as bed height and particle size further add to compositional variability. These fluctuations pose challenges for downstream uses like CHP and Fischer–Tropsch synthesis, which demand stable syngas quality [7]. To address feedstock heterogeneity and process complexity, machine learning approaches are increasingly applied to predict syngas composition and assist in operational control and early decision-making [20].

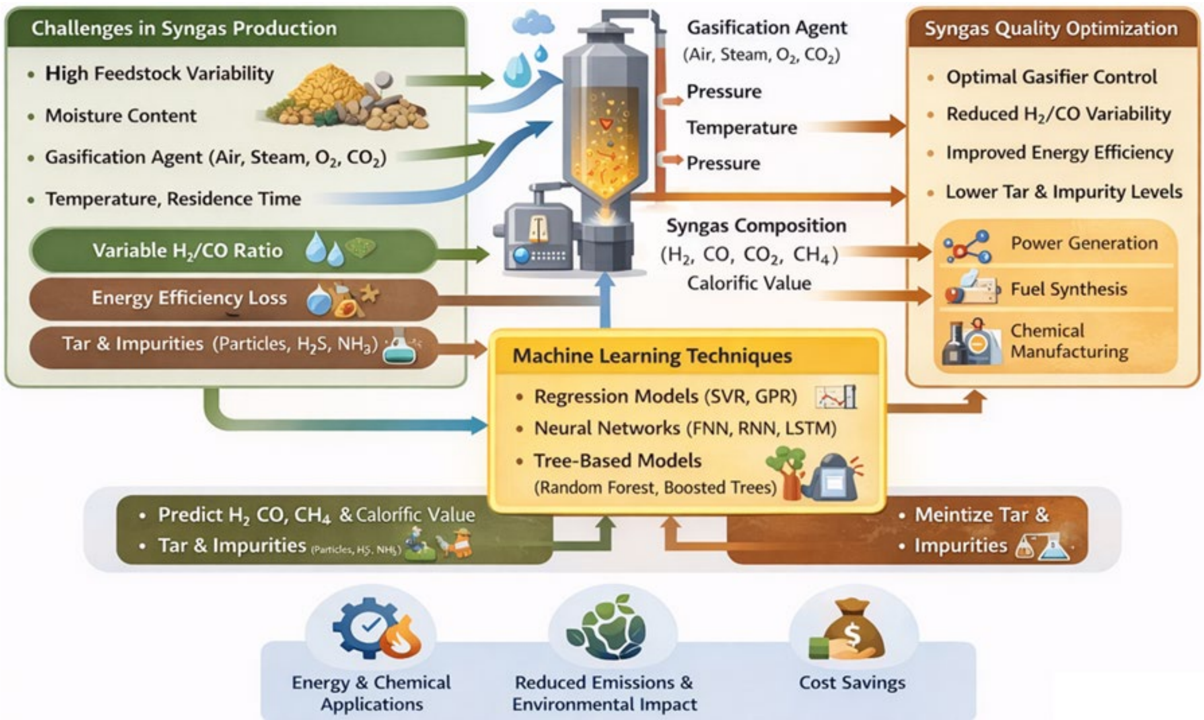

Figure 2. Syngas quality improvement using machine learning–based optimization

2.2. ML Techniques for Optimization

Machine learning (ML) offers effective tools for modelling and optimizing complex biomass gasification processes. Regression-based methods such as linear regression, support vector regression (SVR), and Gaussian process regression (GPR) are widely applied to predict syngas composition from operating variables. SVR is effective in capturing nonlinear relationships, while GPR provides uncertainty estimates that support reliability assessment of predictions [22,23]. Neural networks, including deep learning models, can learn complex patterns in high-dimensional data and accurately predict syngas quality parameters, including hydrogen content and tar reduction trends. Ensemble models such as Random Forests and boosted trees improve prediction stability and accuracy under noisy bioenergy data conditions and have shown strong performance in modelling solar-driven and biomass gasification processes [22]. Advanced approaches, including hybrid ML models and reinforcement learning, further enable adaptive control by adjusting operating conditions in real time, ensuring stable syngas quality under feedstock variability and process disturbances [24–27].

2.3. Case Study Example

The utility of ML for optimization was demonstrated on a pilot biomass gasification plant. The plant measured information on feedstock moisture, particle size, gasifier temperature, pressure and airflows. A feedforward neural network model based on 16 features for hydrogen content prediction with an accuracy of 95% was developed. Based on these predictions, the operators rescaled the gasifier operating temperature and coal feed rates without shutting down the system, to stabilize H_2 and CO levels and decrease tar formation by 20%. This improvement in syngas quality control led to a positive impact on the downstream catalytic steps, played an important role on energy efficiency and illustrated that ML can be integrated with syngas engineering.

Table 2. Syngas Quality Improvement Using Machine Learning

Category	Key Aspects	Machine Learning Role	Outcomes / Benefits
Syngas Characteristics	H_2, CO, CO_2, CH_4 composition, calorific value, impurities	Prediction and monitoring of syngas quality parameters	Improved efficiency in power generation and fuel synthesis
Feedstock Variability	Biomass type, moisture, lignin and volatile content	Handling heterogeneous and high-dimensional data	Stable syngas quality under variable feedstock
Operating Conditions	Temperature, pressure, residence time, gasifying agent	Modeling nonlinear operational effects	Optimized H_2/CO ratio and higher energy content
Gasifier Design Factors	Bed height, particle size, reactor configuration	Data-driven prediction beyond mechanistic models	Robust control of syngas composition
Syngas Production Challenges	Tar formation, fluctuating composition, impurities	Early deviation detection and corrective actions	Reduced tar and improved catalyst performance
Regression Models	Linear regression, SVR, GPR	Prediction with uncertainty estimation	Reliable syngas quality forecasting
Ensemble & Tree-Based Models	Random Forest, Boosted Trees, Extra Trees	Accurate nonlinear modeling of noisy data	High prediction accuracy (R^2 > 0.92)
Neural Network Models	FNN, RNN, LSTM, deep learning	Learning complex and dynamic gasification behavior	Accurate steady-state and time-series prediction
Hybrid Optimization Models	GA-ANN, Bayesian optimization	Hyperparameter tuning and multi-objective optimization	Improved prediction and tar suppression
Reinforcement Learning	Adaptive control of temperature, feed rate, airflow	Model-free real-time optimization	Autonomous and stable syngas quality control
Case Study Example	Pilot biomass gasification plant with 16 inputs	ANN predicted H_2 with 95% accuracy	20% tar reduction and stabilized H_2/CO ratio

Table 2 summarizes how machine learning techniques are applied to predict, monitor, and optimize syngas quality under variable feedstock and operating conditions. It highlights the role of advanced ML models in improving H_2/CO ratios, reducing tar formation, and enhancing overall gasification efficiency.

3. Enhancing biofuel stability

Biofuels, including biodiesel, bioethanol, and other biomass-derived fuels, are increasingly important for sustainable energy production. However, maintaining their **stability during storage and use** is a significant challenge. Biofuel degradation can reduce energy content, affect engine performance, and increase maintenance costs. Machine learning (ML) offers innovative solutions for predicting, monitoring, and mitigating biofuel instability, improving reliability and shelf life.

3.1. Biofuel stability issues

The stability of a biofuel involves several chemical and biological reactions. The most important issue is oxidation: in the case of biodiesel, due to the presence of double bonds in the fatty acid chains which react with oxygen by developing peroxides and acids causing fuel deterioration. Phase separation can also occur when bioethanol is mixed with water or when biodiesel is separated from glycerol or other impurities, decreasing uniformity and causing difficulty in burning. Moreover, fuel quality can be compromised by microbial contamination that results in growth of biofilm and acid product under wet conditions within storage tanks. These instabilities result in reduced storage life, and also affect engine operation indicating the necessity for adaptive monitoring and control regimes. To overcome these challenges, ML could study the composition of the fuel, storage conditions, environmental impact to predict degradation kinetics and key parameters affecting stability. In this research, with the help of different ML models like Random Forest (RF), XGBoost (XGB) and Support Vector Machines (SVMs), biodiesel parameters and fatty acid profile are effectively predicted which are important oxidative stability indicators [6]. This predictive ability can lead to strategies for improved stability, e.g. optimization of antioxidant doses and storage conditions [15,28]. In addition, ML algorithms can discover new additives and blending strategies to improve the stability of biofuels from huge datasets on chemical properties and degradation pathways [2]. Additionally, bio-oil instability due to high moisture, oxygen and carbonyl content requires advanced stabilization and hydro-deoxygenation processes that may be improved through use of ML for prediction of quality as a function of biomass type and reaction conditions leading to a predictable fuel character [29].

3.2. ML approaches

Machine learning provides several approaches to address biofuel stability challenges:

3.2.1. Predictive modelling

ML models can predict degradation of biofuels with input parameters storage temperature, humidity, feedstock composition and concentrations of stabilizing additives. Regression algorithms, neural networks, or other ensemble models process historical and in-the-moment data to predict oxidation rates, phase separation risks or the likelihood of microbial growth to trigger pre-emptive interventions before quality suffers. For example, through computational chemistry degradation pathways can be defined and inform the development of protective agents as well as enhanced storage protocols [30]. This enables the creation of quantitative structure property relationships using ML methods to predict oxidative stability as a function of molecular structure, thus speeding the design and development of new stable biofuel formulations [31]. In addition, ML models, such as Random Forest and Support Vector Regression have been successfully used to predict the main fuel properties (flash point, density and viscosity) when it comes to evaluating the quality of both fuels and their stability [32].

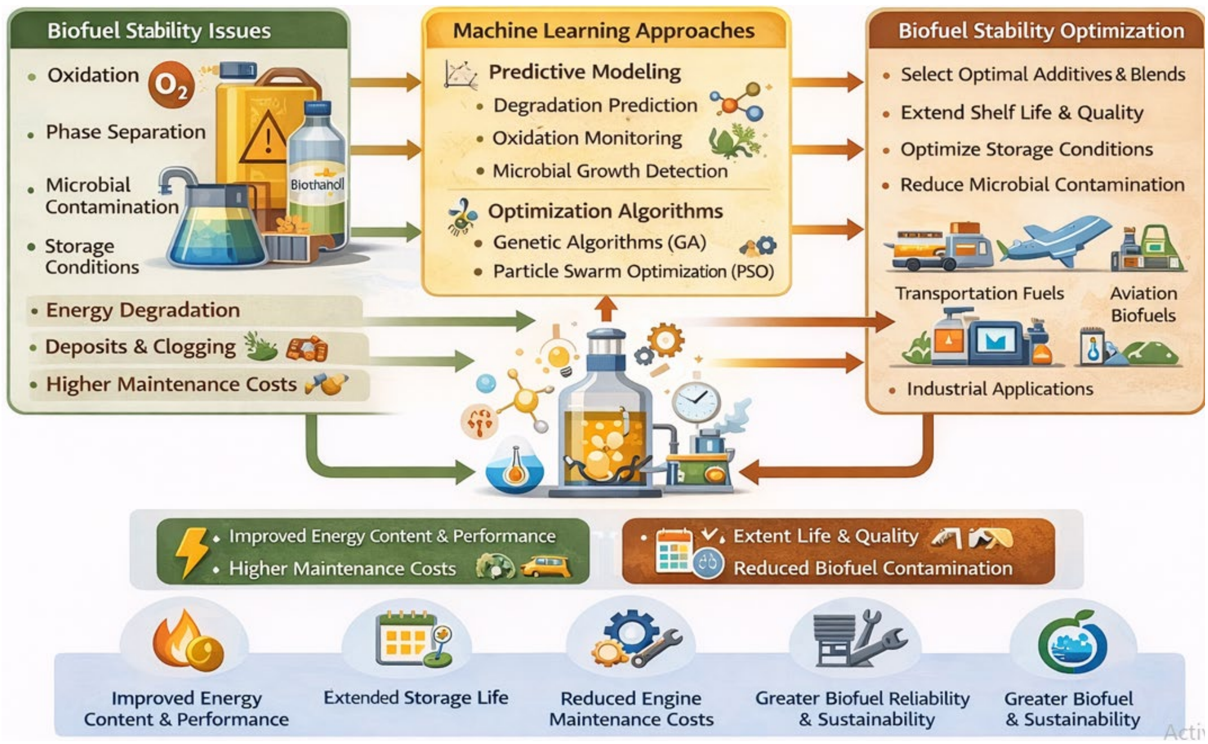

Figure 3. Enhancing biofuel stability using machine learning–based prediction and optimization

Figure 3 presents how machine learning techniques are applied to predict biofuel degradation mechanisms such as oxidation, phase separation, and microbial contamination. ML-based predictive, optimization, and anomaly-detection models enable proactive control of additives, blending ratios, and storage conditions. These strategies significantly extend biofuel shelf life, improve fuel quality, and reduce maintenance and operational costs.

3.2.2. Optimization algorithms

Genetic algorithm (GA) and particle swarm optimization (PSO) can be employed to generate the optimal biofuel blend with stabilizing additives. Through simulating a number of feedstock ratios and additive types – these algorithms optimize crude formulations for two contradicting hardness, that is, maximum oxidative stability with the minimum separation (jointly with desirable combustion properties). Such models can accommodate system parameters (alcohol/oil molar ratio, catalyst weight, and reaction temperature, mixing intensity) to predict predominance metrics such as fatty acid methyl ester content, fuel viscosity and heating value leading to holistic optimization [30]. Such optimization can be further improved using the state-of-the-art ML methods such as CatBoost method which effectively deals with categorical features and overfitting to generate better biodiesel making recommendations [15]. Also, machine learning together with metaheuristic optimization have demonstrated to be very effective to calibrate dual-injection engines optimized for both bio-fuel performance and stability [33]. This simultaneous strategy is used to determine the best operation conditions and fuel formulations with acceptable levels of nitrogen species, for long term stability and high combustion efficiencies [6, 34]. Furthermore, it is possible to estimate the engine performance for biofuel blends using ANN methods and hybrid models can be used to accurately predict the engine behavior and model triple-blended biofuel-based engines with high accuracy, thus also introduce stability and efficiency in the biofuels [6,28].

3.2.3. Anomaly detection

Unsupervised features, such as clustering and auto encoders, identify early indicators for biofuel decay. By on-line monitoring chemical and physical parameters, these models detect deviations with respect to the "normal" behavior, thus allowing timely remedial actions such as addition of antioxidants or changes in storage conditions. This pre-emptive response reduces fuel waste and protects against equipment damage due to deteriorated biofuels. The marriage of machine learning and biofuel production, storage will provide a powerful tool for improved stability/fuels prediction/optimization of the fuel compositions as discussed in this work, responding to the urgent needs for bio-energy sustainability [6, 30]. Other than stability, machine learning is also important for biofuel production process optimization especially in transesterification where models predict biodiesel yield as a function of catalyst type and reaction conditions [30]. Particularly, supervised learning algorithms are widely employed in predicting biodiesel yield and optimizing production parameters, which provides an obvious route for further improving process efficiency and product quality [15,32].

3.3. Practical applications

In applications, monitoring systems enhanced by ML provide a better control over biofuel quality when compared to the regular sample-based analysis. For example, the predictive models can warn the staff when oxidations are getting close to a prescribed threshold value which may require antioxidant additives. Fuel life could similarly be extended based on recommendations for optimal additive packages by optimization algorithms. ML algorithms can increase the shelf life of biofuels by 20–30%, decrease occurrences of phase separation, and reduce microbial contamination risks. These upgrades provide better storage and handling as well as excellent engine operation and less maintenance.

Table 3. Enhancing Biofuel Stability Using Machine Learning

Aspect	Description	Machine Learning Techniques	Key Outcomes / Benefits
Biofuel Types	Biodiesel, bioethanol, bio-oil, and other biomass-derived fuels	Data-driven analysis of fuel properties	Improved reliability and shelf life
Biofuel Stability Issues	Oxidation, phase separation, microbial contamination, moisture effects	ML-based degradation prediction models	Reduced fuel degradation and quality loss
Oxidative Degradation	Reaction of unsaturated fatty acids with oxygen forming peroxides and acids	RF, XGBoost, SVM for oxidative stability indicators	Enhanced oxidative resistance and energy content retention
Phase Separation	Water contamination and impurity separation	ML prediction using composition and storage data	Improved fuel uniformity and combustion performance
Microbial Contamination	Biofilm formation and acid production in storage tanks	Classification and anomaly detection models	Reduced microbial growth and maintenance costs
Predictive Modelling	Prediction of degradation kinetics and fuel properties	Regression models, ANN, SVR, ensemble learning	Early intervention before quality deterioration
Molecular-Level Prediction	Structure–property relationship analysis	Computational chemistry + ML (QSPR models)	Faster development of stable biofuel formulations
Fuel Property Prediction	Flash point, density, viscosity, heating value	Random Forest, Support Vector Regression	Improved assessment of fuel quality and stability
Optimization of Additives	Selection and dosing of antioxidants and stabilizers	GA, PSO, CatBoost	Optimal balance between stability and performance
Blend Optimization	Optimization of feedstock and additive ratios	Metaheuristic optimization + ML models	Reduced phase separation and improved combustion
Engine Performance Optimization	Calibration for stable biofuel combustion	ANN and hybrid ML models	Higher combustion efficiency and long-term stability
Anomaly Detection	Detection of early signs of degradation	Clustering, autoencoders (unsupervised ML)	Reduced fuel waste and equipment damage
Storage & Monitoring	Real-time monitoring of chemical and physical parameters	ML-enabled predictive monitoring systems	Proactive quality control

Aspect	Description	Machine Learning Techniques	Key Outcomes / Benefits
Practical Impact	Industrial storage and engine applications	Integrated ML-based decision support systems	20–30% increase in biofuel shelf life

Table 3. (*Continued*)

The **table 3** summarizes how machine learning enhances biofuel stability by predicting and mitigating degradation mechanisms such as oxidation, phase separation, and microbial contamination. It highlights ML techniques like regression models, neural networks, ensemble methods, and optimization algorithms used for monitoring, additive selection, and blend optimization. Overall, these approaches improve fuel reliability, extend shelf life by 20–30%, and ensure better engine performance and reduced maintenance.

4. Air pollution control

Air pollution is a significant concern in bio-energy production, as biomass and other feedstock combustion can release harmful pollutants into the atmosphere. Controlling emissions such as nitrogen oxides (NOx), sulfur oxides (SOx), carbon monoxide (CO), and particulate matter is essential to protect human health, comply with environmental regulations, and reduce the environmental footprint of bio-energy plants. Machine learning (ML) has emerged as a valuable tool to **predict, monitor, and mitigate emissions** in real-time, addressing the variability and complexity inherent in bio-energy systems. **Figure 4** illustrates how machine learning models integrate real-time operational and environmental data to predict and control emissions such as NOx, SOx, CO, particulate matter, and VOCs. ML-based predictive, optimization, and fault-detection strategies enable adaptive process control and early mitigation of emission peaks. These approaches ensure regulatory compliance while improving energy efficiency and reducing environmental and health impacts.

4.1. Emission challenges

There are several complexities when it comes to emission control in bio-energy plants. The feedstock composition varies which in turn affects the combustion temperature, reaction kinetics and pollutant formation. Environmental operation conditions as those of the air- to-fuel mixture, temperature and pressure also affect NOx, SOx, CO, and particle? emission rates. In addition, since process dynamics such as start-up, load change and transients may lead to emission peaks that are hard to be forecasted and managed. Conventional control approaches are sometimes based on predetermined set-point values or periodic sampling, which in practice may be too slow to respond for efficiency reasons or regulatory constraints. Here the machine learning predictions are indispensable, allowing real-time adaptations and an active emission control [2,8]. The innovative concept enables bio-energy plants to ensure optimal result in emissions also during varying load, which enhances both environmental compliance and process efficiency. Through the mining of data points pertaining to input and output operating parameters, ML (machine learning) algorithms can pick up on complex relationships between them that affect pollutant formation in a manner more sophisticated than traditional statistical analysis, resulting in finer control [6]. Also, ML may connect with Geographic Information Systems (GIS) to locate and monitor polluted sites better, leading to an efficient bioremediation, resource use of land for sustainable biomass production [6,35]. Highly accurate models to predict emissions of pollutants in general and NOx in particular are essential for meeting environmental standards, which are evermore restrictive [36].

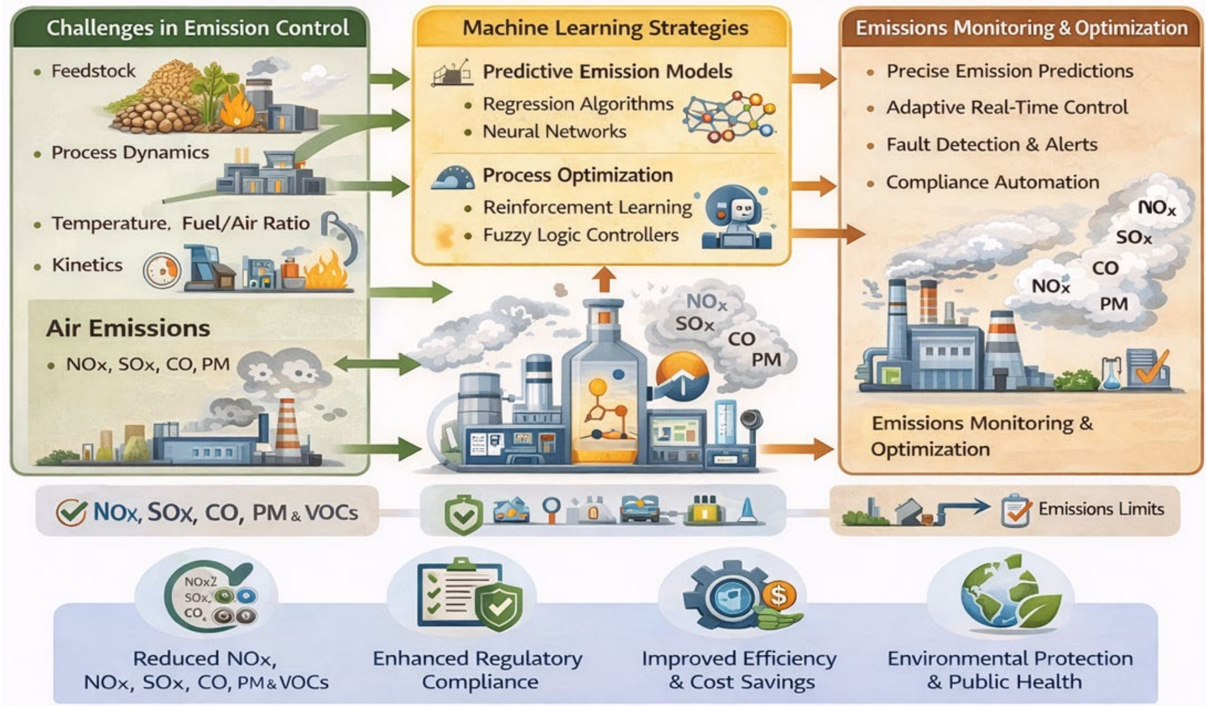

Figure 4. Machine learning–based air pollution control and emission optimization in bioenergy plants

4.2. ML-based strategies

Machine learning provides advanced solutions to monitor and control emissions effectively:

Predictive Emission Models: Regressions, neural networks, and ensemble methods can anticipate the concentrations of pollutants based on live operational data including temperature, airflow, and feedstock characteristics. By predicting such emission spikes, operators can take pre-emptive measures to alter combustion or gasification conditions in order to minimize pollutant formation before it happens. This anticipatory strategy can be used to dynamically vary parameter settings (e.g. air-fuel ratio) for keeping emissions within legal limits, especially of key pollutants such as NOx [37]. Although such models have been widely used for NOx prediction in coal-fired power plants and diesel engines, the application of these models to biochar production is a new adaptation for which there is also lack of recent literature [37]. Additionally, such models can incorporate ambient measurements ranging from physical sensor readings to environmental conditions, giving a holistic understanding of emission dynamics and detailed predictive powers.

Process Optimization: RL and fuzzy logic controllers provide dynamic control approaches to adjust operating parameters so as to maximize the reduction in emissions. RL agents are responsible for forming best control recommendations through interactions with the plant environment, nonlinearity and uncertainty of emission behavior are addressed by fuzzy logic systems. The approaches described herein allow real-time adjustment of emissions while maintaining high energy efficiency. Likewise, ML can predict the optimal parameters for biochar production in order to minimize NOx for instance, a use case where RF have shown themselves effective in prediction and mitigation of these pollutants as they provide models that simulate the physics of pyrolysis machines [38–41].

Fault Detection: ML algorithms can find out early indications of anomalous equipment conditions, including clogging filters, broken scrubbers and malfunctioning sensors among others. Early diagnosis is useful to avoid uncontrolled emissions, less maintenance cost, and comply with environmental laws. Approaches like anomaly detection and clustering are especially useful for the monitoring equipment health and operation anomalies. Such models are able to recognize departures from a so-called "normal" operating condition by examining multivariate time series data from different sensors, alerting operating staff prior to issues developing into major emission events. Further, in applications such as pollution control, deep learning models (e.g., Convolutional Neural Network and Transformer) can predict and even proactively curb the spread of pollution by integrating data from various relevant sources [42-50]. For example, Gradient Boosting Machines have been successfully employed to predict NOx produced by industrial boilers [51-53] which suggests a potential for similar application in bio-energy systems. Moreover, these machine-learned models can predict crucial system-level performance parameters and provide a platform for real-time prediction while isolating important P as to GHG reduction through Causal Impact Analysis [54-62]. AI-power prescriptive analytics can provide even higher reduction in emissions from the identification of trade-offs between environmental impact and operation cost, resulting in actionable intelligence for plant operators to realise an optimal balance [63-65].

4.3. Real-world implementation

The ML based applications in the field of emission control have successfully been used with proven advantages. For example, an ML-based emission prediction system was developed for a biomass-fired power plant in which real-time operational parameters were used to project the NOx concentration. Through proactive optimization of combustion conditions 15% reduction in NOx level was accomplished with constant energy efficiency of the plant. These data-driven methodologies demonstrate that ML can successfully narrow the gap between environmental compliance and operational performance, thereby yielding economic as well as ecological benefits. This change from conventional based approach to intelligent emission management process innovates environmental benefits and sustainable appeal of bio-energy facilities in the long-term perspective [66-76]. Moreover, continued progress in ML including fusion with advanced deep learning models and RL bodes well for improved accuracy of prediction and control in a wide range of pollutants beyond just typical NOx and SOx but PM as well (PM1, PM2.5, PM10), VOCs [77-84]. The use of ensemble methods based on trees, like gradient boosting, can help to improve predictive emissions monitoring systems beyond the "black box" character present in classical artificial neural networks and provide more interpretable models for regulatory compliance and decision making [85-90]. In addition, machine learning models are capable of handling big data to forecast pollutant concentration and spatio-temporal variability, which can be used to devise efficient intervention programs for urban air quality control [91-98].

Table 4. Machine Learning Applications for Air Pollution Control in Bio-Energy Plants

Focus Area	Key Challenges / Aspects	Machine Learning Approaches	Outcomes and Benefits
Emission monitoring and mitigation	NOx, SOx, CO, PM, and VOC emissions due to feedstock and process variability	Real-time predictive modeling, adaptive control algorithms	Regulatory compliance, reduced environmental and health impacts
Emission variability and complexity	Feedstock composition changes, combustion conditions, transient operations	Supervised ML, data mining, GIS-integrated ML systems	Accurate emission prediction and improved process stability
Emission forecasting	Uncertainty in emission spikes during dynamic operation	Regression models, ANN, ensemble learning	Early prediction of NOx, SOx, CO, and PM levels
Emission reduction with efficiency	Balancing emission control and energy performance	Reinforcement learning, fuzzy logic controllers, random forest	Dynamic optimization with reduced emissions and stable efficiency
Equipment and sensor health	Hidden faults causing sudden emission peaks	Anomaly detection, clustering, CNN, transformer models	Early fault detection and prevention of emission events
Industrial-scale validation	Integration with existing plant control systems	ML-based real-time emission control platforms	Demonstrated NOx reduction and long-term sustainability

The **Table 4** summarizes how machine learning supports air pollution control in bio-energy plants by addressing emission variability, process complexity, and equipment reliability. It shows the role of ML in predictive emission modeling, real-time process optimization, and early fault detection to control NOx, SOx, CO, particulate matter, and VOCs. Overall, the table highlights that ML-based approaches improve regulatory compliance, reduce environmental impact, and maintain energy efficiency under dynamic operating conditions.

5. Integration and future prospects

The integration of machine learning (ML) with advanced sensing and control technologies is paving the way for the next generation of bio-energy plants. By combining Internet of Things (IoT) sensors, automated control systems, and predictive ML models, it is possible to create **"smart" bio-energy plants** that optimize fuel conversion efficiency, maintain biofuel stability, and minimize emissions in a unified system. These integrated approaches enable real-time monitoring, predictive maintenance, and adaptive control, resulting in higher operational efficiency, reduced environmental impact, and more reliable energy production.

5.1. Smart bio-energy plants

Intelligent bio-energy plants rely on IoT sensors, for instance, for the continuous monitoring of feedstock composition, gasifier or combustion working conditions, biomass storage characteristics and emission levels. ML analyses this data for prediction of syngas quality, video biofuel degradation detection and real-time pollutant concentration forecast to allow pro-active adaptation. Robotic control systems subsequently carry out these corrections online in real time, optimizing performances on the fly. For instance, feed rates, temperature and additive dosage can be adjusted to optimize hydrogen yield or discourage oxidation in biodiesel, or NOx formation -- all without human intervention. The fusion of IoT, ML and automation here is acting as a paradigm to move away from rule-of-the-thumb big book e.g. adaptive bio energy plants being completely driven by data. Sense-reason-act intelligent systems go further than react and control, using predictive analytics to sense future operational and environmental conditions allowing pre-emptive changes that can improve overall plant performance and sustainability [99-105]. Such feedback loop allows self-optimization by learning from its experience to optimize control strategies and respond to dynamic changes of operating conditions and feedstock properties [106-110]. More studies could potentially improve the existing AI models by exploring more advanced machine learning algorithms, like XGBoost or support vector machines, to increase the accuracy and performance of biochar safety assessment [111-115]. Furthermore, the smart grid integration with bioenergy systems enables effective control in managing electricity demand and supply, stabilizing the grid operation and increasing optimizing bioenergy generation and delivery [116-120]. This symbiosis of smart grids and bioenergy plants also supports the integration of various renewable energy resources leading to a more robust and sustainable energy system. Smart integrated bio refineries under process: The introduction and subsequent integration of smart into the existing bio refinery infrastructure makes extensive use of machine learning, digital twins and decision-support systems to ensure optimal resources efficiency, flexibility towards market demands and rapid commitment towards a low-carbon economy [121-125].

5.2. Challenges and opportunities

However, there are also several challenges related to the realization of smart bio-energy plants, although the potential appears to be high. Quality of the data is paramount – ML models need sensor data to make predictions, and the higher frequency (quality), the better. Model generalization is also an issue as ML models should work robustly with different feedstocks types, seasonal biomass variations and varying operations. It is necessary to design ML-based control strategies that respects environmental norms, safety standards and best practices in industry that govern regulatory compliance.

But despite the roadblocks, there are also major opportunities. Hybrid ML approaches, which integrate first-principle processes models and data driven performances for reliability and interpretability are expected to receive more attention in further research. Real-time adaptive control schemes, exploiting digital twins of bio-energy plants, may replicate and test scenarios of plant operations before applying them on-line to the real system. These advances may potentially also promote the faster move towards fully autonomous high efficiency low emission bio-energy plants, making ML one of the key enabling technologies for sustainable energy generation.

6. Conclusion

This review has critically examined the role of machine learning in addressing three persistent challenges in bio-energy plants: variability in syngas quality, instability of biofuels, and control of air pollutant emissions. Across gasification, fuel processing, storage, and combustion stages, the evidence shows that data-driven models provide clear advantages over conventional control and optimization methods, particularly in handling nonlinear behavior, feedstock heterogeneity, and dynamic operating conditions. Machine learning models enable accurate prediction of syngas composition and calorific value, supporting stable downstream energy conversion and chemical synthesis. In parallel, predictive and optimization-based approaches for biofuel stability allow early identification of degradation risks and informed selection of additives, blends, and storage conditions, leading to longer shelf life and improved fuel reliability. The application of ML to emission monitoring further demonstrates its value in real-time prediction and mitigation of NOx, SOx, CO, and particulate matter, allowing proactive compliance with environmental regulations while maintaining energy efficiency. When integrated with IoT sensing, automation, and advanced control systems, machine learning forms the foundation of smart bio-energy plants that are more efficient, adaptive, and environmentally responsible. Future progress will depend on robust data acquisition, model generalization across diverse feedstocks, and the adoption of hybrid and uncertainty-aware frameworks. Overall, machine learning emerges as a practical decision-support technology for enabling resilient, low-emission, and sustainable bio-energy systems at industrial scale.

Author Contributions

Conceptualization and study design were performed by **Sonali Shrikant Patil** and **Anant Sidhappa Kurhade**, who defined the research objectives, scope, and overall review framework for machine learning applications in bio-energy systems. Literature survey, data collection, and synthesis of recent research on syngas quality prediction, biofuel stability, and emission control were carried out by **Sonali Shrikant Patil, Snehal Mayur Banarase, Dinesh Keloth Kaithari**, and **N. Bharathiraja**. Methodological analysis, interpretation of machine learning models, and preparation of technical tables and conceptual figures were completed by **Santosh Bhauso Takale, Pratik V. Lepse, Pushparaj Sunil Warke**, and **Muralidhar Ingale**. Draft manuscript preparation and structured technical writing were undertaken by **Sonali Shrikant Patil, Snehal Mayur Banarase, and Pushparaj Sunil Warke**. Critical review, validation of scientific content, and refinement of discussion and conclusions were conducted by **Anant Sidhappa Kurhade** and **N. Bharathiraja**. Supervision, project administration, and final approval of the manuscript for publication were provided by **Anant Sidhappa Kurhade** as the corresponding author. All authors reviewed, edited, and approved the final manuscript and accept responsibility for the integrity and accuracy of the work.

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Conflict of interest

The authors declare no conflict of interest

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